Chapter 7

# Product Performance Optimization

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## Chapter Outline



## 1. INTRODUCTION

New product development (NPD) is a crucial aspect that companies need to be increasingly successful at to survive in today's highly competitive market (Costa & Jongen, 2006). Nevertheless, the success rate for new products in food and other consumer packaged goods is notoriously low (Stewart-Knox & Mitchell, 2003), with an estimated 75%–90% of new products being withdrawn from the market within 1 year of launch (Dijksterhuis, 2016; Köster & Mojet, 2012). This startling state of affairs points to the need for effective methods to guide product development toward maximizing product performance in the marketplace.

One of the most important steps in NPD is product optimization. The goal of this step is to obtain directions for formulating products that align as closely

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as possible with consumers' ideals (Ares, Varela, Rado, & Giménez, 2011). Operationally, optimization consists of identifying the set of product properties that maximize a certain product performance indicator, such as product acceptability or overall liking. The conventional approach in sensory and consumer science is to collect liking data on a sufficiently large range of products and to relate them to the sensory characteristics and/or formulations of the test products through regression models, with the goals of (1) identifying the point or region in the product space that is preferred by consumers, (2) identifying the underlying product attributes ("drivers of liking") that define this ideal region, and (3) formulating recommendations on how new products should be formulated (or how existing products should be modified) to maximize consumer liking (van Trijp, Punter, Mickartz, & Kruithof, 2007).

Several optimization approaches are available to this end, with the primary differences pertaining to whether the perceptual data are obtained by an external trained panel or from consumers, and to whether the ideal region is to be estimated from the data or indicated directly by the consumers. Situated within this context, the first part of this chapter provides an overview of the main approaches to product optimization used in sensory and consumer science.

In addition to optimization based on liking, sensory scientists have become increasingly interested in including other measures of product performance. These include, among others, emotional responses, conceptual associations, cognitive–attitudinal measures, and health and wellness potential. Motivated by the need to better understand and ultimately predict consumers' product experiences, this move "beyond liking" has been one of the most prominent trends in the sensory and consumer field in recent years. These advances are reviewed in the second part of the chapter, which also provides a discussion of incorporating such measures in the context of product optimization.

## 2. OPTIMIZATION BASED ON SENSORY ATTRIBUTES AND LIKING

### 2.1 Preference Mapping Approaches

The sensory properties of food and beverages are a critical factor in determining consumer choices of food and beverages, and certainly the most important factor in determining our enjoyment of these products. Most importantly, both everyday experience and empirical research tell us that the sensory acceptability of foods strongly predicts consumption (Hellemann & Tuorila, 1991; Sidel, Stone, Woolsey, & Mecredy, 1972), making it a very reasonable optimization criterion in the context of NPD. Owing to this, sensory scientists have long been interested in understanding the relationship between specific sensory properties and food acceptability, to identify those that maximize liking within a specific product category, as well as for specific consumer segments within that category.

The result has been the development of a sophisticated array of statistical methods to quantify the relationships between sensory product properties, typically evaluated by a trained sensory panel using descriptive analysis, and acceptability ratings, typically evaluated by a consumer panel using, e.g., the 9-pt hedonic scale (Lawless & Heymann, 2010; Macfie, 2007). This class of methods is collectively known as preference mapping (McEwan, 1996). In its most basic form, preference mapping relies on linear modeling of consumers' individual liking ratings from the sensory intensity scores or, more often, a combination of linear modeling following some data reduction technique (Næs, Brockhoff, & Tomic, 2010). This form of preference mapping is usually referred to as "external", as opposed to "internal" preference mapping, which only makes use of the consumer liking data to create the product space (Macfie, 2007). The relationship between the sensory attributes (the predictor matrix) and the consumer liking data (the response matrix) is modeled using tools such as principal component regression or partial least squares regression. The first two principal components are always retained as independent variables in the preference map though sometimes, for specific data sets, it may be reasonable to retain a higher number of components.

Although it is possible to use average acceptability ratings as the dependent variable, it is more customary to fit separate models for each consumer, showing which sensory product attributes contribute to his or her respective preference ratings. The reason for fitting individual consumers comes from the important realization that, even within a narrow product category, consumers often exhibit rather heterogeneous preference patterns. In such a situation, a model that included only some aggregate measure of acceptability would be of little use. Conversely, capturing this heterogeneity in the data analysis enables the segmentation of consumers into clusters characterized by similar preference patterns. According to Thomson (2007), between three and eight segments are typical within a single product category. Preference mapping can thus provide valuable information to product developers, as it enables the development of products that cater to the preferences of specific consumer segments. Danzart (Heyd & Danzart, 1998) introduced the idea of defining contours on the preference mapping space showing the number of consumers who are predicted on the basis of their initially fitted model to a score greater than a fixed "cut-off" score (for example, on the 9-pt hedonic scale a suitable cut-off might be 7). Fig. 7.1 shows an example of this type of analysis for a data set concerning 16 cocktails (Lê & Husson, 2008).

In its most basic form, preference mapping relies on linear modeling, i.e., it assumes that consumer preferences either decrease or increase with increasing intensity of any specific attributes. This is usually a valid assumption within the conditions tested. However, if the sensory space is sufficiently large, it may be reasonable to expect that consumers will like a specific attribute up until a certain "optimal" point, after which their liking will decrease. If that is the case, more advanced modeling based on second-degree polynomial regression

