Reprinted from IFPress (2018) 21(1) 3,4

Consumer-Centric Product Mapping: LSA vs. EPM

Benoît Rousseau and Daniel M. Ennis

Background: Why do consumers of products or services like them and/or purchase them? This is a classic, complex question with numerous methods to address it and with answers that depend on the specific application. In previous publications we have emphasized the central role of providing a consumer-perceived benefit[1] and measuring that benefit. From the viewpoint of analytic methods, we have also discussed the value of approaching this problem from a process-driven consumer perspective[2] as opposed to a product or service perspective. Analytic methods to find variables that, for example, drive liking can be broadly classified into two groups. The first group begins with product or service descriptive information and incorporates liking or other hedonic information *post hoc*[2]. The second group includes methods that begin with liking *a priori* and add descriptive information to attempt to explain the liking analysis[2,3]. An example of the former is External Preference Mapping (EPM) and an example of the latter is Landscape Segmentation Analysis® (LSA), a form of unfolding. In this technical report we discuss a particular weakness of EPM and contrast it with an analysis based on LSA.

Scenario: You work for a large manufacturer of fruit-flavored soft drinks. You conduct a category appraisal of citrus-flavored beverages to study the performance of some new category entrants and make recommendations on product improvement opportunities. You select a set of 12 products[4] that include your main brand, two of your main competitors and 9 other products selected to span the sensory space (labeled P_1 through P_{12}). You generate the products' sensory profiles using your trained internal descriptive panel. You also obtain hedonic information from 250 regular users of the category on a 9-point hedonic scale.

EPM is used to link the two data sets and uncover the category's drivers of liking. To that end, you first conduct a principal components analysis (PCA) to generate a space into which the 250 consumers will be regressed based on their liking ratings of the 12 products. The first two factors account for 53% of the variance contained in the descriptive analysis data. Figure 1 illustrates the first two components of the sensory space from the PCA.

When attempting to regress the 250 consumers individually onto the sensory space, you realize that many of them cannot be regressed successfully using any of the typical four regression models - vectorial, circular, elliptical, or quadratic. In your case, the poor fitters constitute 45% of your respondent population. This type of result is regularly observed by practitioners who use EPM.

You investigate the consumer liking data by conducting a cluster analysis to help explain your results. There seems to be two consumer groups of similar sizes driven by their liking patterns. The main difference between the two groups is that Group 1 likes $\mathbf{P_1}$ and rejects $\mathbf{P_4}$ while Group 2 shows the opposite trend: Positive to $\mathbf{P_4}$ but rejecting $\mathbf{P_1}$.

It is pretty clear from your PCA map in Figure 1, that $\mathbf{P_1}$ and $\mathbf{P_4}$ are located very close to each other. This means that when considering the sensory attributes that explain the most variance in the descriptive data, as summarized in the first PCA plane, $\mathbf{P_1}$ and $\mathbf{P_4}$ are similar. Consequently, many consumers cannot be regressed successfully into the space since their liking patterns are not compatible with the PCA product structure. The PCA result requires that consumers should like P_1 and P_4 similarly since the first two principal components as assumed to be the drivers of liking. It is apparent that you need to study the assumptions behind the EPM model to see if you can resolve this apparent discrepancy.

