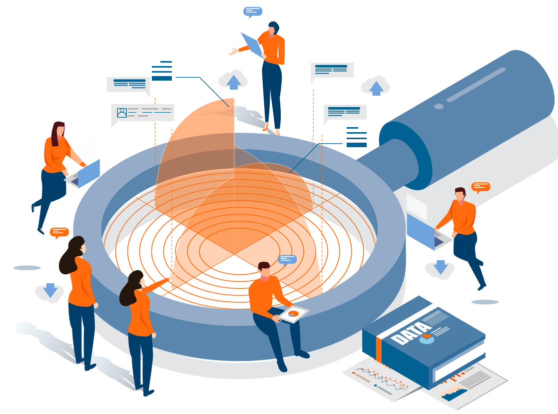
MarketVision RESEARCH



MARCH 2017

ADVANCED ANALYTICAL METHODS FOR SENSORY RESEARCH

IDENTIFYING MARKET OPPORTUNITIES AND INDIVIDUAL PREFERENCES

This document discusses the application of multivariate research methods to sensory research. Specifically, this document describes an approach that MarketVision has found extremely useful in identifying market opportunities and guiding product enhancements for sensory products.

In many areas, researchers deal with attributes in which “more is better.” For example, more miles per gallon are better assuming other things remain constant; a lower price for the same product; the faster a computer the better. Many similar examples can be identified.

Some attributes, however, have “optimal” levels that are not extreme. The most common examples are sensory attributes of food products. Too much salt or too little salt, for example, both decrease the appeal of a product. Complicating this further is the realization that different people might all have different “optimal” levels of salt, for example. Traditional methods that rely on aggregate level analysis of overall liking will likely blur these subtleties.

EXAMPLE

Consider a simple example with five respondents rating their overall liking on a nine-point scale for three products that vary in salt intensity. Product A has a very high salt intensity and Product C a very low salt intensity. Respondents 1 and 2 have a preference for a saltier product, while respondents 4 and 5 dislike a saltier product—preferring a lower salt product. Respondent 3 is relatively salt insensitive; that is, her overall rating doesn’t vary based on the salt intensity of a product.

By traditional measures such as mean overall rating, all three products are equally liked. Looking at the top box measure, Product B would seem the winner. However, recall that Product B is not salty enough for respondents 1 and 2 and at the same time is too salty for respondents 4 and 5.

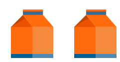
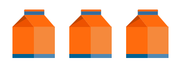
OVERALL LIKING

Salt Intensity	Product A	Product B	Product C
Respondent 1	9	7	5
Respondent 2	8	7	6
Respondent 3	7	7	7
Respondent 4	6	7	8
Respondent 5	5	7	9
Mean Rating	7.0	7.0	7.0
% Top 3 Box (7, 8 or 9)	60%	100%	60%

Any approach to identifying optimal flavors must deal with each individual's preferences. A method that aggregates across people who might have differing tastes will fail to provide clear direction on market opportunity.

The issue for guiding development of sensory products, however, is not limited to identifying the right amount of a single sensory dimension in a product overall. This time we expand our example shown above to include five products and a dairy intensity dimension. Note that we still rely only on a single measure of overall liking.

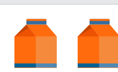
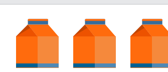
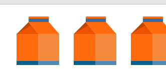
OVERALL LIKING

	Product A	Product B	Product C	Product D	Product E
Salt					
Dairy					
Mean Rating	7.0	7.0	7.0	7.4	7.2
% Top 3 Box (7, 8 or 9)	60%	100%	60%	100%	80%

Not only does Product D have a 100% top box measure, but also its mean overall liking rating is the highest of all the products studied. Here we more clearly have a winner—at least until we look at each individual respondent's ratings.

This time, each respondent's highest rating has been highlighted. Once again, we see that the product that is somewhat good for everyone is not optimal for anyone. Two respondents really like Product A, two really like Product C, and one really likes Product E. From this limited example, it is not clear that this market warrants three separate products. It is clear, however, that the market optimal product, Product D, will likely fail to provide the optimal product to any given individual or market segment.

OVERALL LIKING

	Product A	Product B	Product C	Product D	Product E
Salt					
Dairy					
Respondent 1	9	7	5	8	7
Respondent 2	8	7	6	7	7
Respondent 3	7	7	7	8	9
Respondent 4	6	7	8	7	7
Respondent 5	5	7	9	7	6
Mean Rating	7.0	7.0	7.0	7.4	7.2
% Top 3 Box (7, 8 or 9)	60%	100%	60%	100%	80%

Identifying optimal intensity levels must not only identify each individual's preferences, but must identify each individual's preferences on many dimensions. Any method that aggregates across people or only considers one dimension will fail to provide direction for optimal product design.

Another way to think about this idea of combinations of preferences is to examine the same respondents' ratings, but instead of looking at the ratings of products, summarize the liking by levels of the two sensory dimensions we have studied. For example, what is the mean rating for all products with a high salt intensity?

By reviewing the data this way, we can add one additional measure, which represents respondents' sensitivity to each dimension. The sensitivity can be represented as the range between the lowest summary rating and the highest summary rating.[1] This range indicates how much impact that dimension has on each respondent's overall liking. For example, the first respondent's range of liking for salt intensity has a range of three points compared to only one point for the third respondent. Put another way, the first respondent's overall liking is influenced a great deal by the salt level while the third's overall liking is influenced only a little.