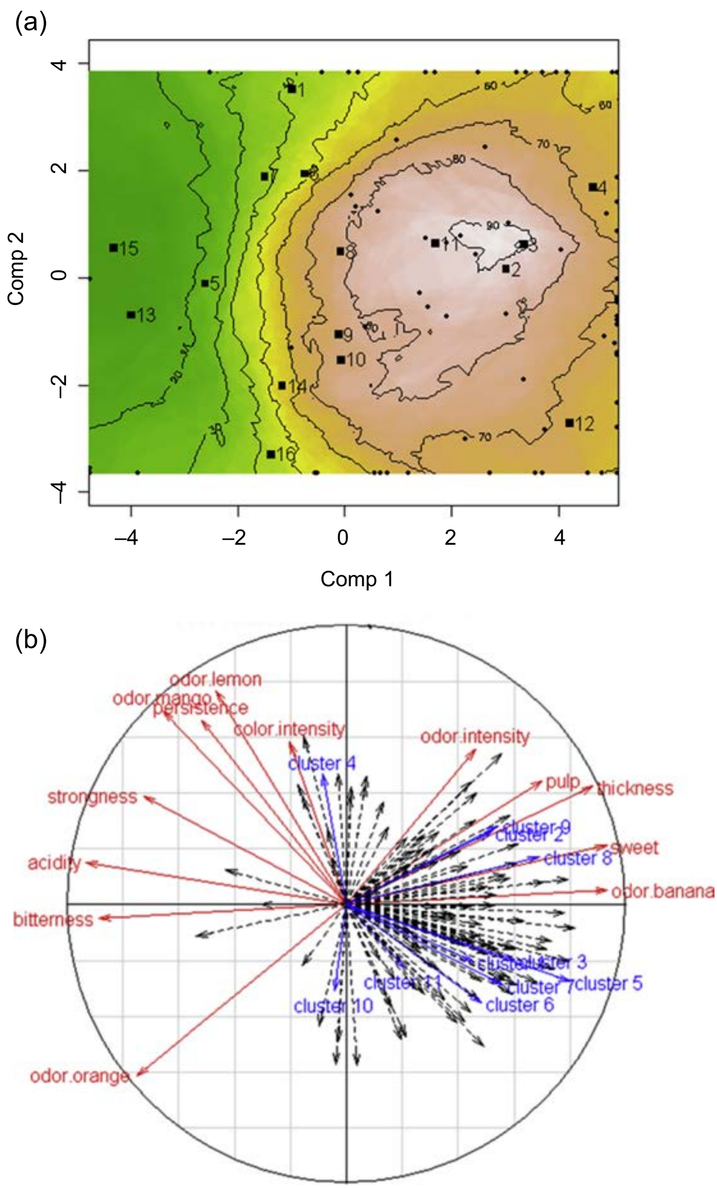



**FIGURE 7.1** External mapping for 16 cocktails evaluated by sensory descriptive analysis with a trained sensory panel, and later submitted to an acceptance test with 100 consumers. (a) The scores plot illustrating the positions of the products (labeled 1–16) on the first two components from a principal components analysis model from the sensory data. (b) The loadings plot showing the correlation of the two components with sensory variables as well as with each consumer's hedonic score. The latter are represented as unlabeled vectors, whose direction and length represent, respectively, the direction of increasing preferences and the degree of model fit. Most consumer preferences appear positively correlated with the first principal components identifying the attributes *sweetness*, *thickness*, and *banana odor* as primary drivers of liking. This is confirmed by the contour plot superimposed on the scores plot, which identified the region between products 2, 3, and 11 as the one of consumer liking. The data set is available in `R` (R Development Core Team, 2015), and this particular analysis can be done using the `carto` function from the `SensoMineR` package (Lê & Husson, 2008).

approaches will usually provide a better fit to the data. The linear model identifies the direction of increasing preferences ("the more the better"); polynomial models will instead identify "ideal points" on the map. An example of preference maps obtained using the vector (linear) model and the ideal point (quadratic) model is shown in Fig. 7.2, using data from a study on low-fat cheeses (Johansen, Hersleth, & Næs, 2010). The reader is referred to McEwan (1996) for an in-depth discussion of the different modeling approaches.

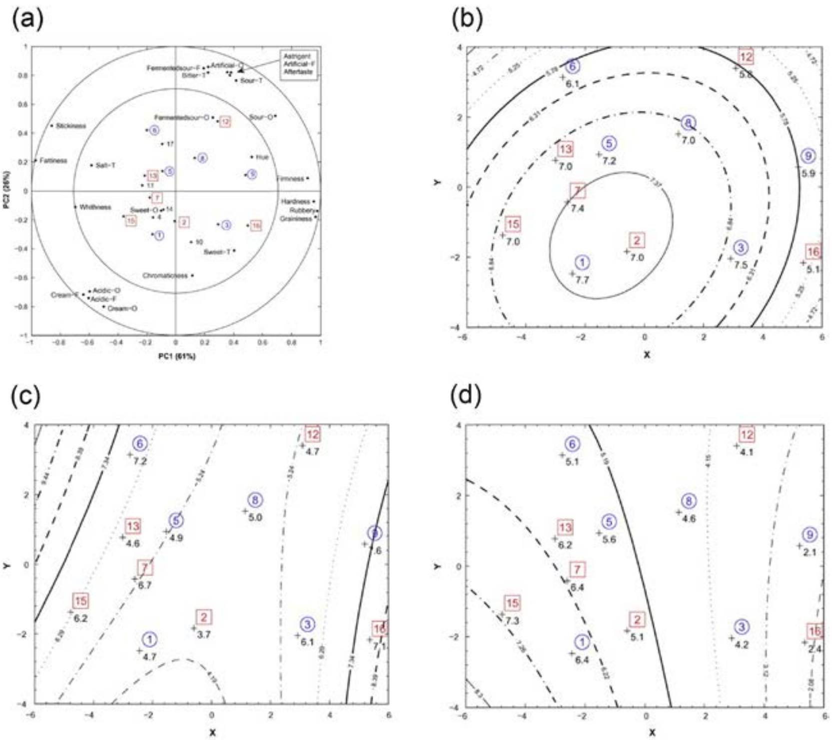


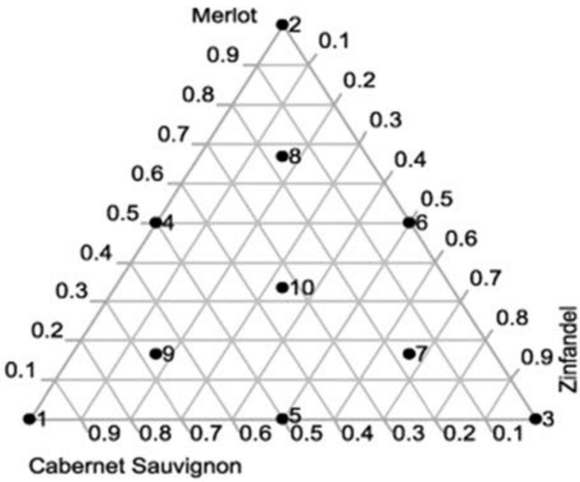

**FIGURE 7.2** External preference model of consumer preferences for 17 low-fat cheese products using a polynomial model including linear and quadratic terms for two principal component analysis (PCA) components (Johansen, Hersleth, et al., 2010). (a) The correlation loadings plot for a PCA illustrating relative differences for the 17 products based on significant sensory attributes. (b–d) Preference maps and contour plots for three different consumer clusters. Preferences for consumers in the first cluster (b) are best described by a quadratic ideal point model with liking maximized for products toward the center of the plot, such as product 1. The second cluster is again described by a quadratic model, but in this case the squared terms for the two components have opposite signs. This generates a "saddle point" model (c), with the highest preferences going in two different sensory directions. The third and final cluster (d) has a linear preference structure mostly driven by products in the bottom left quadrant, but without reaching optimum hedonic scores. As preferences in this cluster are linearly (i.e., the more the better) related to creamy and acidic flavors, increasing these attributes in, e.g., products 15 and 1 would optimize these products for this consumer segment. *(Reprinted with permission from Elsevier.)*

Product developers can use preference maps as a tool to understand which sensory attributes should be modified to achieve that optimum. The usefulness of such models is highly dependent on the choice of the product space. The best results are achieved when the test products (1) cover a sensory space that is representative of the product category and (2) are chosen according to an experimental design that allows maximum interpretability with regard to the formulation that can deliver on the identified optimum. Once a new reformulated product is available, it can be submitted for evaluation to the trained sensory panel to obtain a new sensory profile, which can then be plugged into the preference mapping model available to obtain a prediction of its expected performance (in terms of consumer liking) and to assess how close it is to the identified optimum. As noted by Thomson (2007), some iterations of product development, sensory profiling, and preference mapping may be necessary to obtain a near optimal product, which is then submitted to confirmatory product testing with the target consumer group.

