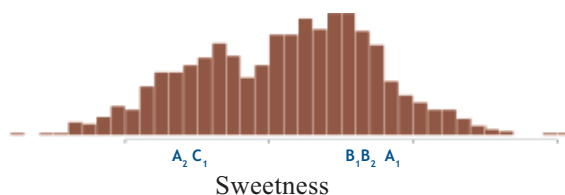


**Background:** We send our children to less than ideal schools, we drive less than optimal cars (for longer than we care to admit), we can always think of a neighborhood that we would prefer to live in, and we consume foods that, based purely on their sensory effects, we would prefer to forego. It may be said as a general rule that people do not choose consumer products that maximize their satisfaction from the sensory effects of the products themselves. In making consumer product choices, people make tradeoffs and pay penalties to consume the products and services that they choose. While these ideas may not be particularly novel, it is interesting to consider how one might measure the hedonic penalties paid to consume typical consumer products. Companies invest largely in product performance optimization for consumer products and services, and it is worth thinking about how to use this information and how to interpret it to achieve better market performance in the context of sensory penalties.

In previous reports we have discussed how to find individual ideal and product maps to study both latent segmentation and the drivers of consumer choice<sup>1,2</sup>. Using the same ideas, we have also shown how motivations for product consumption, product-concept fits and product portfolio optimization can be evaluated in this mapping framework<sup>3,4,5</sup>. The purpose of this report is to consider how penalties are measured when consumer choice does not correspond to a consumer's ideal on one or more sensory drivers of liking or preference. The report will consider three elements: The location of consumers' ideals on a sensory driver, an image component of the ideal points, and how consumer behavior relates to the measurement of penalties. A key interest is the development of strategies that minimize the sensory penalty paid to switch among your own brands while maximizing the penalty to switch to competitors' brands.

**Scenario:** Liking data from a representative sample of 1000 consumers of your beverage brands and your competitors have been collected. These evaluations are based on blind and branded product tests. You have a well established brand A and your main competitor has two established brands B<sub>1</sub> and B<sub>2</sub>. You have recently introduced A<sub>2</sub> and a second competitor has C<sub>1</sub>. You are interested in knowing why your main competitor's two brands seem to perform so well and especially why loyalty to the brand family of this competitor is much higher than for your brands. Your second competitor generally receives lower liking ratings than other brands among users of this product.



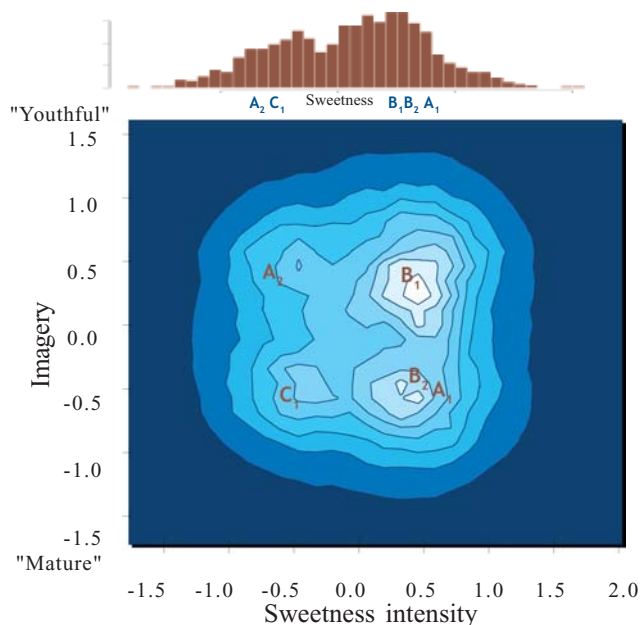
**Figure 1.** Plot of the frequency of occurrence of ideals in sweetness intensity.

**Performance and Image Ideals:** Analysis of blind product testing allows us to evaluate product performance without the possible effect of branding and its associated imagery. This is obviously important if interest centers on improving product performance through product design features that matter to consumers. Since consumers are influenced by variables other than sensory performance, such as perceived health, imagery, what their friends are choosing and what will help them to fit in, there must be an associated sensory penalty paid for the consumption of those products that the consumer would not choose on a blind basis. Switching among brands and loyalty to a brand family may depend on achieving an understanding of the tradeoffs that consumers make between the satisfaction that they derive from the performance aspects of the product and unrelated cognitive components that drive their purchasing choice. If consumers transition from a product with one imagery to another during their consuming lives, they will be more likely to switch to a product that reduces the sensory penalty that they have to pay to make the transition. Consumer product companies who understand this principle design products so that brand switchers will remain within their brand families.

