CHAPTER 4

Sensory and Consumer Approaches for Targeted Product Development in the Agro-Food Sector

Davide Giacalone
University of Southern Denmark, Odense, Denmark

Contents

Case Studies in the Traditional Food Sector
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WHAT IS SENSORY AND CONSUMER SCIENCE?

Successful innovation is vital for companies' survival and growth, yet it is well known that 75%–90% of new food and beverage products fail to meet their financial objectives, and are withdrawn from market within one year from launch (Köster and Mojet, 2012). There are of course many reasons behind this, but generally such high numbers show quite painfully the fact that most product developers devote considerable time and money to products that should have revealed their flaws at the moment of inception or early stages of development (Dijksterhuis, 2016).

The need to integrate sensory and consumer research in product development is an emerging trend in industries where consumer-driven innovation is important, particularly in the food and beverage sector. Sensory properties of food and beverages are key benefits that must cater to the target consumer's preferences and expectations, if repeat purchase, and hence market success, are to occur.

Sensory and consumer science is a multidisciplinary scientific area focusing on understanding how humans perceive and respond to food and beverages (as well as consumer products generally). It is a valuable tool throughout the new product development (NPD) process to understand how different ingredients, formulations, and processing parameters are reflected in the sensory profile of the products, and hence enables product developers to design products to meet the preferences of sensory-based consumer segments.

Sensory evaluation is usually defined as "a scientific method used to evoke, measure, analyse and interpret those responses to products as perceived through the senses of sight, smell, touch, taste, and hearing" (Stone and Sidel, 2004). At the onset of the field, sensory evaluation was mainly carried out by product specialists (e.g., wine tasters, perfumerists, brewmasters, etc.) upon whose expertise companies relied for guidance on product development and quality assurance. Recognizing the complexity of sensory evaluation and the large interindividual variability of human perception, modern sensory science has evolved to meet today's market challenges by adopting more robust approaches based on panel evaluations, and conducted following scientifically agreed standards. It comprises a wide portfolio of methods that are customarily divided into analytical methods to characterize the sensory properties of a product, and affective methods that measure consumers' acceptance or preference. In a product development context, the power of sensory science is perhaps most fully unlocked when sensory and consumer data are combined together, usually by means of multivariate statistical techniques, to uncover which sensory properties drive consumers' preferences, thereby enabling the design of products that deliver optimal benefits to their target group.

This chapter provides a brief walkthrough of sensory and consumer approaches that are particularly relevant in the NPD process. The first part takes an application perspective and reviews typical sensory projects, namely product reformulations, benchmarking, opportunity identification, preference mapping, consumer segmentation, and product optimization. The second part addresses the increasing need for integrating sensory and marketing approaches to NPD and how this can be achieved in practice. Finally, the chapter concludes with some considerations regarding the use of sensory approaches available for small and medium-sized companies (SMEs) in the food sector, a segment that has so far not taken full advantage of sensory evaluation in their NPD activities.

APPLICATIONS OF SENSORY/CONSUMER INSIGHTS IN NEW PRODUCT DEVELOPMENT

Reformulations and "Me-Too Products"

Although one intuitively associates NPD with developing of whole new products or product line extensions, a large number of NPD projects in the food and beverage domain actually consist of reformulating existing products. This is usually done in order to reduce costs (e.g., by replacing an ingredient with a less expensive one), comply with changing regulations, or increase the product value (e.g., reducing the salt content of a cheese product to increase its healthiness). It is possible that two products are different in terms of their physicochemical composition, but that this difference is not perceptible to humans. Product developers exploit this situation in reformulation projects by changing the product without the consumers noticing the difference. Hence, the central issue the product developers must face in reformulation projects is to benchmark the new version of the product with the original one, and make sure that they perform the same, lest they run the risk of alienating existing consumers.

A particular class of sensory methods known as "difference testing" is particularly relevant in product reformulation projects. Difference tests are designed to detect the degree of difference between two very similar products (O'Mahony, 2007). The simplest form of difference test consists in presenting assessors with two samples simultaneously and asking them to evaluate their differences. This can be done according to a predefined criterion (e.g., "choose the sweetest sample") or by simply asking assessors whether the samples are identical or not. The former variant is known as a paired comparison test (In the psychology field, this method is better known as a two-alternative forced choice (2-AFC)), whereas the latter is known as a same–different test. Choosing one or the other depends on the test objectives, in particular on whether the product developer is aware of the sensory attribute(s) which might have changed in the new product. In either case, the number of correct responses from the assessors is then compared to the expected results in the case of no differences, usually by means of a binomial test or a chi-squared test (the null hypothesis is that in the long run, if there is no difference between the two products, assessors will pick the two products an equal amount of times) to conclude whether the reformulation is different from the standard. If no significant differences are found, the product developer may assume that the new (cheaper, healthier) formulation may replace the existing one without loss of market share. For this assumption to be robust, however, it is important to manage the power of the test to minimize the chances of a false-negative result. Sample sizes in particular need to be large for the power to be high (80%–90%), and differences between test protocols need to be taken into account (Ennis, 1993).

A visual representation of some common difference-testing protocols is given in Fig. 4.1. A detailed discussion of these

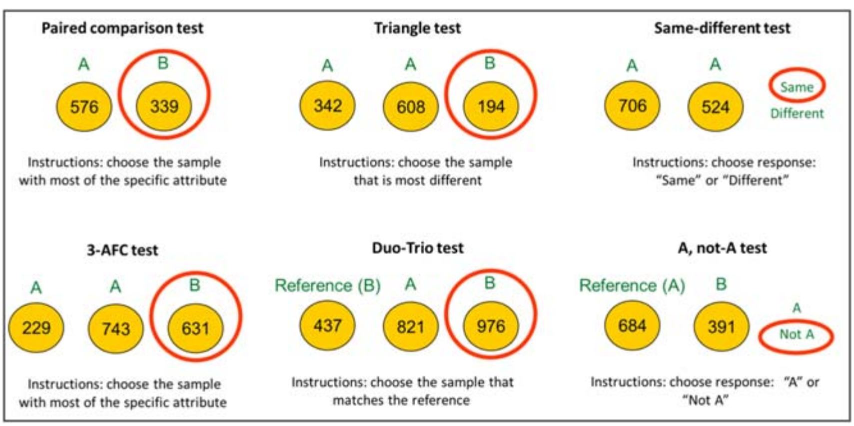


Figure 4.1 Schematic of some common discrimination testing methods.

methods is beyond the scope of this chapter but interested readers are referred to Lawless and Heymann (2010).

A related and very common type of NPD project, where difference testing is very useful, is when a company wants to copy a competitor's product that is doing well on the market to try stealing some of its market share. Here, difference testing enables the product developer to ascertain whether their product is sufficiently close from a sensory point of view to that of the competitor.