Preference mapping models are flexible models with regard to the input data. For example, physicochemical data on the products can be used to model consumer preferences, either in addition to the sensory data or as a stand-alone (see e.g., Thybo, Kühn, & Martens, 2004).

A related strategy, which is particularly useful in product optimization, is to develop a product set according to an experimental design with systematic variation around key ingredients or processes. The design factors (e.g., two ingredients for which upper and lower limits have been defined), as well as their interactions, are used to model consumer preferences directly, using either linear or polynomial regression. This type of data analysis is a form of response surface methodology (RSM, Giovanni, 1983), where by consumer acceptability is used as the optimization criterion. It is extremely useful as a product optimization tool to infer the optimal combination of design factors from the data. Accordingly, numerous publications attest to its usefulness for a variety of purposes. As an example, let us briefly consider an application of RSM to optimize red wine blends made from three grape cultivars: Cabernet Sauvignon, Merlot, and Zinfandel cultivars (Dooley, Threlfall, & Meullenet, 2012). In this case study, the factors were the relative proportions of the three grape varieties in the blend; thus, a mixture design (Arteaga, Li-Chan, Vazquez-Arteaga, & Nakai, 1994) was used to select a subset of wine blends (Fig. 7.3). Because the optimization criterion was maximization of consumer liking, the blends selected from the mixture design were subsequently tested with a consumer group ($N=108$) that evaluated them using the 9-pt hedonic scale.

The RSM model for these data was obtained by regressing the individual liking scores to identify the area in the experimental space where liking is maximized. The main outcome in this analysis is shown in Fig. 7.4(a) and (b), which visualizes optimal product spaces for two different consumer segments. (Note that consumers were split into two segments prior to this analysis. This step may often be necessary in practical applications when consumer preferences are too




| 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 7.3** Application of response surface methodology to product optimization of red wine blends. The figure shows the mixture design used for selecting the set of wine blends for the consumer testing. *(Reprinted with permission from Dooley, L., Threlfall, R.T., Meullenet, J. (2012). Optimization of blended wine quality through maximization of consumer liking.* Food Quality and Preference, 24*, 40–47.)*

heterogeneous.) The two models identified the following optimized wine blends for the two consumer segments:

- Segment 1 (Fig. 7.4(a), $N=60$): 68% Cabernet Sauvignon + 26% Merlot + 6% Zinfandel
- Segment 2 (Fig. 7.4(b), $N=48$): 27% Cabernet Sauvignon + 2% Merlot + 71% Zinfandel

Additional details on this case study can be found in Dooley et al. (2012). RSM has been a staple of sensory-based optimization since its introduction to the field by Giovanni (1983). Other "pedagogical" examples of this technique in the context of product optimization can be found in the study by Felberg, Deliza, Farah, Calado, and Donangelo (2010), in which the authors used the same approach to estimate optimal concentrations of key ingredients (instant coffee,

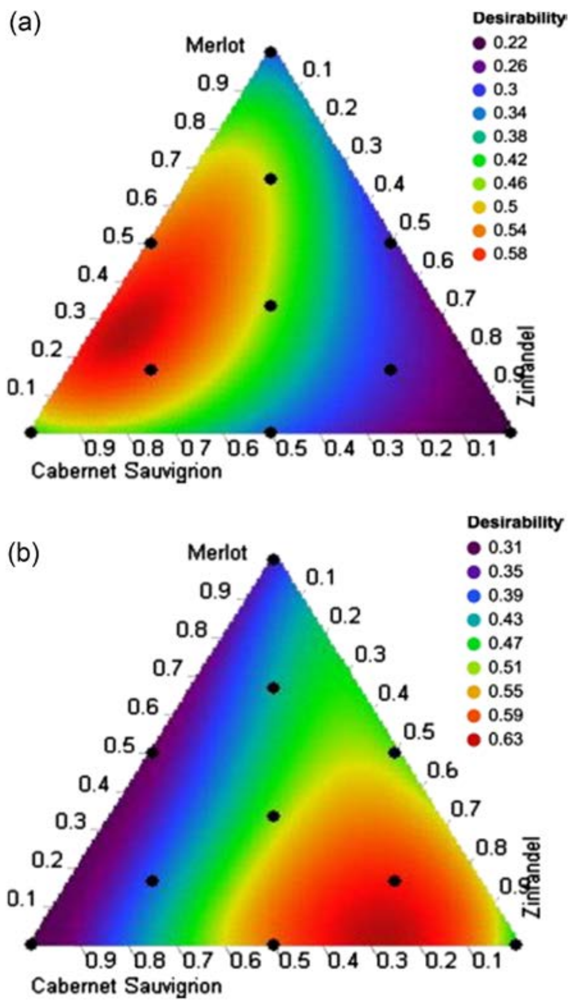



**FIGURE 7.4** Location of maximum liking (on a 9-pt scale) and optimized wine blends for two consumer segments. Consumer liking ratings were converted using a desirability conversion formula where by the lowest value (0 on a 9-pt scale) corresponds to a value of 0.0, the middle value (each consumer's mean value across all samples) corresponds to 0.5 desirability, and the upper value (9) corresponds to a desirability of 1.0. *(Reprinted with permission from Dooley, L., Threlfall, R.T., Meullenet, J. (2012). Optimization of blended wine quality through maximization of consumer liking.* Food Quality and Preference, 24*, 40–47.)*

sugar, and soymilk) for soy-coffee beverages, and in a study by Khare, Biswas, Balasubramanium, Chatli, and Sahoo (2014) in which RSM is used to optimize processing conditions (drying time and steaming time) for chicken meat noodles.

It should be noted here that RSM (and preference mapping generally) is a flexible approach, and many other optimization criteria are sometimes considered (yield and/or production cost, for instance). Methods that allow simultaneous optimization on multiple criteria are also available (see, e.g., Khuri & Mukhopadhyay, 2010), although in this author's experience, their application in sensory and consumer science is very limited.

Other extensions of preference mapping include three-block methods to model the preference data from both product sensory data and any background characteristics of the consumer sample (Thybo et al., 2004). This is an extension that is particularly useful in the marketing of new products, as it can reveal whether the consumer segments have any relation to relevant consumer characteristics such as age, gender, ethnicity, etc., that may support a more targeted positioning of the product. This approach enjoyed some initial popularity as shown in several publications (Frandsen, Dijksterhuis, Martens, & Martens, 2007; Giacalone, Bredie, & Frøst, 2013; Plaehn & Lundahl, 2006; Thybo et al., 2004; Vinzi, Guinot, & Squillacciotti, 2007). Although promising, it has yet to become mainstream in sensory and consumer analysis, in part because of its inherent complexity and in part because of the limited software support for this type of analysis.

