



New metrics for evaluating preference maps

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Abstract

Preference maps provide a visual representation of market structure, usually depicting brand or product alternatives, product attributes, and customers in a single graphic. Using measures of consideration and attribute sets to establish criterion validity, we develop a set of metrics that can be interpreted managerially and that allow managers to evaluate maps based on their ability to accurately represent market structures for products, attributes, and consumers. Using a Monte Carlo simulation, we test the stability of the metrics for a variety of scenarios and compare them to statistical stress. Our results show that the metrics can help identify specific sources of noise and can therefore be used to interpret map fit at a more disaggregated level than stress. We apply the metrics on an empirical example and use them to develop a reweighted map for a focal product.

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Introduction

Preference maps are designed to help managers understand the market structure that they are facing and thus help them make decisions about (new) product positioning and design (e.g., Green, 1975; Winer & Moore, 1989, Kaul & Rao, 1995). Managers can use these maps to identify their main competitors, potential product attributes, and attractive customer segments. Preference maps are intuitive and convey in graphical manner information that would otherwise be difficult to express (Carroll & Green, 1997; Natter & Mild, 2003).

Ironically, however, the greatest benefit of preference maps, namely the intuitive presentation of information in a single graphic, has also led them to be considered with some skepticism (e.g., DeSarbo, Young, & Rangaswamy, 1997, Lilien & Rangaswamy, 2003). First, preference maps offer only summary information, meaning that some information is lost in the graphical representation process. In the aggregation of information across customers, products, and attributes, the configuration for individual customers, products, or attributes may become distorted. Second, preference map configurations change as products or attributes are added or eliminated; while these changing configurations may reflect actual consumer decision-making processes, they lead to difficulties in interpretation: it is possible to create multiple preference maps for the same market, and consequently the choice of a particular map may appear somewhat arbitrary. Finally, the statistical criteria used to establish a map's goodness-of-fit do not provide any insights regarding a map's usefulness or accuracy in representing the market. In particular, because they are aggregated measures of fit, they do not allow the researcher to identify specific areas where the graphical representation may not be entirely accurate. From a managerial perspective however, identifying whether the area around one's product is well represented appears essential.

Indeed, preference maps provide a picture of consumer mindsets regarding a given market and reflect consumer preferences for certain products and attributes (see Day, Shocker, and Srivastava, 1979). Clearly, firm actions influence consumer mindsets and hence preference maps, and it is thus essential to understand the interplay between consumer perceptions and company actions in order to obtain a meaningful picture of the competitive structure of a market for a specific product. DeSarbo, Grewal and Wind (2006) provide a detailed discussion of the inter-linkages between demand and supply perspectives, with a particular focus on asymmetric competitive relationships. Such relationships often emerge due to different company (product) sizes (shares); in such situations, the smaller company often decides to watch the larger company's actions, whereas the larger company may choose not to watch the small company's actions. The result is that the preference mapping of asymmetric competitive relationships can become a difficult task, leading to inappropriate configurations. DeSarbo et al. (2006) propose the use of consideration set data to calculate an asymmetric distance measure and thereby account for asymmetric competition. In order to avoid conflicts related to representing asymmetric relationships, they recommend computing maps for each focal brand (in addition to a general market map)¹. This approach seems very useful for companies that use such maps for their product positioning decisions because the representation conflict (if any) can be resolved in favor of the focal product. However, multiple maps may also lead to confusion because alternative interpretations may be derived from different market views. It would hence be useful to have some diagnostic tools that help managers decide whether a specific map for their brand is necessary (or, in a new develop-

¹ In a further paper, DeSarbo and Grewal (2007) propose mapping both perspectives (from and to the brand) on a single map; while this approach is very attractive for maps that only include brands or products, it becomes cumbersome on complex maps that also include product attributes and consumer ideal points.

ment context, whether a map focusing on a specific attribute is necessary). This would require metrics that can be interpreted at the level of a single product or attribute.

In summary, we argue that existing criteria used to establish a map's goodness-of-fit such as statistical stress are too aggregated and cannot be meaningfully interpreted. Our objective is therefore to develop a set of metrics that can be applied towards evaluating the fit of preference maps at a disaggregated (and interpretable) level. To this end, we use consumer consideration and attribute sets as criteria to evaluate preference map fit. We develop five metrics: product-product recovery, attribute-attribute recovery, product-attribute recovery, the recovery rate of consideration sets and the recovery rate of attribute sets. Using a Monte Carlo simulation, we test the sensitivity of these metrics with varying numbers of products, attributes, consumers, consideration set sizes, and different levels of noise. We conclude that these metrics allow for a more fine-grained identification of sources of noise in the data than a standard stress statistic would. We illustrate the use of these metrics with an empirical application in the sweet snacks market to help demonstrate how the metrics can be used by managers to identify the extent to which individual products or attributes are accurately represented on preference maps and to develop weighted maps for single products or attributes.