In some situations, rather than simply looking at the proportion of correct responses, it may be useful to quantify the degree of difference, and decide how much of a difference one would allow and still call the products "equivalent" from a sensory point of view. Traditionally this has been done by applying a correction for the guessing level to estimate the proportion of individuals who are actually able to detect a difference between the two products ("true discriminators") from that of those who performed the task correctly by guessing alone. This is done using a simple formula known as Abbot's formula (Lawless and Heymann, 2010):

$$C = D + P_G(N - D)$$

where P_C is the total number of correct answers, D is the number of true discriminators, and P_G is the guessing probability of the test.

Here is an example. A winemaker wants to develop a new "terroir" version of an existing wine by using indigenous yeast strains, but wants to know whether he can expect the same quality level and consistency achieved by using common yeasts. For this purpose, he develops two batches of wine, one of which he ferments using *Saccharomyces. cerevisiae* and the other using the new yeast strains (obviously both wines come from the same grape juice and there are no differences in winemaking parameters).

He conducts a triangle test ($P_G = 1/3$) with 30 assessors and 15 of them correctly identified the odd sample. This is enough to conclude that the two wines are different at $P < 0.05$. But how many of them could really detect a difference? Applying Abbot's formula to the present situation ($C = 15$, $N = 30$ and $P_G = 1/3$) and solving for D, we obtain that $5 = 2/3D$ and thus $D = 7.5$. That is, we estimate that around 25% of the people were actually able to taste a difference in the wine. Notice that this proportion of "true discriminators" is much lower than the total proportion of correct responses (15/30 or 50%).

The key message for the winemaker is that although there is a difference between the two wines, not everyone will be able to taste it. Actually, according to the data most people (75%) won't. They can then decide, based on this information, whether they want to go ahead with the new version using the indigenous yeasts, or stick to the current product.

Ultimately, it is up to the product developers to make a call on how much of a difference is important, depending on the context of application. Lawless and Heymann (2010) suggest taking into account the type of consumers and the type of product when formulating decision rules. For example, for products with a high inherent degree of variability, such as wine, larger differences may be tolerated, than in categories where consistency is a must. Likewise, very frequent/loyal product users can be expected to be sensitive to even very small differences compared to less frequent consumers.

Estimating the size of sensory differences can also be done for example using Thurstonian probabilistic approaches (Ennis, 1993), a class of mathematical models that link the proportion of correct responses in a difference test to the magnitude of the underlying sensory difference between the two products, taking into account the specific cognitive strategies required by the different test protocols. One of the main advantages of

Thurstonian modeling, over the proportion of discriminators approach, is that it provides an estimate of the sensory difference that is independent of the test protocol considered, and therefore makes it easier to compare results across different methods. This approach has substantially increased in popularity in recent years, and indeed many of the models that are helpful in the context of NPD make use of Thurstonian estimates to quantify differences between products (see Delwiche (2007) for a comprehensive introduction to the topic).

Sensory Profiling and Category Benchmarking

When moving from reformulation to actual new products and product lines, one of the first step the product developer does is to scan the market space to see what is "out there." This process is known as category benchmarking, and sensory methodologies play an important role here in identifying key sensory attributes associated with different products. The class of sensory tests that is most useful in this situation is known as descriptive analysis (DA) or simply sensory profiling (Lawless and Heymann, 2010). DA is traditionally carried out with a small panel (8–12) of expert assessors who have been screened for desired characteristics (sensory acuity, familiarity with the product, availability, etc.) and have been thoroughly familiarized with the target product categories and with the test procedures. In its most classical form, DA requires assessors to evaluate a range of products on a series of sensory attributes using intensity scales. The assessors typically receive some training aimed at developing a standardized sensory lexicon (e.g., through the use of standard reference material), so that there is no ambiguity as to what each attribute actually means, and at using the scale consistently so that assessors also learn to quantify the sensory attributes consistently ("calibrating" the panel). The goal of DA is to profile a product on all of its perceived sensory characteristics so in principle assessors may rate products on all sensory modalities (e.g., appearance, sound, aroma, taste, texture, and flavor). Sometimes only a subset of sensory modality is considered (e.g., texture and flavor), for instance if differences in the other sensory modalities are trivial or irrelevant to the test objectives.

Several types of analyses can be done on these data. In product category benchmarking, one of the most important outputs would be in the form of perceptual maps that characterize the main differences between current offerings in the market. These are obtained by multivariate data analysis techniques, e.g., principal component analysis (PCA), that reduce the DA data to a low-dimensional (usually 2D) space, thereby allowing a convenient visualization of perceived similarities and differences between the focal products. Additionally, it is also possible to project on the same planes vectors corresponding to the individual sensory attributes, so that the sensory attributes responsible for these differences can be identified.

As an example, Fig. 4.2 reports an example from a study of 18 extra-virgin olive oils (EVOOs) from the Campania region in Italy (Lauri et al., 2013), analyzed by PCA. The differences and similarities between the products are shown in Fig. 4.2A. The interpretation of this perceptual map is straightforward: products that appear closer to each other have similar sensory characteristics, whereas products far apart have different sensory characteristics. Fig. 4.2B shows the sensory attributes underlying these differences.

DA is one of the most powerful tools used in sensory analysis, and is extensively used in the food industry to guide NPD, but also for other important applications such as tracking product changes over time to determine shelf-life and/or to understand packaging effects, to investigate the effects of ingredients or processing parameters on the final sensory quality of a product. DA is known to produce valid and robust results, as documented by numerous publications (Murray