## 2.2 Consumer-Based Approaches (JAR, Ideal Profile, and CATA)

One of the drawbacks of preference mapping approaches is that the sensory space is defined externally (e.g., by a trained panel). The validity of this approach relies on the assumption that the space produced by the trained panel both (1) is representative of how consumers perceive products and (2) produces dimensions that pertain to preferences: a rather strong assumption that has been challenged in the literature (Jaeger, Wakeling, & MacFie, 2000). This, together with the increasing recognition that consumers are capable of evaluating sensory properties, has prompted interest in developing methods based directly on consumer perceptions. One such method that is very popular for product optimization is the just-about-right (JAR) scale. This is a type of quantitative consumer test where by consumers evaluate a product on specific sensory attributes. JAR scales are essentially bipolar scales with the central point labeled "just about right" and the poles "too much" or "not enough." Both line scale and category scales (3-, 5-, 7-, and 9-point) are used, and the results are easily visualized by plotting the distribution of consumer responses for each point of the scale. As an example, Fig. 7.5 shows two hypothetical distributions of JAR responses for two products evaluated on the attribute "saltiness."

In most cases, JAR evaluations are elicited concurrent with acceptability testing from the same consumers. Combining these two types of information (liking and JAR) enables the product developer to estimate the impact of deviations from the JAR level on consumer liking. Typically, this is done using "penalty analysis," a simple procedure where by the data are initially separated into groups below, above, or at the JAR level. Then, the mean liking ratings for each group are calculated, and the mean of each non-JAR group is subtracted from the mean of the JAR group. The resulting difference (the "mean drop") represents the reduction in product acceptability when the attribute intensity is not optimal.

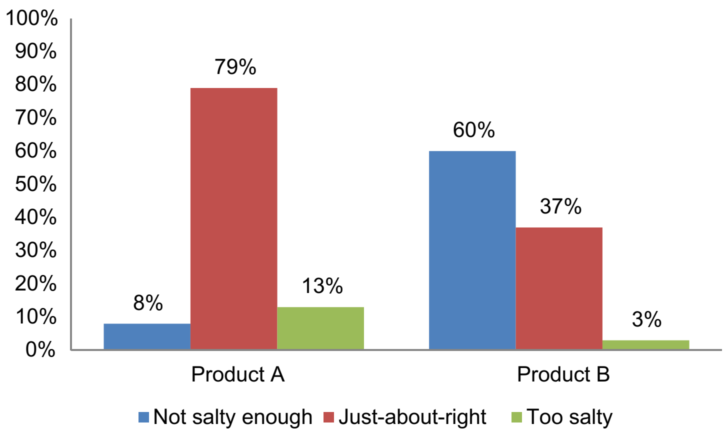



**FIGURE 7.5** Hypothetical distribution of just-about-right (JAR) responses for two products relating to the attribute "saltiness." The plot shows that the JAR response for product A approximates a normal distribution, indicating that this product has a near optimal intensity in that attribute. By contrast, product B shows a skewed left distribution, suggesting that there is a need to enhance the saltiness in that product.

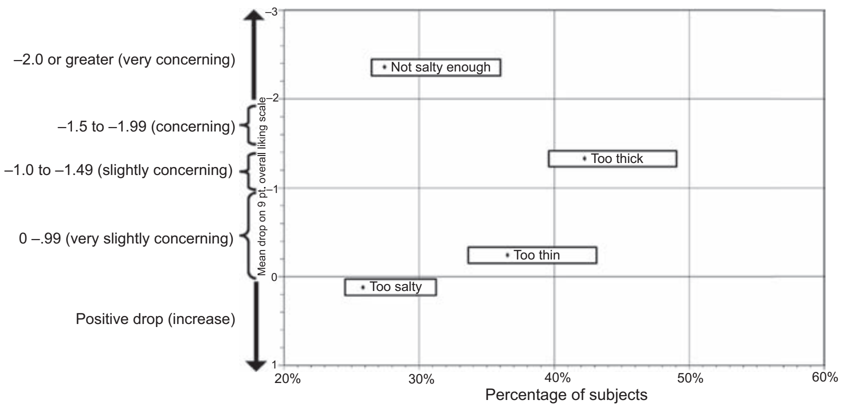



**FIGURE 7.6** Penalty analysis showing the effect of deviations from the JAR level in two product attributes (saltiness and thickness) on liking. The horizontal axis represents the percentage of respondents that ticked each specific point on the JAR scale. The vertical axis shows the mean drop in liking for the group of consumers that ticked that point. Combining these two information penalty analyses provides product developers with an indication of which attributes should be given priority (i.e., those with the largest impact on liking) in further optimization efforts.

Fig. 7.6 shows a typical output from penalty analysis, in which the mean drop in liking is plotted against the percentage of consumers ticking that scale point. This is typically useful information for product developers as it enables them to assess whether the deviations from ideal are large enough to justify any product adjustment, as well as identifing the sensory attributes that should be given priority in further optimization efforts, i.e., those that cause the largest drop in acceptability and are perceived as non-JAR by many consumers.

As the examples in Figs. 7.5 and 7.6 illustrate, JAR scales provide directly and intuitively information regarding direction for product optimization: an attractive feature both for product developers and any stakeholders (e.g., clients, marketing personnel, etc.) to whom the results are going to be communicated.

Work by Worch and colleagues has extended the concept of JAR scales into the so-called ideal profile method (IPM) (Worch, Lê, Punter, & Pagès, 2013). This test method combines JAR scales with elements of classical sensory profiling, as it requires consumers to rate both *perceived* and *ideal* intensity of sensory attributes. In the same test, consumers also rate liking for the product. Thus, IPM provides a comprehensive data set including sensory profiles of the products, liking scores for the products, and ideal intensities for the rated attributes. Because optimization is usually done on aggregate data, the first step in the analysis usually consists of checking whether unique or multiple ideals exist. This is an important aspect to monitor because product optimization relies on the assumption that consumers can reliably associate the product tested with one unique ideal within that product (sub)category (Worch et al., 2013), provided that the category is sufficiently narrow.[1] Assuming that more than one product is being tested, consumers will in effect rate ideal intensities as many times as there are products, thus enabling the experimenter to rate the consistency of these ideal ratings also *within* individual consumers. At the level of individual attributes, the assumption that a unique ideal exists can be tested using analysis of variance using ideal ratings as the dependent variable and product and consumers as main effects. Multivariately, uniqueness can be assessed by computing a principal component analysis (PCA), and looking at the uncertainty around the position of the ideal product in the map visualized through confidence ellipses obtained from a data resampling technique. Fig. 7.7 shows an example of the main analysis from IPM data from a study on a skin cream (Worch, Crine, Gruel, & Lê, 2014).

In particular, Fig. 7.7(a) shows the PCA scores for the plot based on the product's perceived and ideal sensory characteristics. These are located consistently in the top left of the plot, and the fact that the confidence ellipses around the ideal points overlap is taken as evidence that consumers do in fact have a unique ideal for this set of products at which to aim during the optimization process. Results at the level of individual attributes can be visualized using, e.g., spider plots as shown in Fig. 7.7(b), to effectively visualize the distances between perceived and ideal product characteristics. Similar to JAR, complementary analyses are also possible when including liking ratings to evaluate the order of importance of deviations from ideal for liking. Different analytical approaches for this type of analysis on IPM data are discussed in Worch, Dooley, Meullenet, and Punter (2010).