We can continue to add products and sensory dimensions to this example. Imagine eventually having 250 respondents each having indicated their overall rating for 12 products, each of which is summarized on, for instance, 20 sensory dimensions. It should be clear that we could develop, for each respondent individually, an optimal level of each sensory dimension. That would produce 250 unique product specifications, should we wish to uniquely satisfy each person individually.

As we saw in the previous example though, there are frequently similarities between people's optimal levels. For instance, the five hypothetical respondents would have at most three unique product specifications because the optimal levels for respondents 1 and 2 are identical, as are those for respondents 4 and 5. In actuality, there are frequently a limited number of combinations of optimal levels that satisfy a large portion of all respondents. These combinations are identified by cluster analyzing all respondents' individual-level optimums. This cluster analysis will identify groups of respondents who have a similar set of optimal levels for all dimensions studied.

Once we have determined the market segments and identified the optimal levels for each, we will investigate how closely existing products match each segment's optimal levels. Segments whose optimal levels are going unmet represent opportunities for new product/flavor development.

OVERALL LIKING

	Salt Intensity				Dairy Intensity			
				Range				Range
Respondent 1	9.0	7.5	6.0	3.0	8.0	5.0	7.5	3.0
Respondent 2	8.0	7.0	6.5	1.5	7.5	6.0	7.0	1.5
Respondent 3	7.0	7.5	8.0	1.0	7.0	7.0	8.5	1.5
Respondent 4	6.0	7.0	7.5	1.5	6.5	8.0	7.0	1.5
Respondent 5	5.0	7.0	7.5	2.5	6.0	9.0	6.5	3.0

Optimal levels, to be useful in product redesign, must be shared by a large enough segment of the market to justify the development of a specialized product flavor. Any appropriate method to identify market opportunity must combine people into market segments based on the similarity of their optimal levels.

While this is an extreme simplification from the actual process, it communicates the basic idea behind our analyses. In practice, we don't calculate mean ratings by intensity but use multivariate techniques to derive non-linear response surfaces at the level of the individual. This also allows us greater latitude in the exact measurement of the sensory dimensions. Typically, these are mean intensity ratings provided by an expert sensory panel for each product on each dimension. In this way, each product can have a unique value on each dimension, and we are not limited to the coarseness of low, medium, and high descriptors, as used in the example.

ANALYSIS REQUIREMENTS

The inputs to these tests are critical. Ideally, the products tested would be created based on the principles of experimental design. This approach is often unrealistic. However, it is important to ensure that the products tested represent a range of the key product characteristics of interest, and that the different sensory characteristics of the products vary independently, or as independently as practical.

One of the strengths of this approach is the repeated measures nature of the respondent task. This approach allows us to control for the response style characteristics of different individuals, which is extremely valuable in any segmentation exercise. However, the researcher must be attentive to fatigue, or satiety, among respondents. It is possible to have respondents complete the evaluations over multiple sittings. This often introduces non-monotonic order effects, which must be controlled for with advanced methods.

This analysis does have a few unique requirements.

First, prototype products must be available for which the respondents can provide an overall liking.

Second, each product must be described technically on each sensory dimension under investigation. These technical ratings are typically provided by members of an "expert" sensory panel who can discriminate between the dimensions being studied. However, technical ratings from many other sources can also be used, such as lab derived measures of viscosity, density, color, or fluidity.

Then, since we have an independent intensity rating for each dimension, all we ask the respondent to indicate is how much they like the product overall. Analytically, we can combine the respondent's overall rating with the sensory measures to decompose the overall liking to its components. Not only does this make the respondent task easier, it also produces much more reliable data. By making the respondent task easier, only really requiring one question per product, we increase the number of products each respondent can evaluate —enhancing the benefit of within- subject experimentation.

We resist the temptation to ask respondents to indicate their liking of the specific intensities of flavor dimensions. We are interested in the consumer's overall liking of the product and not their perception of the various ingredients or product characteristics. Consumers have an extremely difficult time answering questions about toothpack or mouthfeel, for example, so such characteristics are typically left off the questionnaire even though they have proven important in explaining preference for one prototype over another.

Further, respondents are frequently unable to discriminate between dimensions with the precision necessary. Put another way, they cannot "tease apart" the various components underlying the overall flavor they are sensing. Even product characteristics that are clearly understood, such as saltiness, are difficult for respondents to answer reliably. By avoiding asking respondents about any flavor dimensions, the product characteristics that are intentionally excluded because they are not consumer friendly, are not clearly understood by the consumer, or might be accidentally excluded by the researcher cannot limit the ability to infer the source of the consumer's preference.

We also like the indirect measurement of our approach. Research has shown that by telling the respondent the product characteristics you are interested in, you increase their sensitivity to those characteristics.

To combat these limitations of measuring optimal intensities and to meet the needs outlined above, we have found this multivariate approach extremely powerful as a tool to aid market opportunity identification and product/flavor design. In essence, the output from this research is a "recipe" for each segment indicating the combination of optimal intensity levels on sensory dimensions. This output provides a very clear direction for new product development.

[1] *In actuality, the sensitivity is the slope of the preference function.*