1. Assessing the fit of preference maps

Before discussing in detail the metrics, we first present the main facets that disaggregated fit measures used on maps with a simultaneous representation of products, attributes, and consumers would ideally address.

Product representation fit. Preference maps provide a representation of competitive market structure, and one of their key functions is to help companies identify key competitors (Carroll & Green 1997) as a basis for (re)positioning decisions (e.g., Dickson & Ginter, 1987; Dillon, Domzal, & Madden, 1986), product line decisions (e.g., Gilbert & Matutes, 1993), or advertising budget allocation decisions (e.g., Winer & Moore 1989). Particularly in markets where a wide range of products is offered, competitors might not be easy to identify (Hahn, Won, Kang, & Hyun, 2006); in a given choice situation, consumers may choose from a rather diverse set of brands (Chakravarti & Janiszewski, 2003; Ratneshwar, Pechmann, & Shocker, 1996). Such situations make the identification of competing brands particularly tricky and make preference maps potentially very useful—to the extent that the products are accurately represented on the map.

Attribute representation fit. A second key objective of preference maps is the identification of attractive product attributes. This information can then be used as an input for product development efforts (Lilien & Rangaswamy, 2003) or for the design of online recommendation agents. The majority of recommendation agents are feature-based, first asking consumers to rate a few attributes or to identify the attributes that they consider to be relevant for their decision; this information is then used to interactively generate the appropriate set of products recommended to a given consumer (see for instance Häubl and Murray (2003), Häubl and Trift (2000), and Xiao and Benbasat (2007)). These developments in screening behavior therefore bring to the fore the importance of ensuring that accurate combinations of attributes are represented on preference maps.

Product-attribute representation fit. A third goal of preference maps is the combined representation of products and attributes. Managers use preference maps to identify the attributes that con-

sumers associate with their products and with those of their competitors. This information is of great managerial relevance and can be used for positioning and advertising purposes (Dickson & Ginter, 1987). A preference map should therefore provide an accurate representation of the associations between products and attributes.

Consumer representation fit. Many preference maps also depict consumers, typically as ideal points representing a given consumer's preferences on the map. Preference maps that include consumer ideal points enable managers to fulfill two additional objectives: identifying relevant (groups of) consumers for (1) products and (2) specific attribute combinations. First, companies use preference maps to single out consumers (or groups of consumers) who are mapped close to their products. Combining further behavioral and socio-demographic information about these consumers enables managers to gain a deeper understanding of their customers; this information can then serve as the basis for media planning, advertising, or direct marketing campaigns (DeSarbo, Grewal, & Scott, 2008). Second, companies may use preference maps to identify those consumers who are attracted by specific combinations of attributes; this information can be used to help design online recommendation agents (Xiao & Benbasat (2007).

Combining these two objectives, companies can also utilize preference maps to identify attractive consumers (or consumer segments) whose needs are not yet adequately served by existing products. Preference maps can help identify attractive market niches or, when used in combination with product attribute information, they can help decide which repositioning strategies to follow (DeSarbo, Kim, Choy, & Spaulding, 2002; DeSarbo et al., 2008; Lilien & Rangaswamy, 2003; Natter, Mild, Wagner, & Taudes, 2008). Consumer representation therefore allows companies to identify the number and profiles of consumers that are attracted to certain products or attribute combinations. This information can, however, only be used when managers believe that

preference maps accurately represent consumer preferences—that is, that the representation of consumers on the map is accurate.

In summary, we identify five key objectives for companies that use preference maps: identifying the accurate competitors, combinations of product attributes, and associations of products with attributes and, for each consumer, identifying both relevant products and relevant attributes. In the following section, we develop a set of metrics that can be used to establish goodness-of-fit separately for each of these five objectives.

2. Proposed metrics and their operationalization

Preference maps are typically generated based on information provided by consumers about their preferences for specific products or attributes. We focus in this research on maps that simultaneously depict products, attributes, and consumers. In the graphical representation process, some of the information from the original data set may be lost and inconsistencies may occur in the representation of single products, attributes, or consumers as a result of the multidimensional scaling procedure. The key idea behind the proposed metrics is to use self-reported consideration sets to establish map criterion validity. Specifically, we propose to use two self-report measures (product consideration set and attribute set) to test the extent to which the information contained in these sets is accurately recovered by the preference maps after the graphical representation process².