1. For example, in a study about coffee beverages, it may be reasonable to assume that each consumer has a unique ideal for a regular black coffee. However, the sensory characteristics that are ideal for black coffee will not be the same for other product subcategories like cappuccino, espresso, etc.

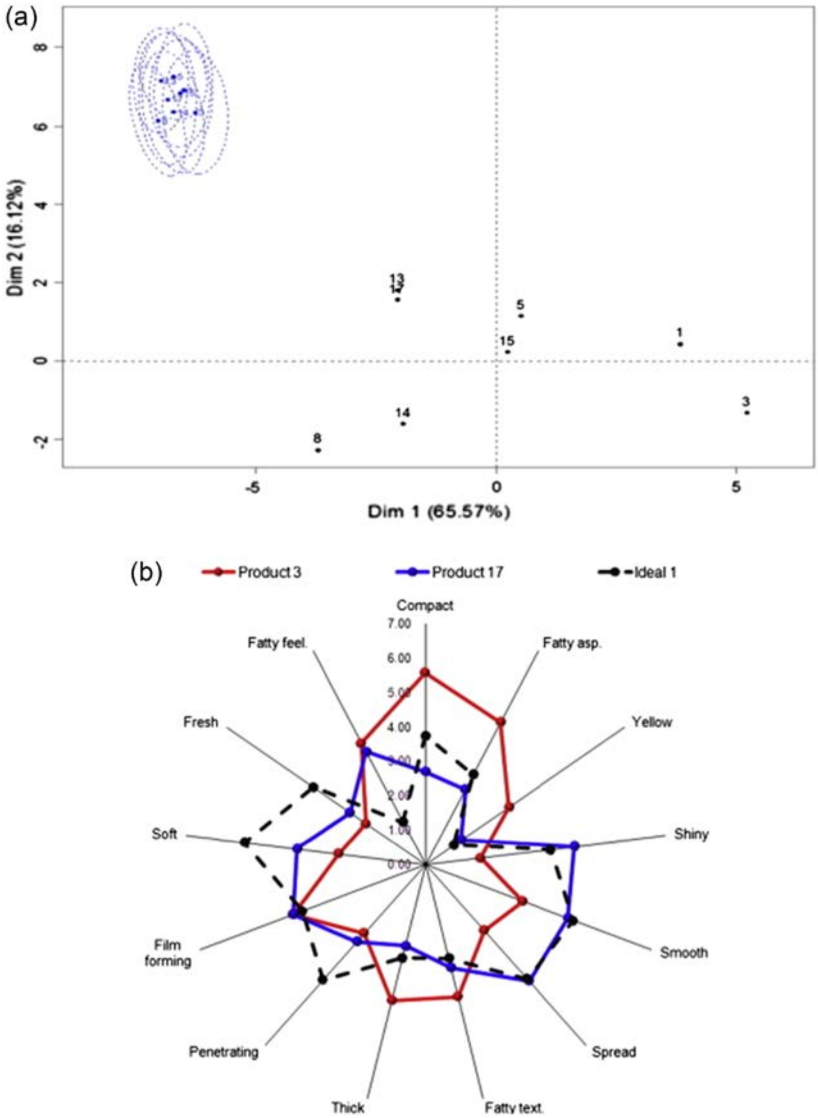



**FIGURE 7.7** Example of results from an application of the ideal profile method for optimization of skin creams (Worch et al., 2014). (a) A multivariate representation of sensory differences between the products as well as the position of the ideal product (in the top left, with confidence ellipses checking – and in this case confirming – the agreement on the ideal at the panel level). (b) A spider plot with sensory profiles of two tested products against the profile of the ideal product, on an individual attribute basis. *(Reprinted with permission from Elsevier.)*

Although IPM and the JAR are simple and powerful scales that address the main limitation of preference mapping (namely the risk of having a nonrepresentative sensory space), they also have limitations. In addition to pitfalls common to any type of scales used with consumers (halo effects, context effects, expectation errors, attribute interpretation, etc.), JAR has very specific issues of its own. First, it is a cognitively demanding type of response as it requires both an evaluation of the perceived intensity and a judgment of the ideal. In particular, it is assumed that consumers actually know and can reliably communicate their ideal intensity of a sensory attribute. Many sensory professionals question that assumption: for example, it is possible that a consumer may indicate that he or she would prefer a product to be more salty, but if presented with such a product he or she would find it too salty, even keeping all other attributes unchanged (Rothman & Parker, 2009). In the context of IPM, Worch et al. have provided some indications that consumers' ideals are consistent/nonrandom (Worch, Lê, Punter, & Pagès, 2012), although systematic research on this topic is remarkably scarce. Other potential problems with JAR scales include the risk that consumers conflate cognitive and sensory aspects: for example, attributes associated with negative health outcomes, e.g., "salty" or "sweet," may always be judged as too much, even though in fact reducing that attribute would result in a less liked product.

A last criticism often encountered is that JAR scales may introduce a bias in consumers' hedonic responses to the tested products. This relates to the general problem that providing sensory information and liking correspond to fundamentally different ways to evaluate a product (Prescott, Lee, & Kim, 2011): the former is an analytical task that requires a subject to mentally "decompose" the stimulus into separate sensory impressions and to rate the intensity of each of them, whereas the latter is a synthetic task that integrates all sensory information into a global judgment of liking/disliking. Coeliciting both types of information within the same test has been found to bias hedonic ratings, usually in the form of *lower* ratings than those obtained when eliciting only liking information (Popper, Rosenstock, Schraidt, & Kroll, 2004; Prescott et al., 2011). Importantly, Popper et al. (2004) found in a comparative study that JAR scales have the highest potential to alter hedonic response among different types of questions (such as intensity ratings of sensory attributes and liking for individual attributes), ostensibly because of the high cognitive load required from the respondent.

Some of the risks inherent in the use of JAR and IPM can possibly be reduced through careful pilot testing and ballot design. However, some researchers have proposed the use of alternative approaches to guide product optimization. Check-all-that-apply (CATA) questions (Adams, Williams, Lancaster, & Foley, 2007) are an example of one such approach. CATA is a rapid product profiling technique that consists of a list of attributes, from which consumers are asked to check all those deemed applicable to the sample being evaluated. CATA questions have risen tremendously in popularity in recent years, mainly because of their simplicity and rapidity. More to the point, CATA questions are easier to process than either intensity or JAR scales, and accordingly, considerable evidence has been presented that concurrent coelicitation of product attributes using CATA does not bias hedonic scores (Jaeger & Ares, 2014; Jaeger et al., 2013).

The idea of using CATA questions for product optimization was first introduced in a study by Ares and colleagues in a way conceptually very similar to IPM, where by consumers would first complete a CATA questionnaire on the actual products, and then an additional one in which they would check all attributes appropriate in an ideal product (Ares et al., 2011).