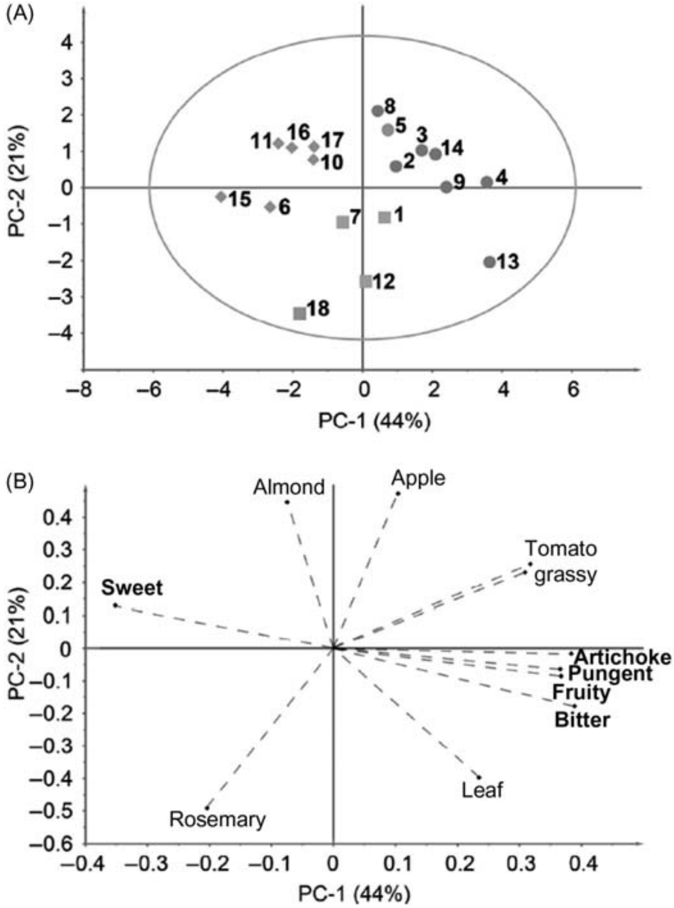


Figure 4.2 Example of a perceptual map obtained from DA data for a sample of 18 EVOOs from Campania, Italy (Lauri et al., 2013). The plots show the first two principal components from a PCA model. Products (numbered 1−18) are shown in (A) and attributes in (B). The horizontal axis represents the direction of maximum difference between the products and accounts for 44% of the variance in the data. Looking at the plot from left to right, the model shows that the main differences between the products is between *sweet* EVOOs (e.g., 15, 11, and 6) and *bitter* EVOOs that are also high in sensory characteristics *artichoke flavor*, *pungency*, and *fruitiness* (e.g., 13 and 4). The vertical axis represents the second PCA component and accounts for an additional 21% of the sensory differences between the EVOOs. This component explains differences in odor quality and separates EVOOs high in *apple* and *almond* flavors (e.g., 8) from oils characterized by a flavor of *rosemary* (18 and 12). *Reprinted with permission from Lauri, I., Pagano, B., Malmendal, A., Sacchi, R., Novellino, E., Randazzo, A., 2013. Application of the magnetic tongue to the sensory evaluation of extra virgin olive oil. Food Chem. 140, 692−699.*

et al., 2001). The only drawback of DA is that it is relatively costly and labor intensive, which limits its application in small and medium-sized (SMEs) food producers (Giacalone et al., 2013a,b). Several alternatives to classical DA exist, however, that can produce valid results with a relatively minor loss in precision. I shall return to this issue later in the chapter and discuss recent developments in the field that have opened up significant new opportunities to SMEs.

Preference Mapping, Segmentation, and Opportunity Identification

One of the most powerful sensory applications in NPD is in linking product sensory information to consumer preferences. As mentioned earlier, the former are usually (though not always) obtained from a trained panel, whereas the latter should always be obtained from a representative sample of the target consumer population. In this type of sensory test, consumers evaluate and are asked to indicate their preferences for a pair of products, or to rank a set of products from most to least preferred. A common alternative to this, especially when evaluating a larger number of products, is to have consumers evaluate products individually, and indicate their degree of liking or disliking for each product using so-called "hedonic" scales. Several such scales are available, the most widely used being the nine-point hedonic scale (Peryam and Pilgrim, 1957). Typically, food companies set action standards on the basis of preference or acceptance data. For example, a decision to go forward with a new product project can be based on the proportion of consumers ticking the top two boxes in a nine-point hedonic scale, or the acceptability score being higher than a certain cut-off point.

If both sensory and consumer preference data on the same products are available, these two data matrices can be related by means of multivariate statistical techniques to uncover which sensory properties drive consumers' preferences, thereby enabling the design of products that deliver optimal benefits to their target group.

Let us consider an example from the dairy industry. Frøst (2006) investigated consumer preferences ($N = 81$) for nine vanilla yogurts developed according to an experimental design to vary in protein content, sucrose content, and vanilla flavor concentration. A sensory characterization of the same samples was obtained separately by a trained panel, and the two datasets were then related to obtain a preference map. Fig. 4.3 shows the main output from a preference mapping analysis, namely interperceived product differences (Fig. 4.3A) and the relationship between the different product attributes and consumer liking scores for the yogurts (Fig. 4.3B).

Preference mapping plots are easy to interpret. The direction of each consumer vector represents the direction of increasing liking for each individual consumer. The length of the vector is directly proportional to the amount of variance explained by the first two preference dimensions for each consumer. In this yogurt example, the majority of consumers are located on the left side of the preference map (Fig. 4.3) in the direction defined by products H, I, and D. These products are characterized by high sucrose content and vanilla flavor concentration. Accordingly, Fig. 4.3B shows that attributes associated with these products are *sweetness* and *vanilla flavor* intensity, as well as *creaminess*, *smoothness*, and *caramel flavor*. These attributes may be considered "drivers of liking" for the consumers who are located in the corresponding area of the plot. Nevertheless, Fig. 4.3B also shows that there are also some groups of consumers who exhibit quite different preferences patterns from this group. In particular, there seem to be a segment of consumers with high liking for yogurts with fatty mouthfeel and coconut flavor, which are positively loaded on the second component (upper part of the plot in Fig. 4.3B),