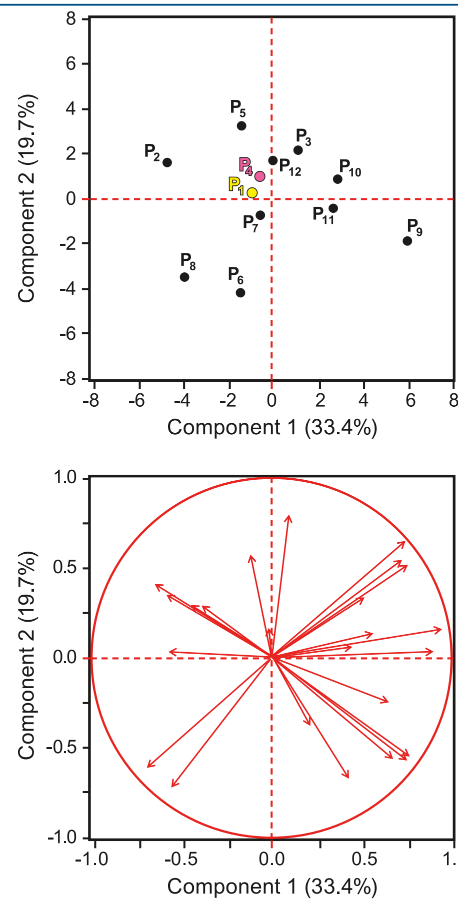

Figure 1. PCA Components 1 and 2. Product structure and sensory directions.

Two Spaces: Preference mapping techniques can be categorized based on the information they use to create the product space. EPM uses the sensory descriptive information to create the sensory space and then regresses the consumers using their liking ratings. Therefore, the assumption is that the most obvious variables, those found in the first two components of the space, are the attributes driving consumer liking. In typical EPM analyses, it is assumed that sensory characteristics present in higher dimensions are not as important to consumer hedonics. It is possible, through trial and error, to explore other combinations of principal components and accept the poorer explanation of the descriptive data that they provide when a major principal component is eliminated. This method is usually not very satisfactory.

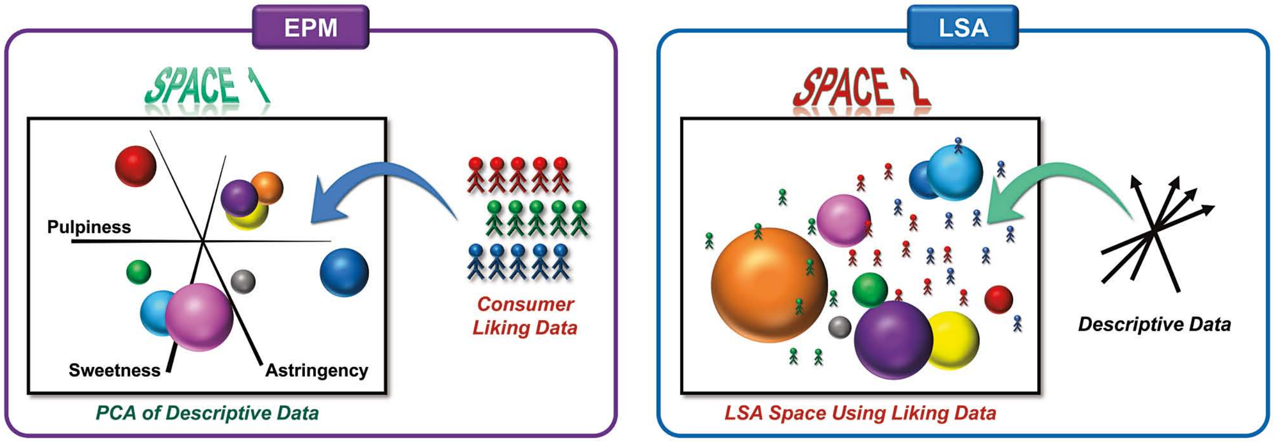

Figure 2. Two modeling approaches - EPM and LSA.

In the evolution of mapping methods to explain liking, or other measures of hedonicity, it is understandable that researchers who approach the problem from a descriptive analysis viewpoint would adopt a method such as EPM. However, a researcher who approaches the problem from the consumer-centric direction will see the problem differently. In this case, the product space is only based on the liking information from the consumer and then the sensory descriptive information is used to explain the drivers of liking space. LSA is a method based on this principle and takes into account the psychological process used by the consumer to generate a liking score. Figure 2 summarizes the difference between the EPM and LSA approaches.