Other authors have proposed the use of penalty analysis based on CATA responses to understand drivers of liking and directions for product reformulation (Ares et al., 2017; Plaehn, 2012). Because CATA responses are usually handled as binary (1 = attribute checked, 0 = attribute not checked), the effect of that attribute on liking can be readily estimated by comparing the mean liking ratings of the consumers who checked that attribute versus those who did not. The results can be visualized similar to JAR data, i.e., by plotting the mean change in liking when an attribute is checked versus the proportion of consumers that checked it. The only difference is that in JAR scales the focus is on mean liking drops due to deviations from the JAR point. For CATA data, one looks for the difference in the mean liking of each product when an attribute is checked and when it is not checked, which could be in either direction. The significance of the mean drop/rise in liking can be estimated by simple one-way ANOVA, but also by more advanced multivariate methods like partial least squares regression (see Plaehn (2012) for an overview).

As an example of this type of analysis, let us consider a case study about optimization of rye bread, in the context of a larger project about development of food products enriched with whey protein hydrolysates (WPH) targeted at elderly consumers (Song et al., 2015). The objective of the study was to explore the potential of rye bread, a traditional Danish product, for protein enrichment with WPH, and more specifically to identify optimal WPH content. To this end, six samples were developed by systematically varying two experimental factors: leavening agent (sourdough and yeast) and WPH content (0%, 7%, 10%). The samples were then submitted to consumer testing with a population of 134 consumers (age 60+) who evaluated the samples for overall liking and characterized them using a CATA questionnaires with 14 attributes: *dry*, *soft*, *sour*, *moist*, *coarse*, *bitter*, *airy*, *chalky*, *dense*, *metallic*, *off-taste*, *salty*, *yeasty*, and *chewy*. Although all samples were rated above the neutral point of the 9-pt hedonic scale, the results clearly showed the two control samples (0% WPH) to be significantly more liked than the four WPH-enriched samples. In such a context, penalty analysis from the CATA data could help with identifying directions for reformulating this sample. Fig. 7.8 shows this analysis applied to this particular data set. The figure shows the change in overall liking associated with the presence of each of the CATA attributes plotted against the relative proportion of consumers who checked that attribute, with the mean liking value represented by a dotted line (Fig. 7.8). It is easy to see that the textural attributes *moist*, *soft*, and *dry* have the

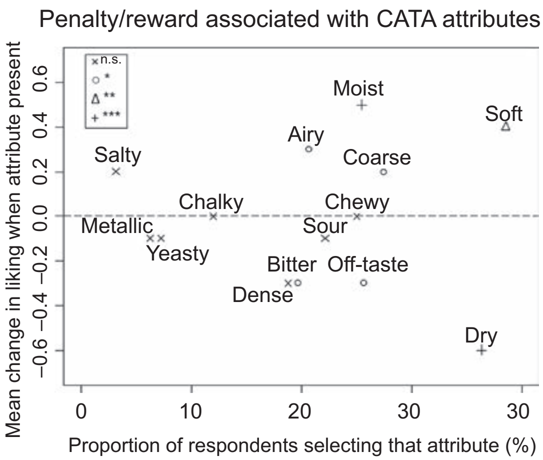



**FIGURE 7.8** Example of penalty analysis on check-all-that-apply (CATA) data. The data are from a study on rye bread samples enriched with whey protein hydrolysates evaluated on a list of 14 CATA attributes. The plot shows penalty/rewards in overall liking associated with the presence of each CATA attribute against the proportion of consumers who checked each specific attribute. Attributes labels are also coded according to the significance of their effect on liking assessed by ANOVA ($^{n.s.}$ $P>.05$, $^{*}P<.05$, $^{**}P<.01$, $^{****}P<.001$).

highest impact on liking. The attribute *dry* in particular was identified as "the" major problem: situated in the bottom right corner of the plot, it has both the largest negative impact on consumer liking and the largest incidence in the data set (Fig. 7.8). Further analyses (not shown here) showed that the frequency of mention for this attribute was linearly related to WPH content, most likely because of the high water binding capacity of this ingredient (Leksrisompong, Miracle, & Drake, 2010). Reducing the dryness was therefore identified as the next direction for optimization of the WPH-enriched samples, and a product developer with sufficient understanding of the product could easily envision how this may be addressed (in this case study, future reformulations could include adding more water to the dough, baking at a lower temperature and/or for a shorter time, or using hydrocolloids).

A variation on the aforementioned strategy is when CATA responses on an *ideal product* are collected. In such case, one would focus on mean drops in overall liking as a function of the percentage of consumers who checked an attribute *different than for the ideal product*, thus rendering the analysis conceptually identical to JAR scales. This variation has been presented in a study by Ares et al. (2017), and it was validated by showing that the CATA profile of the ideal product provided by consumers was similar to that of the samples with the highest liking score.

Because of the increasing popularity of CATA and its already mentioned advantages compared to JAR and intensity scales, it is expected that the application of this method in product optimization will become more widepread.[2] CATA questions have been extended to include the temporal evolution of sensory profiles (Castura, Antúnez, Giménez, & Ares, 2016). This extension, known as TCATA, could prove to be a very useful development in the context of product optimization as most other methods do not take into account this temporal aspect of sensory perception and may therefore miss crucial information for understanding consumer preferences (see Chapter 9).

## 3. PRODUCT OPTIMIZATION "BEYOND LIKING"

### 3.1 What Should We Optimize Toward in the Product Development Process?

Preference mapping and the other approaches discussed thus far, when properly conducted and interpreted, have brought a high level of sophistication and accuracy to product optimization. While these approaches have been, and continue to be, of great practical value to the food industry, they suffer from a common limitation: they consider liking/sensory acceptability as the only criterion for product optimization.

Generally speaking, a single-minded reliance on a specific measure of product performance—such as liking or willingness to pay—as the criterion to guide product development and optimization projects is ineffective in today's highly competitive innovation ecosystem. Unfortunately, several studies have shown that liking is, in and of itself, not a very good predictor of product marketplace success (see, e.g., Rosas-Nexticapa, Angulo, & O'Mahony, 2005).

Accordingly, sensory and consumer scientists have increasingly become interested in a broader set of product performance measures that may be more predictive of consumers' actual product choices in the marketplace. This trend has characterized the field since 2006 and substantially broadened the focus of the sensory profession. The remainder of this chapter reviews briefly some of these new performance measures, highlighting their potential in practical product development and optimization.