² One alternative to the approach proposed here would have been to use decomposed measures of stress to identify sources of inconsistencies in the maps. We found however that decomposed stress measures were not able to correct for differing consideration (and attribute) set sizes and were not as good indicators of the level of noise in the data as the proposed metrics.

Product consideration sets (hereafter referred to as consideration sets or CS) are well known in the marketing literature. Campbell introduced the concept as early as 1969 and defined a consideration set as the set of brands/products that a given consumer will consider when facing a specific purchase decision. Paulssen and Bagozzi (2006) persuasively argue for the use of consideration sets to represent market structure. Because consideration sets include those products that consumers consider to be substitutes for one another for a given purchase, these products are also in direct competition with one another. While many researchers (e.g., DeSarbo & Jedidi, 1995; Katahira, 1990) recommend developing preference maps directly on the basis of the information contained in consideration (or evoked) sets, we follow DeSarbo et al. (2006) and suggest using consideration sets as an external criterion to establish the validity of a given graphical representation. Moreover, because we are interested in maps that also include attributes and consumers, we also propose to use self-reported attribute sets as the second criterion for establishing the validity of graphical representations. We define an attribute set (referred to as an AS in the remainder of the paper) as the set of attributes that a consumer takes into consideration when deciding to purchase a given product. This notion is therefore analogous to the consideration set but focuses on attributes instead of products; it is consistent with recent research on online recommendation agents that suggests how consumers often reduce the number of alternatives by first selecting the features (attributes) of relevance to them (Häubl & Trift, 2000; Xiao & Bensabat, 2007). It is also consistent with the logic of adaptive conjoint analysis, in which respondents first select relevant attributes and then only select from product combinations that match the selected attributes (levels) (see for instance Bradlow (2005)). Because preference maps represent attributes and not attribute levels, we ignore attribute levels but simply state that each consumer, when faced with a given product choice situation, considers a set of attributes that is relevant to his/her decision and

ignores other attributes. We therefore consider attribute inclusion in the attribute set to be of a binary nature, with single attributes included in the set and others excluded³.

Using consideration sets and attribute sets as criteria to validate preference maps, we then develop five metrics, each of which addresses one of the facets described in the introduction of the paper. Because one of our objectives was to propose metrics that are intuitive and easy to understand, we developed the metrics as correlation coefficients or as recovery rates—that is, as percentages of correct representations. In general, the metrics compare information obtained through the self-reported consideration and attribute sets (coded as “*prime*” in our equations) with information derived from the model-based preference maps (coded as “*second*” in our equations). The starting point for each metric is therefore the inclusion of products or attributes in the self-reported sets. We define the following:

$x'_{ip}=1$ if Customer i has Product p in his/her self-reported CS, 0 otherwise.

$x'_{ia}=1$ if Customer i has Attribute a in his/her self-reported AS, 0 otherwise.

Using the preference maps and the distances estimated following the multidimensional scaling procedure, we can calculate the implied distances from each customer to each product and each attribute on the map. Using these distances, we identify, for each consumer, the products and attributes that are mapped closest to the consumer; these then constitute his/her model-derived consideration and attribute sets⁴.

³ Note that, if attribute levels are of interest, the model may easily be extended to include such levels, with each attribute level being represented individually on the map, thereby creating an attribute set that consists of acceptable attribute levels.

⁴ We restrict the analysis to pure distance maps and do not refer to joint preference and perceptual (vector) maps where axes are often interpreted as latent constructs. In distance maps, we rarely interpret the whole (rotated) axes as latent constructs but rather restrict such latent construct interpretations to areas. Often, for instance, bundles of relevant attributes (which should consequently be located close to each other on a map) indicate typical usage situations or goals of customers located close to these areas. Hence, the metrics that we propose help assess the usefulness of a map with respect to pure distance interpretations.

To illustrate the transformation logic, we first focus on products and customers. The transformation of the distances on the map into model-based consideration set memberships is based on two factors: the Euclidean distances and the self-reported consideration set size (*CSS*): Product p is in Customer i 's modeled-derived (map-based) consideration set (CS_{ip}) if the distance between Customer i and Product p ($distance_{i,p}$) on the map is among the CSS_i shortest distances (where CSS_i is the consideration set size for Customer i) between i and all products $p=1,\dots,P$. We posit that the composition of these modeled-derived consideration sets is such that brands within this threshold (CSS_i) are jointly and deterministically considered by Customer i and thus actively compete with each other. Because we do not focus on the estimation of consideration set size at this point, we take the self-reported consideration set sizes to define the cut-off value for the relevant distances between a focal consumer and products on the map.