An advantage of LSA is that, unlike EPM, it does not assume in advance which attributes drive consumer liking. Using a process model, it creates a sensory space that best represents the consumer liking information and then regresses the descriptive data to explain the map. This approach allows the identification of potentially relevant sensory characteristics that may (or may not) be present in higher dimensions of a PCA.

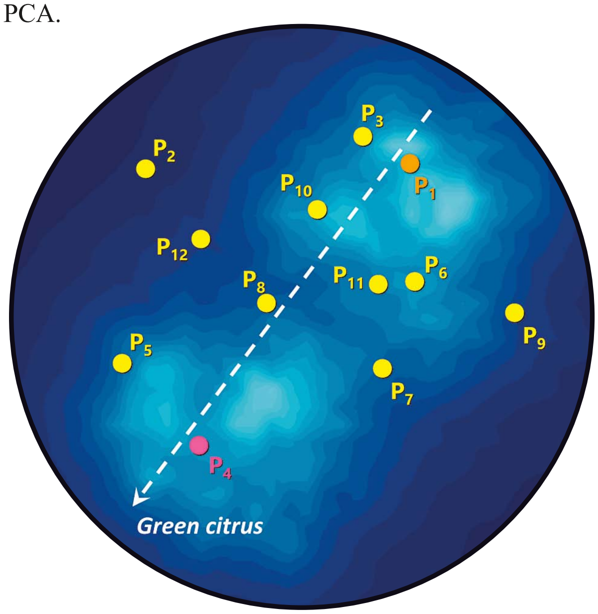

Figure 3. Landscape Segmentation Analysis® of lemon-flavored soft drink data.

Using Unfolding on the Lemon-Flavored Soft Drinks Data: You use LSA to analyze the category appraisal data. The map you obtain is shown in Figure 3. The resulting product space is quite different from that found with PCA on the descriptive data. The most important difference is that $\mathbf{P_1}$ and $\mathbf{P_4}$ are no longer located next to each other, but are found at the center of two clusters of consumers as outlined by the lighter colored areas. The main driver of liking separating the two clusters is green citrus, an attribute best explaining the fourth component of the PCA. On that fourth dimension $\mathbf{P_1}$ and $\mathbf{P_4}$ are well separated. However, EPM did not capture this main attribute because consumers were fit on the first two dimensions. EPM assumes that only the most obvious differences are drivers of liking. By using an unfolding model, such as LSA, the product space is built around the characteristics relevant to the consumers' hedonic reactions.

Conclusion: Many preference mapping techniques are available to link consumer and descriptive information. These techniques all are built on specific assumptions and it is important for the practitioner to understand their underlying models. Typically, EPM assumes that the variables explaining the most variance in the descriptive analysis data are the most important and thus must drive liking. If this is not the case, a large proportion of consumers will not fit on the map. An unfolding technique such as LSA does not make this assumption and thus provides a consumer-centric solution irrespective of the underlying sensory-based product structure. Using a technique that does not offer this flexibility can result in misleading findings and conclusions.

References

1. Ennis, D.M. (2012). Invention and innovation. In J. Beckley, D. Paredes & K. Lopetcharat (Eds.), *Product innovation toolbox: A field guide to consumer understanding and research* (pp. 32-44). Ames, IA: Wiley-Blackwell.
2. Ennis, D. M. and Ennis, J. M. (2013). Mapping hedonic data: A process perspective. *Journal of Sensory Studies,* **28**(4), 324-334
3. Rousseau, B., Ennis, D. M., and Rossi, F. (2012). Internal preference mapping and the issue of satiety. *Food Quality and Preference,* **24**(1), 67-74.
4. Rousseau, B., Ennis, D. M. and Ennis, J. M. (2017). Selecting products for a category appraisal with constraints. In D. M. Ennis, J. M. Ennis, and B. Rousseau (Eds.), *Tools and applications of sensory and consumer science* (pp. 96-97). Richmond, VA: The Institute for Perception.