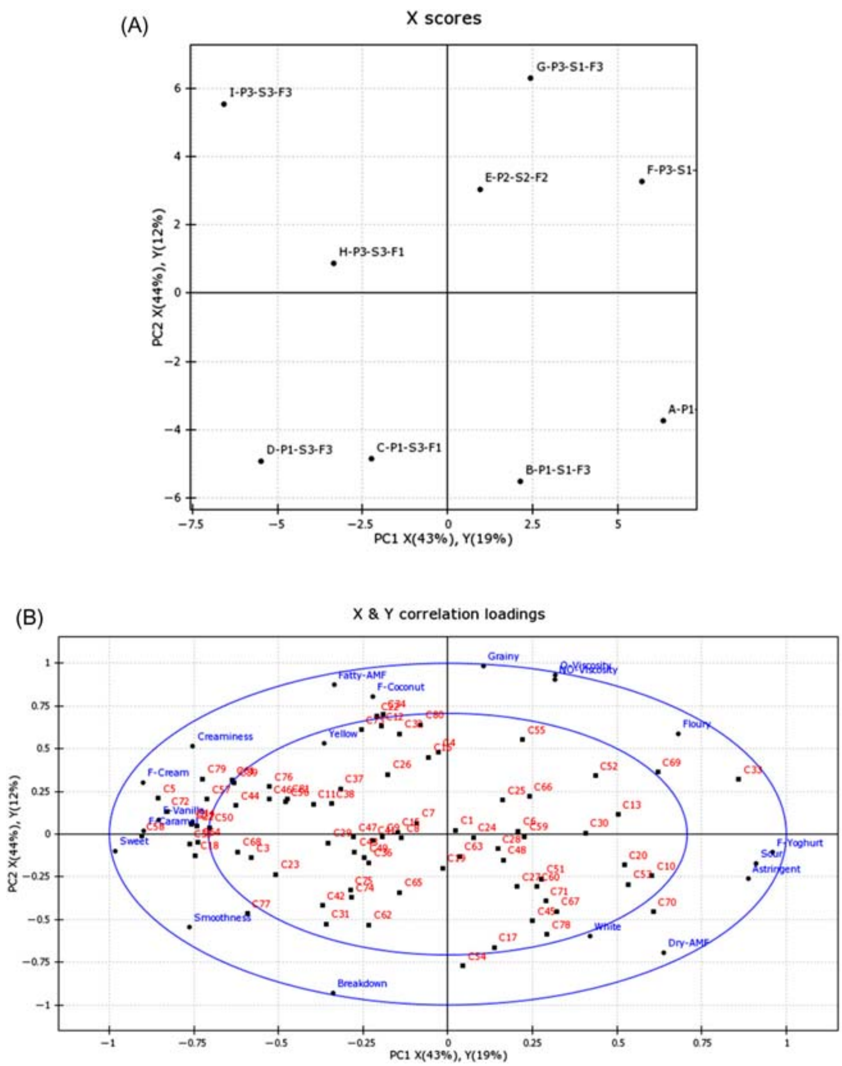


Figure 4.3 Preference mapping for a set of vanilla yogurt. (A) The interperceived product differences and (B) the correlation between the intensity of different product attributes and the preference patterns of the individual consumers. The model is based on principal component regression using the sensory profiling data as predictor matrix and consumer preferences as response. This is referred to as "external" preference mapping in the field (MacFie, 2007). *Data from Frøst, M.B., 2006. Liking and exposure: first, second, and tenth time around. Physiol. Behav. 89, 47–52.*

and a more sizeable segment of consumers who prefer products characterized by whiteness and dry mouthfeel like product B. Very few consumer vectors are positively loaded on the first component, which is associated with the low-sugar, low-protein samples (A and F). This means consumers generally disliked these products which were characterized as high in the attributes *sour*, *astringent*, and *yogurt flavor* (Fig. 4.3B). An exception is consumer "33" (possibly a sour yogurt aficionado), who is extremely fond of products with these characteristics.

This example shows nicely the reason for fitting vectors to individual consumers, as opposed to simply considering average hedonic response: even within the simplest product category, consumers often exhibit quite different heterogeneity in their preference. Capturing this heterogeneity analytically is extremely important to give an accurate representation of the data: averaged values can be very misleading if one is dealing with, say, a bimodal distribution of hedonic responses where people either love or hate a product (a common situation in preference tests). Moreover, understanding systematic variation in sensory preferences enables developers to segment the consumer populations into distinct clusters characterized by similar preferences in terms of sensory characteristics, and thus allow for product differentiation by developing products that cater to the tastes of different consumer segments.

In its common form, preference mapping relies on linear modeling of the relationships between sensory and preference data, which assumes that consumers' preferences either decrease or increase with increasing intensity of any specific attribute (e.g., if a consumer likes sweetness in vanilla yogurts, their liking for the product will increase with increasing intensity of sweetness). This is often a reasonable assumption within the condition tested. However, if the span in the sensory space is sufficiently large, a more reasonable assumption is that consumers will like an attribute until a certain "optimal" intensity, after which an increase in the intensity of that attribute will start to impact liking negatively. If that is the case, more advanced modeling based on second-degree polynomial regression approaches can be applied to the data, in order to identify such "ideal points" on the map. McEwan (1996) provides a comprehensive overview of the different modeling approaches available to the sensory analyst.

In practice, product developers can use ideal point modeling results to guide the formulation of a new product (or a reformulation of an existing one, of course) towards the optimum. Once the new product has been created and evaluated (e.g., by a DA panel), the results can be "plugged" in the IPM space to obtain a preference prediction and, usually after a few iterations, obtain a near "optimal" product (Thomson, 2008). Occasionally, the experimenter may find that the ideal point is located in an area of the map not covered by a product. If that happens, preference mapping can become a useful tool to identify new opportunities for NPD.

Let us note here that preference mapping is a flexible framework with regards to the input data. For example, it is often of interest to include physicochemical data on the products in the predictor matrix (in addition to the sensory data or as a standalone), especially if the product set is chosen according to an experimental design. Likewise, the response matrix can consist of other variables than liking, such as willingness to pay for the products, purchase likelihood, stated interest, etc. Additionally, there are a number of useful extensions to the classical preference mapping approach in situations where one wants to combine more than two data blocks, such as when one wants to relate preference data, not only to product characteristics, but also to the background of the consumers. The latter is usually an attractive concept to marketing personnel who are typically very interested in knowing whether preference clusters correspond to any specific consumer types in terms of sociodemographic (e.g., age, gender) or behavioral (e.g., frequency of product usage) characteristics. For a preference mapping application, readers can refer to Giacalone et al. (2013a), where the technique is used to model consumer preferences for a set of craft beers from sensory product characteristics and consumer background characteristics simultaneously.

Product Optimization

Once an opportunity window has been identified, it is necessary to develop a product formulation that can deliver on that. As we have seen, preference mapping gives some indications on the attributes that are most associated with consumer preferences, as well as suitable regions for introducing new products. However, more accurate methods are usually needed to narrow the focus and identify optimal prototypes. This section discusses two methods that are particularly relevant in the product optimization phase: just-about-right scales (JAR) and response surface methodology (RSM).

JAR are an often-used instrument in product optimization studies. In this type of test the product developer asks a consumer to evaluate a product on specific attributes. In particular the consumer is asked to evaluate if the amount of a specific sensory attribute (e.g., sweetness) in a product is "too much," "not enough," or "just about right". This is usually done with 3 or 5-point scales where the middle point represents the JAR level. The results of this type of evaluation are usually analyzed by plotting the distribution of responses for the various options of the scale. An example of JAR results for two hypothetical products is shown in Fig. 4.4.

Here, a symmetric distribution centered around the JAR level would be a desirable outcome, whereas a skewed distribution would indicate that improvements are needed. For example, one of the products in Fig. 4.4 was rated as having not enough of that attribute by 55% of the respondents. Let's

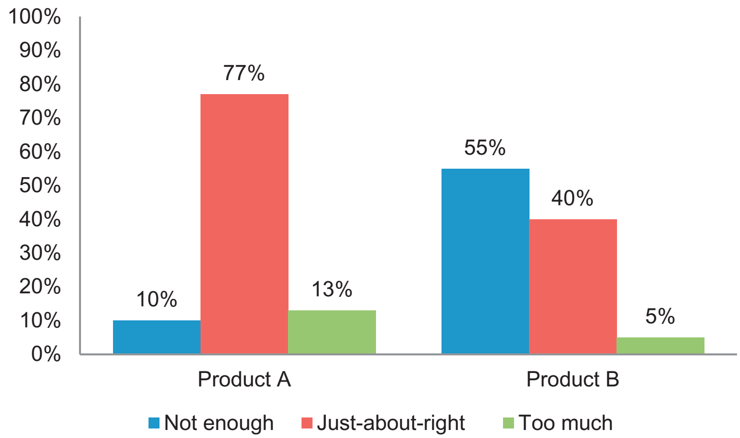


Figure 4.4 Hypothetical distribution of JAR responses for two products showing a normal distribution (Product A), indicating an optimal intensity of that attribute, and a skewed distribution (Product B), indicating needs for improvement in that attribute.

say that attribute were "salty" and the product developer assumed that saltiness is an important driver of liking. If that is the case, the product developer would most likely increase the salt content in the product prior to subsequent testing.