**Location of Ideal Points from Blind Product Testing:** Using a method that we have described previously<sup>1,6,7</sup>, called Landscape Segmentation Analysis® (LSA) you find that liking is driven by one main sensory variable, sweetness. Figure 1 is a histogram plot of the distribution of ideal points on this variable along with the location of the brands that have been tested. There is a lot of variation in consumers' ideals. However, from the bimodality of the ideal point distribution on sweetness, it can be seen that there is one large group who prefer sweeter products and a smaller group who prefer less sweet products. Both of your main competitors' products appeal to the same consumers – those who like sweeter products. So also does one of your brands, A<sub>1</sub>. Your recent introduction and your second competitor's product were designed to appeal to the smaller group who prefers the less sweet product. Why would your competitor produce two almost sensorially identical products on the main variable that drives liking in this category?

**LSA Map Based on Branded Product:** LSA analysis of branded product leads to a more complete picture of consumers' ideals than the blind data analysis. Figure 2 shows the 2D LSA map. Superimposed on this map is the unidimensional distribution of ideals on sweetness, sometimes referred to as the marginal distribution. The additional dimension that has emerged is associated with imagery. In this example, the north - south direction represents imagery that appeals to either younger (more northerly) or mature (more southerly) consumers. Apparently the two brands of your main competitor, although sensorially similar on sweetness, are very different brands with appeal to different consumers. Your brands appeal to more diverse consumers – consumers who relate to a younger image along with lower sweetness and those who prefer sweeter products with a more mature image. Your second competitor's product would appeal to mature consumers who prefer less sweetness. We have so far described two of the three ele-

ments mentioned earlier: The location of ideals on the sensory driver (sweetness) and the image component of ideals. What brands do consumers actually purchase and are they satisfied with them?



**Figure 2.** An LSA map based on branded product data showing an image and a sensory variable. The contours show densities of individual ideals (lighter are more dense.) Above the figure is a plot of the ideal sweetness values with the product positions indicated.

**Brand Choice and the Penalty Matrix:** From Figure 2 it can be seen that very few consumers have ideal points located exactly at product positions. A measure of how satisfied they are can be obtained from the distance between their ideals and the product positions. Based on distances between the location of the individual consumers' ideals for the brand they choose most often and the location of the products on the sensory driver sweetness, we can construct a sensory penalty matrix. Table 1 is the corresponding matrix for Figure 2. In general, it can be seen that the diagonal entries of Table 1 are similar, except for  $C_1$ . This means that consumers who typically choose these products pay about an equal sensory penalty for them. Some  $C_1$  consumers may choose this less sweet brand as they mature because of, for instance, health or weight concerns and are dissatisfied with its taste. It can be seen that  $A_1$ ,  $B_1$ , and  $B_2$  consumers (particularly  $B_1$  and  $B_2$  consumers) would pay about an equal penalty if they switched brands. As  $B_1$  consumers mature, their switch to  $B_2$  would be seamless (it has one of the lowest penalties in Table 1.) Your product positions,  $A_1$  and  $A_2$  are not favorable to future growth. As  $A_2$  consumers mature they will switch to  $C_1$ , which shows a lower penalty than their existing brand. You have no youthful appearing brand to act as a feeder for  $A_1$ . Table 1 explains why your first competitors' consumers are loyal to its brands,  $B_1$  and  $B_2$ , and why you lose consumers through brand switching.

Products	Brand Consumers				
	$A_2$	$C_1$	$B_1$	$A_1$	$B_2$
$A_2$	0.28	0.41	1.01	1.15	1.02
$C_1$	0.26	0.37	0.91	1.05	0.93
$B_1$	0.93	0.76	0.25	0.25	0.24
$A_1$	1.18	1.01	0.33	0.28	0.33
$B_2$	0.98	0.81	0.25	0.24	0.24

**Table 1.** A penalty matrix showing sensory penalties for brand consumers (columns) to consume products (rows). The larger the number, the greater the penalty.

**Conclusion:** The measurement of penalties paid by consumers to consume less than sensorially optimum products is important in making product positioning and new product decisions. The combined use of blind and branded product testing data along with individual ideal point analyses, make it possible to calculate a penalty matrix. The information in this matrix may be used to design product families that facilitate within family switching and at the same time discourage consumers from venturing out into other brand families as the imagery of one brand is replaced by another in their product purchasing lives. Vulnerability to changes in the market can be visualized using this type of analysis and guide the design of product portfolios.

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