The same logic is replicated for the identification of map-based attribute sets, depending on the distances between individual customers and attributes and on the attribute set size (*ASS*).

We therefore obtain the following from the maps:

x''_{ip} is the model-derived CS-membership; it is therefore equal to 1 if the map indicates that Customer i has Product p in his/her CS and it is equal to 0 otherwise (i.e., a hard partition based on distance and *CSS*; $\Pr(CS_{i,p}=1)=x''_{ip}$).

x''_{ia} is the model-derived AS-membership; it is equal to 1 if the map indicates that Customer i has Attribute a in his/her AS and equal to 0 otherwise (i.e., $\Pr(AS_{i,a}=1)=x''_{ia}$).

2.1 Product and attribute-centered recovery

Product-product recovery. The first metric focuses on the recovery of product associations. Intuitively, this metric tests the extent to which preference maps accurately identify asymmetric competitive structures. For each product represented on the map, this metric calculates the extent to which maps allow us to recover the product's main competitors. For this purpose, using the self-reported consideration sets, we first compute the extent to which the same products are simultaneously included in consumer consideration sets. Using the map distances, we then determine for each product which other products are mapped closest to one another. These two estimates are systematically compared to one another to obtain a recovery rate with respect to product-product associations. Intuitively, the metric reflects the extent to which products that are often included simultaneously in consumer consideration sets and therefore seen by many consumers as being in competition with one another are also represented close to one another on the preference map.

We define the relative consideration set overlap, $CSO_{pq} = \frac{\sum_{i=1}^I \frac{x'_{ip} x'_{iq}}{\sum_{j=1}^I \sum_{h \neq p} x'_{jp} x'_{jh}}$, as the number of consumers who have two products in their consideration set at the same time, adjusted for the total


number of overlaps between the focal product p and all other products; i.e., larger values for $CSO(CS)_{pq}$ indicate a stronger competitive relationship between p and q in terms of this overlap measure. Hence, similarly to the conditional probability of considering Product q conditional on having p in the consideration set (DeSarbo, Grewal & Wind 2006), CSO_{pq} is an asymmetric measure of competitive relationships.

After calculating these measures, we rank them in decreasing order. Table 1 lists the required data for a sample calculation for Product $p=1$, which shows a total number of overlaps with other

products of $\sum_{i=1}^I \sum_{h \neq 1} x'_{i1} x'_{ih} = 87$. Using the map distances, we then rank the distances between Product 1 and all other products from the shortest to the longest. Intuitively, we would expect that

products with greater overlap (the number of consumers who simultaneously have two products in their consideration sets), such as Products 1 and 2, ($CSO_{1,2}=34/87$) should be placed closest to each other on the map. However, on the derived (hypothetical) map, the product with the third-largest original overlap ($CSO_{1,4}=17/87$) is actually the one that is mapped with the shortest distance from Product 1. Column 3 contains the vector of overlaps between Product 1 and all other products in order of decreasing CSO values, whereas Column 5 lists the CSO values of all products in order of competitive strength as suggested by the derived map. The correlation between Columns 3 and 5 indicates how well the respective map reflects competition between Product 1 and all other products (here $r=0.766$). This measure is calculated for each product and can be inspected either for a specific product or brand itself, or as an average over all products.

Table 1: Overlaps in consideration sets between Product 1 and all other products

Order of strength of competition	Competitive order according to CSO	Product 1's CSO with competitors	Order according to map distances	Product 1's CSO with competitors
Strongest competi- tion  Lowest competition	1-2	$CSO_{1,2}=34/87$	1-4	$CSO_{1,4}=17/87$
	1-3	$CSO_{1,3}=25/87$	1-3	$CSO_{1,3}=25/87$
	1-4	$CSO_{1,4}=17/87$	1-2	$CSO_{1,2}=34/87$
	1-5	$CSO_{1,5}=5/87$	1-6	$CSO_{1,6}=3/87$
	1-6	$CSO_{1,6}=3/87$	1-5	$CSO_{1,5}=5/87$
	1-7	$CSO_{1,7}=2/87$	1-9	$CSO_{1,9}=0/87$
	1-8	$CSO_{1,8}=1/87$	1-7	$CSO_{1,7}=2/87$
	1-9	$CSO_{1,9}=0/87$	1-10	$CSO_{1,10}=0/87$
	1-10	$CSO_{1,10}=0/87$	1-8	$CSO_{1,8}=1/87$

Formally, the metric of product-to-product correlation $r(P2P)$ is calculated as follows:

$$r(P2P) = \frac{1}{P} \sum_{p=1}^P r_p(CSO_p(CS), CSO_p(MAP)) \quad (1)$$

where $CSO_p(CS)$ denotes the vector of consideration set overlaps of Product p with competitors in decreasing order of competitive strength, whereas $CSO_p(MAP)$ indicates the vector of consideration set overlaps of p with competitors in the order of increasing map distances.