In this way, JAR scales provide direct guidance as to which product attributes are at an optimal level, and if not, in which direction to orient the product reformulation. This makes them a popular instrument among product developers, and also the potential clients to whom the results should be communicated.

Additional insights can be obtained when JAR scales are combined with hedonic assessment of the products collected in the same questionnaire. If that is the case, the potential impact of deviations from the JAR level on consumer liking can be estimated. This is done through a simple procedure called "penalty analysis," which consists in separating the data into groups below, above, and at JAR levels, and in calculating mean product acceptability for each of the groups. The mean of the

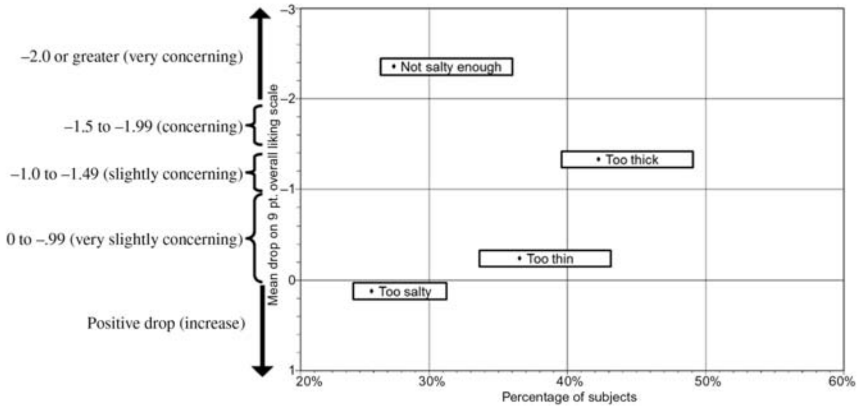


Figure 4.5 Penalty analysis showing the influence on liking of deviation from JAR. The abscissa represents the percentage of respondents that ticked that particular box and the ordinate the mean drop in liking for those respondent that ticked that box. In this plot, two hypothetical product attributes are represented. Product optimization efforts would typically prioritize attributes that have the largest impact on liking.

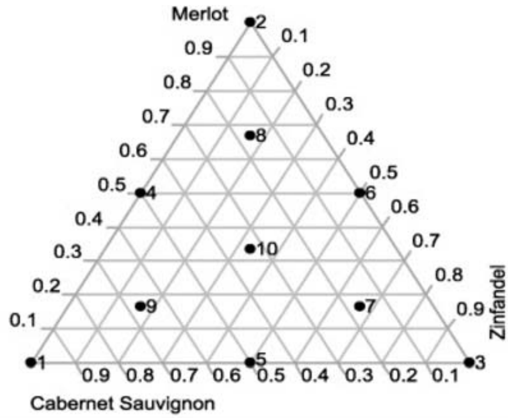
non-JAR groups is then subtracted from the mean of the JAR group. The resulting difference represents the drop in liking when the attribute is not JAR. This process is exemplified visually in Fig. 4.5, where the mean drop in liking is plotted against the percentage of consumers that fell into each category. This type of plotting can be very useful for product developers also to assess which attributes to prioritize in further optimization effort, as one would in principle want to focus on attributes that cause the largest reduction in acceptability score.

JAR scales are especially useful in situations where only one or a few products or prototypes are being tested and/or in which product attributes cannot be varied systematically. The possible drawback of this technique is that it assumes that consumers correctly understand the meaning of the attributes, and also that they actually carry out ideals about their desired optimal intensity. Both of these are strong assumptions that may not always hold in reality.

A more robust strategy is to employ an experimental design with systematic variation around key product attributes, and to estimate the optimal combination from the data. A common approach in food science is to use response surface methodology (Giovanni, 1983), a statistical approach that models the relations existing among some controlled experimental factors and observed results of one or more selected criteria. In sensory-based optimization, the factors are usually ingredient levels, for which upper and lower limits are established, and which are then systematically varied to create products to test. This is done according to a full design, though more often fractional factorial designs are used to reduce the number of combinations and make the test less cumbersome. The statistical basis of RSM is usually a polynomial regression model with either a sensory attribute or consumer liking as a dependent variable, and the ingredient levels (linear, quadratic, and their interactions) as predictors.

As an example, let us look at an application where this approach was used to optimize blended red wines made from Cabernet Sauvignon, Merlot and Zinfandel cultivars for consumer acceptability (Dooley et al., 2012). Since in this case the factors were relative proportions of a blend, a mixture design (Arteaga et al., 1994) was used to select a subset of wine blends (Fig. 4.6), which was subsequently tested with a consumer group ($N = 108$) that evaluated them using the nine-point hedonic scale.

The predictive models were created by regressing the individual liking scores. The response surface methodology assessments of these models are displayed in Fig. 4.7A, B, where the plots show the areas in the experimental space which maximize consumer liking (consumers were split into two clusters prior to this analysis since their preferences were quite heterogeneous). Based on the models, the optimized wine blends identified were 68% Cabernet + 26% Merlot + 6%



Treatment	Cabernet Sauvignon	Merlot	Zinfandel
1	100%	0	0
2	0	100%	0
3	0	0	100%
4	50%	50%	0
5	50%	0	50%
6	0	50%	50%
7	17%	17%	67%
8	17%	67%	17%
9	67%	17%	17%
10	33%	33%	33%

Figure 4.6 Example of application of response surface methodology to product optimization. The plot shows the mixture design used for selecting the set of wine blends for consumer testing. *Reprinted with permission from Dooley, L., Threfall, R.T., Meulleunet, J.F., 2012. Optimization of blended wine quality through maximization of consumer liking. Food Qual. Prefer. 24, 40–47.*

Zinfandel for the first segment (Fig. 4.7A, $N = 60$), and 27% Cabernet + 2% Merlot + 71% Zinfandel for the second segment (Fig. 4.7B, $N = 48$).