### 3.2 Integration of Extrinsic and Intrinsic Product Aspects

Traditionally, sensory scientists have been concerned with "intrinsic" (sensory and hedonic) product properties evaluated under strictly controlled blind test conditions. From a scientific standpoint, this approach makes perfect sense if the goal is to understand the "true" product effect, but in the real-world context

2. This is not to say that CATA questions are always preferable. For example, Ares et al. noticed that JAR scales may be preferable in routine optimization tasks on well-known products when only a few key attributes need to be considered (Ares et al., 2017). As usual, the final choice of method needs to take into account the specific applications.

of product development, this information may be of limited value because consumers basically never encounter the product in such isolated fashion. However, it is well reported in the literature that “extrinsic” elements, such as the packaging, the brand, the product name, etc., can substantially influence consumers’ perceptions and behavior with regard to foods or beverages (Deliza & MacFie, 1996; Johansen, Næs, Øyaas, & Hersleth, 2010). More recently, the substantial body of research on multisensory integration by Charles Spence, Betina Piqueras-Fiszman, and colleagues has demonstrated a multitude of ways in which extrinsic product aspects, such as the color, sound, or feel of the packaging, can influence the consumer’s perception of the taste/flavor of the product itself (Piqueras-Fiszman & Spence, 2015; Spence, 2016; Spence & Piqueras-Fiszman, 2012).

Having established that consumers’ perception of a product can be profoundly influenced by extrinsic product aspects, the utility of blind testing has been put into question (see, e.g, Dijksterhuis, 2016; Spence, 2016). In part, the reliance on blind testing is due to the training of most sensory scientists and the fact that aspects such as price, brand, or packaging are seen as belonging to the domain of marketing (in corporate contexts, they may be also dealt with by different departments). Nevertheless, based on the body of knowledge available at this point in time, it seems no longer viable that consumers should never evaluate a product in its entirety before it actually hits the market shelves.

The possibility of combining sensory and extrinsic product aspects has been explored by a few authors using conjoint analytic approaches (De Pelsmaeker, Dewettinck, & Gellynck, 2013; Raz et al., 2008); see also Chapter 19. Raz et al. (2008) suggest a stepwise approach in practical optimization where by sensory differences are integrated as factors in conjoint analysis together with brand and packaging. This approach should be of great value for selecting the food product with optimal sensory quality as well as the optimal combination of marketing aspects for the target consumer group. Some good examples of this approach include the effect of sensory variation product information on consumer perception of dairy products (Johansen et al., 2010) and the effect of branding and packaging attributes on liking for wine (Mueller & Szolnoki, 2010).

The conjoint framework provides a flexible framework to explore how key intrinsic and extrinsic product attributes interact in determining consumer responses. This process is conceptually represented in Fig. 7.9 for a hypothetical product: here, both intrinsic (ingredient levels) and extrinsic (packaging, type of claim, and price) design factors are experimentally varied to produce product prototypes that will be submitted to consumers’ evaluation on a selected set of performance variables, such as acceptability or willingness to purchase. Oftentimes, the number of possible attribute combinations will be too large for a full profile to be feasible. In this case, the application of incomplete designs (common possibilities include balanced incomplete block design and fractional factorial designs) can be used to reduce the number of product combinations

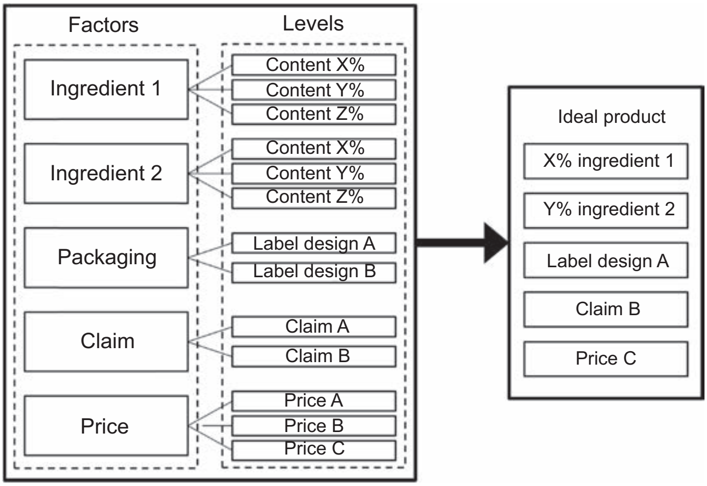



**FIGURE 7.9** Conjoint design for a hypothetical product considering both intrinsic and extrinsic product aspects. *(Modified from De Pelsmaeker, S., Dewettinck, K., Gellynck, X. (2013). The possibility of using tasting as a presentation method for sensory stimuli in conjoint analysis.* Trends in Food Science and Technology, 29*, 108–115.)*

presented to the consumers without loss of statistical properties. Additionally, in some applications, physical prototypes may be replaced by pictorial representations to make the task less cumbersome for the consumers (Jaeger, Hedderley, & Macfie, 2001). Eventually, through calculation of utilities associated with specific attribute levels, conjoint analysis enables the product developer to identify the optimal profile for a product combining both extrinsic and intrinsic product aspects (Fig. 7.9).

Combining sensory and marketing aspects into product optimization is a practice that should be encouraged as it is much needed to increase the external validity of product tests. Generally, a closer integration of sensory and marketing aspects in NPD is happening and expected to continue in the years to come. Corporate structures are extremely important in this context (Moskowitz & Hartmann, 2008); there are many ways in which managers can facilitate (or hinder) a fruitful collaboration between sensory and marketing professionals, and the extent to which they can do so effectively may be crucial for the success of product development in the food industry (Dijksterhuis, 2016; van Trijp & Schifferstein, 1995).

## 3.3 Emotional Responses to Food Products

Moving on in the discussion of performance variables beyond liking, one that has majorly caught the interest of sensory scientists in recent years is product-related emotions (see Chapter 11). This area of research is motivated by the fact that consumer purchase decisions for food and beverage products are often not driven by rational considerations (e.g., regarding price and health information), but are rather impulsive and driven by emotions connected to previous consumption experiences (Jiang, King, & Prinyawiwatkul, 2014). An example could be a chocolate bar product that, in addition to being highly liked, also makes the consumer feel more loved and comforted, or a beer being consumed as a refreshing beverage but one that also elicits feelings of outwardness and conviviality. This area of research originated within the marketing field, originally related to consumers' emotional association with brands, whereas the sensory field started to focus on emotions as recently as the late 2000s (Desmet & Schifferstein, 2008; King & Meiselman, 2010). Since then, there has been a steady and increasing interest in understanding how sensory aspects of foods and beverages relate to the emotions experienced during consumptions, so that food products can be designed to deliver the desired emotional benefits.

Several approaches have been proposed to address the need for measuring emotional responses to food products. Alongside those that focus on physiological responses and facial movements correlated to emotions, by far the most common approach is to use self-reports of experienced emotions using questionnaires. Examples of this include the EsSense profile (King & Meiselman, 2010), EmoSemio (Spinelli, Masi, Dinnella, Zoboli, & Monteleone, 2014), and Geneva Emotion and Odor Scale (Porcherot et al., 2010), among others (for an exhaustive review, see Cardello & Jaeger, 2016). Research has shown that emotional product profiles are reproducible, and they add an additional dimension to liking, in the sense that products equally liked from a sensory point of view may differ substantially in their emotional profile (Porcherot et al., 2010). Thus, emotions may provide a valuable source of product differentiation, and thus help one understand why acceptance data might not always predict market success.