It should be noticed here that RSM is a flexible approach and that many optimization criteria are possible. Rather than maximizing consumer liking, an identical modeling approach could be made by using production costs as a dependent variable, and using cost minimization as optimization criteria. One limit of this methodology is that, in its basic form, it does not allow to simultaneously estimate optimal product

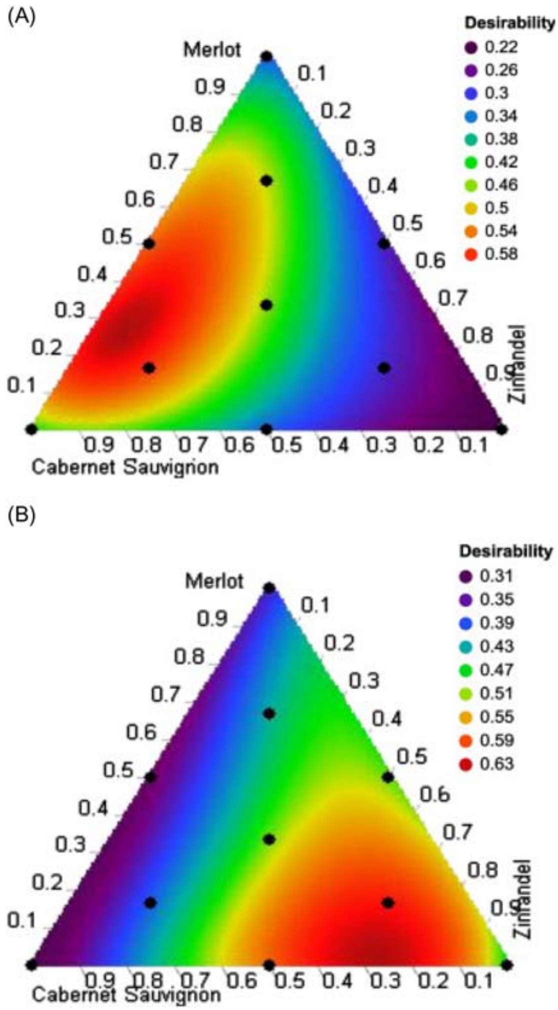


Figure 4.7 Location of highest consumer liking and optimized wine blends for two consumer segments (A and B). Their liking ratings were transformed using a desirability conversion formula where the lowest value (0 on a nine-point scale) corresponds to a desirability value of 0.0, the middle value (each consumer's mean value across all samples) corresponds to 0.5 desirability, and the upper value (9 on a nine-point scale) corresponds to a desirability of 1.0. *Reprinted with permission from Dooley, L., Threfall, R.T., Meulleunet, J.F., 2012. Optimization of blended wine quality through maximization of consumer liking. Food Qual. Prefer. 24, 40–47.*

spaces for more than one criterion at the same time. Extensions that enable optimization on multiple criteria exist (Khuni and Mukhopadhyay, 2010), but in this author's experience their application in food product development is not widespread.

CURRENT TRENDS IN SENSORY AND CONSUMER SCIENCE

Sensory and consumer science is currently a very dynamic field, evolving to meet the needs of industry and the inputs from its related disciplines. Current emerging trends in the field reflect the challenges of continuing successful innovation in a global industry, coping with the ever-changing demands of today's consumers, and helping societies solve diet-related challenges. The remainder of the section focuses on recent developments in the field. The next two sections discuss the increasing involvement of consumers in sensory-related tasks and the change in focus from simple taste or sip tests in blind conditions to more realistic assessments of the product experience. These two trends are currently very strong and have fostered a much-needed collaboration with other fields working within food innovation. The closing section focuses on how SMEs in the agro-food sector can take advantage of sensory and consumer science, as well as recent developments that may open new opportunities for them.

The Blurring Line Between Sensory and Consumer Science

As product innovation becomes faster, sensory and consumer, time and resources constraints require that sensory information is delivered ever more quickly during the development process. While classical sensory approaches are known to produce detailed, robust and repeatable results, they also have certain drawbacks. This is particularly the case for DA, which is a very slow method—particularly because of the extended training phase, as well as a costly one—maintaining a sensory panel is (usually) not affordable for SMEs in the food industry, and can be a significant spending also for large companies. Moreover, the traditional reliance on expert panels has been challenged in recent years also in view of the risk that trained assessors may experience the product differently from the final consumers, or that they focus on sensory characteristics that may be irrelevant for the latter (Ares, 2015), providing high-quality results but with limited external validity.

In order to address these drawbacks, a number of alternative descriptive methodologies have been proposed over the years, most of which require little or no training and are easily implementable with trained panelists or consumers alike. Although the idea that consumers can be used for descriptive tasks has traditionally been highly controversial, it is increasingly accepted due to mounting evidence that, under appropriate conditions, consumers are capable of providing valid and meaningful sensory product information (Ares and Varela, In press).

This has sparked the developments of new rapid methods for product profiling, such as projective mapping (Risvik et al., 1994; Pagès, 2005), flash profiling (Dairou and Sieffermann, 2002), check-all-that-apply questions (Adams et al., 2007), and polarized sensory positioning (Teillet et al., 2010). Consumer panels and/or panels of company employees are increasingly being used for such methods which, if used appropriately, represent significant savings in terms of time, cost, and resources over traditional methods employing trained panels. The savings are primarily realized by bypassing the extensive training phase that characterizes DA and that are needed to calibrate the panel with regards to attributes and the use of scales. On the contrary, rapid methods do not require scaling (e.g., flash profiling) or even bypass the use of attributes altogether in favor of nonverbal assessment (e.g., projective mapping). Although there are clear trade-offs in terms of sensitivity and reliability, for a wide range of applications rapid methods may represent a good compromise. A significant amount of research is currently investigating methodological aspects of rapid methods, in order to validate them and develop best practice for their use in different applications. For an introduction to rapid sensory methods and the current issues in this line of research, the reader is referred to Ares (2015).

Integrating Sensory and Nonsensory Attributes in Product Development

As we have seen, sensory-driven product development has traditionally be oriented towards maximizing sensory acceptability of food and beverages. Accordingly, measures such as the nine-point hedonic scale and purchase intent scales are used routinely in consumer testing of foods, but unfortunately they are relatively poor predictors of repeat purchase in the marketplace. Most importantly, although sensory aspects of food products are very important during the actual consumption (i.e., postpurchase), the product needs to be purchased in the first place. It is therefore important that marketers and product developers jointly work to ensure that NPD decisions are taken with a focus on product performance that goes beyond eating quality. As a result, sensory and consumer scientists have broadened their set of product performance indicators to get a better grasp of consumers' experience with food. Some of these measures are related to the product usage, wellbeing, and emotion associated with consuming food and beverages.

An important aspect that is often considered during the NPD process situation is how different products perform in the target consumption situation(s). Situational appropriateness of products is an important complement to preference testing (Schutz, 1994), in recognition of the fact that foods and beverages are often chosen in response to a particular situation, and that product acceptability in an absolute sense may be a relatively poor predictor of real-life food choices. For example, a consumer may highly appreciate a very complex wine when fine dining, but the same individual would be unlikely to choose it for a routine meal or a picnic. For this reason, incorporating measures of situational appropriateness during product testing is increasingly advocated during consumer product testing, either by recreating realistic consumption situations (e.g., Di Monaco et al., 2014), or by asking consumers to rate the appropriateness of the target product for a series of relevant situations in conjunction with acceptability ratings (Schutz, 1994). The end-goal here is to ensure that the product has not only high acceptability, but also high appropriateness for the consumption context that it is intended for.

Situational appropriateness is especially important when dealing with very novel food and beverage products, because in such cases consumers may find it hard to envisage how to incorporate them in their existing dietary habits, since they cannot rely on memory of previous consumption experiences (Giacalone et al., 2015; Giacalone and Jaeger, 2016). This aspect may be particularly pressing for many small-scale producers working with local ingredients, as their products often have sensory properties unfamiliar to many consumers (Geertsen et al., 2016).

Targeted retail strategies (e.g., placing products thematically) as well as extrinsic product aspects (e.g., using the packaging to display possible usages or culinary applications) can be of great help in helping consumers "understand" the intended product usage and should be given attention during product development.

Emotional responses are another important nonsensory product performance aspect, which have actually become a prominent area of research due to the increasing emotional marketing of food. Examples include a chocolate product that, in addition to tasting great, also makes the consumer feel more loved and comforted, or a beer being consumed as a refreshing beverage but that also increases feeling of outwardness and conviviality in the drinker. Basically, food innovation has shifted the focus from selling a product to selling an experience. Accordingly, there is an increasing interest in understanding how sensory product aspects of foods and beverages relate to the emotions experienced during consumption, so that food products can be designed to deliver the desired emotional benefits.

To address this, quantitative questionnaires for measuring emotional responses to food products have been proposed, many of which originate from within commercial R&D professionals. Examples include the EsSense profile (King and Meiselman, 2010), EmoSemio (Spinelli et al., 2014), and ScentMove (Porcherot et al., 2010), among others. This line of research (for a recent review, see Cardello and Jaeger, 2016) has provided substantial evidence that products that are equally liked from a sensory point of view, may differ substantially in their emotional profile. Thus, emotions might help understand why acceptance data might not always predict market success. Although further research is needed to elucidate how exactly emotions are related to consumer marketplace behavior, there is increasing consensus that emotion measurement provides an additional benchmark for product development. Sensory properties are recognized as part of the brand and many companies actively try to leverage and protect their intellectual property in this area through patenting and trademarking (e.g., Kellogg's owns a patent on the distinct "crunch" of their cornflakes, just as they own the recipe and logo). Accordingly, it has also been pointed out that emotional responses to the product itself should also be in line to those engendered by other product elements such as brand and packaging. The work of David Thomson, for example, shows how to maximize the emotional consonance between product and brand in the context of product development and optimization, and even suggest that sensory product optimization should aim at maximizing product–brand consonance, rather than liking (Thomson, 2008; Thomson and Crocker, 2014a, 2014b).

With respect to the latter aspect, substantial evidence has been recently gathered that extrinsic elements, such as the packaging, can exert a multitude of subliminal influences on the perceived sensory quality of foods of beverages. For example, research by Charles Spence and colleagues has demonstrated that identical strawberry desserts will taste 10% sweeter when eaten from a white container than a black container (Spence, 2013), that wine from a heavier bottle is perceived as having a more intense smell and as being of higher quality (Piqueras-Fiszman and Spence, 2012), and that many consumers are unable to correctly name the flavor of familiar potato chips if eaten from an unfamiliar package (Piqueras-Fiszman and Spence, 2011). In the food industry, the main responsibility for the actual product development is usually within R&D departments, whereas the marketing department is usually in charge for the extrinsic aspects (packaging, labeling, etc.). Given the ubiquitous nature of these multisensory interactions between extrinsic and intrinsic product properties, it seems no longer that the first time consumers evaluate a product in its entirety is actually when the product hits the market shelves. This state of affairs is currently being challenged and at present there is a trend towards a closer integration of sensory and marketing methods in NPD.

How SMEs in the Traditional Food Sectors Can Take Advantage of Sensory and Consumer Methods in Their NPD Activities (and Why They Should)

Given the costs and expertise involved in running sensory and consumer tests, their full exploitation in product development has mostly been a prerogative of large food companies. Small and medium-sized companies, on the other hand, do not usually have access to classical sensory analysis. This need not be the case, however. In particular, the development of rapid sensory methods (see above) has opened up opportunities to carry out robust assessment on early product formulations using, e.g., the company's own employees or small consumer samples. Some rapid sensory methods are very useful in early stages to make sure the product actually delivers on the vision of the product developers. For example, Giacalone et al. (2013a,b) developed guidelines for the application of rapid methods in the world of traditional Danish microbreweries, an industry niche characterized by high competitiveness and an approach to product development that is mostly driven by the subjective views of the brewmaster or product developer. When a product development project starts, the first issue is the design of the brew, such as deciding the brewing style, and then the formulation, i.e., studying the type and quantity of raw materials and the effect of processing. At this stage, the pilot plant can be used to develop initial prototypes that may be evaluated by a rapid sensory method, together with existing products or similar in-market alternatives, to obtain a coarse description of the product space and a summarized description of the underlying sensory dimensions. Projective mapping (Pagès, 2005) is, for example, a method that can be applied to this end. Giacalone and colleagues (Giacalone et al., 2013b, 2016) demonstrate the feasibility of this method for beer evaluation even with untrained subjects. If one is sufficiently acquainted with the method, such a test can be fairly easily arranged for example with available coworkers: a good solution since they will be relatively more expert in the product and will be acquainted with the method. In the work by Giacalone et al. (2013a,b), such a test was used for rapid product screening, to gather feedback on the product and process specifications, and/or for vocabulary generation. In addition, it may serve to document the sensory outcome of experimental brews in a systematic manner.

Once a subset of most interesting prototypes has been selected, a larger-scale consumer test can be conducted to obtain a more precise characterization, for example using CATA questions (Adams et al., 2007). The speed and ease of the CATA method make it perfect for these types of evaluation. Further, CATA can be easily combined with hedonic testing, allowing for concurrent collection of sensory responses and information about consumer acceptability. CATA insights can then be used for optimization purposes, i.e., to check that the prototype(s) have indeed the desired sensory characteristics and revise the formulation accordingly. Geertsen et al. (2016) adopted this approach on product development of juices of sea-buckthorn (*Hippophae rhamnoides* L.) berries, a berry indigenous to the Nordic region, in combination with other locally sourced ingredients. The adopted approach effectively differentiated between SBBs and provided insights with regards to the most promising prototypes and could, therefore, be beneficially applied to support product development efforts among other food SMEs.

At the moment, the knowledge and the need for specialized software needed to carry out sensory tests represents a clear bottleneck. The development of free user-oriented tools, where key information may be obtained as easy-to-interpret plots with minimal user input could give a real boost towards more widespread applications of these methodologies among SMEs.