How emotional responses may best be used in the context of commercial product optimization is a matter for future research. At present, product-related emotions do not have a direct behavioral correlate in the same way as, for example, liking can *ceteris paribus* be linked to acceptance and consumption. Some emotions, such as boredom, have been linked to product rejection both theoretically and experimentally (Sulmont-Rossé, Chabanet, Issanchou, & Köster, 2008). Additionally, correlational data on the EsSense instrument published by Gutjar et al. (2015) suggest that choice was best predicted by the positive emotion *happy* and the negative emotion *bored*. In the majority of cases, however, the relation between food-elicited emotions and consumer marketplace behavior may not be so clear-cut. As we are still in the early stages of the emotion research life cycle, it seems likely that in the near future, this relation will be better understood.

An important point to consider is that emotional responses elicited by the product itself should be considered in relation to those engendered by extrinsic product aspects, in particular brand and packaging, to ensure that they are as closely aligned as possible (Spinelli, Masi, Zoboli, Prescott, & Monteleone, 2015).

To this end, practitioners like David Thomson have developed practical tools to quantify the emotional consonance between product and brand in the applied context of product development and optimization, and suggested that such product–brand consonance should be a primary optimization criterion in and of itself (Crocker & Thomson, 2014; Gutjar et al., 2015; Thomson & Crocker, 2015; Thomson, Crocker, & Marketo, 2010).

## 3.4 Health and Well-Being

Another product performance measure that is growing in popularity is the experience of well-being associated with consuming certain food products (Ares, de Saldamando, Gimenéz, & Deliza, 2014). Food consumption is obviously closely linked to health and well-being, and this relationship is traditionally studied by nutritionists and other health scientists. In recent years, however, the topics of food, health, and well-being have also become prominent within marketing and sensory and consumer science. The concept of well-being is intuitively close to the healthiness of foods, but while the latter is mostly associated with biology and disease prevention, the former is a subjective concept associated with high quality of life in a broader sense (Ares et al., 2014; Meiselman, 2016). Accordingly, studies show that well-being is a multidimensional concept comprising at least five dimensions: physical, social, intellectual, emotional, and spiritual (King et al., 2015).

In the context of product development, health and well-being are seen as an additional and valuable source of product differentiation, as well as a way to make food more appealing to consumers. Producers can now market products that in addition to tasting great can also make consumers feel good (Meiselman, 2016). The demand for health and wellness is currently very strong in the market as witnessed by the fact, for example, that functional food consistently ranks as one of the largest growing market segments worldwide (Bigliardi & Galati, 2013). The trend is expected to increase further as a result of the steady increase in life expectancy, and the necessity of reducing the incidence of lifestyle-related diseases, as well as the increasing presence of the health discourse in the public debate (Giacalone et al., 2016).

As companies will need to meet consumers' demands for a healthy lifestyle, the importance of health and well-being as a product performance indicator will probably increase. This raises the question of how this aspect may be operationalized to provide actionable information to product developers. Similar to emotion research, quantitative tools to measure well-being in response to specific food products and ingredients are now being proposed. Examples include the postprandial wellness questionnaire by Boelsma, Brink, Stafleu, and Hendriks (2010) and the WellSense profile (King et al., 2015). Such tools are growing in popularity in both commercial and scientific applications, and extensions adapted for specific cultures and languages have also started to appear (Ares et al., 2016). For a comprehensive discussion on this line of research, see Chapter 8 (Volume 2).

### 3.5 Fit With Intended Usage Context

One final crucial aspect that is often overlooked in product optimization efforts is the effect that the final consumption context will exert on the product experience (Meiselman, 2008). A common criticism of test results obtained in a common product testing environment, such a sensory testing booth, is that they are not representative of natural consumption situations (Köster, 2003). There is evidence that such data may lack external validity when used to guide product development, in that the optimized product may not reflect the improved acceptance that one might predict. For example, in a simple experiment involving croissants, Di Monaco, Giacalone, Pepe, Masi, and Cavella (2014) demonstrated that evaluating the products in a different testing situation (e.g., the inclusion of a breakfast beverage) not only altered preferences, but actually led to very different conclusions as to which product characteristics were the primary drivers of liking in that product category.

This is obviously a serious issue for product development, and one that is possibly behind the high rate of new product failure. Accordingly, several authors have proposed the use of physical (e.g., Di Monaco et al., 2014; Sester et al., 2013) or evoked contexts (e.g., Hein, Hamid, Jaeger, & Delahunty, 2010, 2012) when conducting consumer testing in central locations, as a means of providing consumers with a meaningful frame of reference for evaluating products. Efforts to measure consumer responses in context are expected to increase significantly in the near future, not least thanks to the increased availability of immersive virtual reality technologies (Jaeger et al., 2017).

From a marketplace perspective, context is also a very important factor in orienting consumers' choices, as it is generally assumed that products are often chosen to fulfill the goals associated with a particular consumption situation (Belk, 1975; Ratneshwar & Shocker, 1991). For example, a consumer may highly appreciate a very complex wine when fine dining, but the same individual would choose a less expensive one for a routine meal or a picnic. There are several ways to assess a product's perceived situational appropriateness, intended here as the degree of perceived fit between a product and a target situation. One that is particularly expedient in practical product development/optimization is the item-by-use (IBU) appropriateness approach, where by consumers are presented with a list of possible consumption situations and asked to indicate how well a product fits each of them (Schutz, 1988, 1994). This approach was originally proposed by Schutz as a natural complement to hedonic testing, as a way to provide further guidance information in product development (Schutz, 1999). Accordingly, the end goal of the IBU method is to ensure that the test products not only have high acceptability, but also have high appropriateness for the consumption context for which they are intended. Research by Giacalone and Jaeger has shown that IBU appropriateness is a strong predictor of consumers' food choices (Giacalone & Jaeger, 2016, 2017), indicating that this aspect should be considered an important product performance criterion at least on par with (and possibly more important than) liking itself.

## 4. CONCLUSION

Product performance optimization is an important task in the development process for foods and other consumer products. This chapter has discussed the main approaches to product optimization used by sensory and consumer scientists. These include both well-established methods to identify the set of product properties that maximize sensory acceptability, such as preference mapping, RSM, and JAR scales, and more novel approaches such as the IPM and the use of CATA questions. While these methods undoubtedly have value and will continue to be the "bread and butter" for many professionals, they may be limited in that they all consider acceptability as the main optimization criterion.

Evidence that acceptability in and of itself has limited value as a predictor of marketplace success has prompted the inclusion of a broader set of performance measures. Some of these, like emotions, have been studied rather extensively in recent years and are already operationalized in product optimization. Other performance measures, like health and well-being, are expected to increase in importance in the near future. 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 earlier in this chapter is a painful reminder that this question is still very open. Still, sensory and consumer scientists have moved a long way from the early days of the profession, and they have shifted from a single-minded focus on sensory acceptability to a broader and more realistic assessment of the product experience. This move has brought the field closer to marketing and behavioral scientists in an interdisciplinary collaboration that is crucial in the context of product development and innovation (van Trijp & Schifferstein, 1996). 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 performance.

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