Collaborations with universities and other knowledge providers also have an important role to play. As an example, some years ago I was involved with colleagues from the University of Copenhagen in developing a short course aimed at professionals working with product development in food and beverage SMEs. The purpose was to teach them how to use fast sensory methods in their product development activities. In the teaching situation we used short animations to teach about the data analysis at a conceptual level. The considerations regarding data analysis have been how to make it operational and simple to use for laymen. The course is now offered regularly at the University of Copenhagen and the reception from the participants has been overwhelmingly positive.

The strategic relevance of sensory and consumer science as a tool for SMEs has been also increasingly recognized by funding agencies. At the time of writing, an important EU-funded project—the INNSENS project (www.innsens.eu)—is being carried out by a European consortium, where the main objective is to provide European SMEs with abilities and competencies that will help them in the process of new product development by means of adequate application of sensory and consumer research. The main outcome of the project INNSENS is a European Commission-funded project aimed at creating an innovative and efficient e-learning training program in Sensory Analysis and Consumer Sciences, specifically designed for small and medium-sized enterprises (SMEs) in the food and drink sector. The training program will be based on an extensive exploration of the needs of SME professionals in several EU countries. Initial results indicate great interest for a potential course. Some of the most interesting topics according to the SMEs were: application of sensory and consumer science in product development, how to plan a sensory study, sensory shelf-life, and rapid sensory methods (Norman and Widen, 2015). The course content has been developed and translated into the different languages represented in the projects. It is now being piloted by 50 European SMEs, with a public release to be expected in the near future.

CONCLUSIONS

This chapter has provided a brief overview on the role of sensory and consumer approaches to product development. Sensory and consumer science is increasingly recognized as a key discipline for food and beverage producers, encompassing different tools for guiding and validating new product development. Hopefully, this chapter has helped readers to become more aware of how sensory and consumer research methods can help in quantifying product performance, and reach go/no go decisions at different stages of the NPD process.

The chapter also focused on current trends in the field that have the potential to widen the application of sensory and consumer science and foster collaborations with researchers in other fields interested in food product development. The question of what constitutes a meaningful measure of product performance is one of the central questions in sensory and consumer science today. The high rate of failure mentioned at the onset of the chapter is a painful reminder that this question is still very open. Still, sensory science has come a long way since its inception and has shifted its focus from simple taste or sip tests in blind conditions to more realistic assessments of the product experience. This move has brought sensory scientists closer to marketing and behavioral scientists in an interdisciplinary collaboration that is very much needed (Van Trijp and Schifferstein, 1995). As this integration is bound to continue in the years to come, we can look forward to better and more meaningful ways to predict product success.

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METHODOLOGICAL NOTES

Sensory Science

Sensory science is usually defined as the scientific discipline used to evoke, measure, analyze, and interpret human reactions to characteristics of foods and materials as they are perceived by the senses of sight, smell, touch, taste, and hearing. It is an interdisciplinary field drawing primarily on psychology, cognitive science, and statistics. As an applied field, the main focus of the sensory scientist has been the development of tools to make accurate and reproducible evaluation of food products using human assessors. Sensory scientific methods are usually divided into "analytical (or objective)" and "affective (or subjective)," depending on the goal and type of assessors (Prescott et al., 2014).

Difference Testing

Difference tests are blind product tests designed to uncover whether a sensory difference between two products exists. Difference testing has many uses in the food industry, such as gauging whether an overall difference is present between two products, estimating product shelf-life, and determining whether shifts in processing or ingredients have significantly changed an existing product. A common difference testing method is the triangle test, in which an assessor is presented with three samples of which one is different and two are alike, and is asked to indicate the odd one out of the three. After several trials, the number of correct responses is compared to the number one would expect just due to chance (e.g., in a triangle test, an assessor would get the answer right about 33% of the time even if they cannot taste a difference) to establish whether a "true" difference exist (Lawless and Heymann, 2010).

Sensory Descriptive Analysis

Sensory descriptive analysis (DA) is a method to generate a quantitative profile of a set of food products based on sensory attributes. DA is typically used to understand how different ingredients and processes affect the sensory quality of foods and beverages, e.g., in the context of product development and category benchmarking. Broadly defined, the DA process consists of (1) recruitment of a panel of assessors (8–12), (2) generation of sensory attributes relevant to describing the products, (3) concept alignment with regards to the meaning of the attributes, (4) calibration of the panel with respect to attribute intensity scaling, (5) evaluation of the products, usually with at least two separate evaluations, and (6) statistical analysis of the data collected (Lawless and Heymann, 2010).

Principal Component Analysis (PCA)

Principal component analysis (PCA) is a mathematical method to reduce the dimensionality of a data table. PCA is especially useful for handling large data tables where a set of observations (e.g., food products) are measured on several variables (e.g., sensory attributes, chemical composition, etc.). One may look at individual variables and samples, but this is not very efficient where there are many variables, and also any covariation with other variables would not be observed, which may lead to important patterns being ignored. PCA is a technique that replaces the original variables with a lower number of variables called "principal components." These principal components are defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is uncorrelated to the preceding components. PCA results are usually explored using plots that enable an efficient visualization of the tables. The most important plots come in the form of "scores" and "loadings" representing, respectively, the positions of the original observations on each principal component, and the correlation of each of the original variables with each principal component (Bro and Smilde, 2014).

Preference Mapping

Preference mapping defines a group of multivariate statistical techniques designed to model and visualize consumer preferences for a set of target products. The goal of such analysis is to develop a deeper understanding of consumer preferences than what would be obtained by, e.g., simply considering mean product ratings. Preference mapping can be used to assist the product developer in segmenting consumers, understanding which product attributes are related to consumer preferences, and optimizing product in order to maximize liking (MacFie, 2007).

Response Surface Methodology

Response surface methodology (RSM) is a statistical method to model the relationships between several explanatory variables and one or more response variables. The main idea of RSM is to use a designed experiment with systematic variation around key factors (e.g., ingredient contents in a food proportion) to obtain an optimal response. Statistical approaches such as RSM can be employed to optimize food products towards maximizing a relevant response variable, such as consumer liking or willingness to pay (Giovanni, 1983).

Rapid Sensory Methods

There has recently been significant development in the methods used to capture sensory response to food products. Rapid sensory methods represent a set of techniques that can be used as alternatives or complementary to conventional descriptive analysis. They are called "rapid" because they usually include little or no training of the assessors, allowing for significant time and cost savings. Examples of rapid methods include projective mapping, check-all-that-apply questions, flash profiling, and sorting methods. These methods produce generally coarser results than conventional descriptive analysis, but represent a good compromise solution for many applications and also for small and medium-sized companies that typically do not have the time and/or resources for more formal sensory assessment (Delarue et al., 2015).