One advantage of this metric is that it can also be reported at the individual product (brand) level. Therefore, a company that relies on preference maps can use this metric to determine whether its own products and/or those of its major competitors are consistently displayed on the map. This is a major advantage of the technique over standard goodness-of-fit measures because stress measures do not provide this type of information. Furthermore, in unfolding procedures that incorporate a weighting procedure (for the relevance of objects in a configuration), trade-offs concerning representation conflicts can be operationalized. Thus, based on the resulting metrics for the focal product, one can decide whether to switch to the individual product sub-map (DeSarbo et al. 2006) or whether the focal product's weights in the MDS/unfolding procedure should be increased. In contrast to DeSarbo et al., we display consumer ideal points on the map. Because we focus on a complete picture of the market—including products, attributes and customers—we propose to use only one map and to (re)weight the products' and attributes' impacts on the solution based on their relevance (CSO , $CSASO$) to the focal product if the metrics of the general map indicate a poor representation of the relevant map area. We will provide a detailed illustration of this issue on an empirical dataset later in the paper.

Attribute-attribute recovery. Following the same logic as for the product recovery rate, the second metric focuses on the recovery of correct attribute associations. It therefore captures the extent to which attributes that are often considered simultaneously by consumers are also mapped close to one another on the preference map. $ASO_{ab} = \frac{\sum_{i=1}^I x'_{ia} x'_{ib}}{\sum_{j=1}^I \sum_{h \neq a} x'_{ja} x'_{jh}}$ denotes the number of customers who declare in self-reports that they considered both Attribute a and Attribute b in their purchase decisions, adjusted for the total number of overlaps between the focal attribute a and all other attributes h. We then compare these estimates of attribute set overlaps with the distance-based attribute set overlaps to assess the recovery of attribute sets through the map. Formally, this metric of average attribute-to-attribute correlation $r(A2A)$ is computed as follows:

$$r(A2A) = \frac{1}{A} \sum_{a=1}^A r_a(ASO_a(AS), ASO_a(MAP)) \quad (2)$$

Product-attribute recovery. The third metric focuses on the correct representation of the associations between products and attributes. The intuition behind this metric is that when a given consumer selects specific products in his/her consideration set and also a set of attributes for the same choice situation, the products selected should have (some of) the attributes that are considered important by this consumer. Therefore, the simultaneous inclusion of specific attributes and products in consumer sets should reflect consumer perceptions that these products also have the desired attributes. Based on this assumption, we therefore first calculate, for each product-attribute combination, the extent (number of customers) to which it is simultaneously included in each consumer consideration and attribute set, adjusted for the total number of overlaps between

the focal product p and all attributes: $CSASO_p(CS, AS) = \frac{\sum_{i=1}^I x'_{ip} x''_{ia}}{\sum_{j=1}^I \sum_b x'_{jp} x''_{jb}}$. We then compare the self-reported product-attribute associations with the map-based distances. Formally, the recovery rate of the product-attribute associations ($r(P2A)$) can be calculated as follows:

$$r(P2A) = \frac{1}{P} \sum_{p=1}^P r_p(CSASO_p(CS, AS), CSASO_p(MAP)) \quad (3)$$

3.2 Recovery rates of consideration (attribute) sets

The last two metrics address the representation of customers on the maps. Intuitively, these metrics tap the extent to which, for each consumer, the products (attributes) present in that particular consumer's consideration (attribute) set are also the products (attributes) mapped closest to this consumer's ideal point on the preference map. Formally, the recovery rate of the consideration set ($HR(CS)$) is computed as follows:

$$HR(CS) = \frac{1}{I} \sum_{i=1}^I \frac{\sum_{p=1}^P x'_{ip} x''_{ip}}{\sum_{p=1}^P x'_{ip}} \quad (4)$$

Because the hit rate systematically depends on the consideration set size relative to the number of products (for instance, a given customer who has 90% of the products in his/her consideration set would have a hit rate of 90% for a random dummy vector, indicating CS membership for those competitors who belong to the 90% with the shortest distance on the preference map), we calculate a corrected hit rate that accounts for this fact⁵. For this purpose, we calculate the con-

⁵ Note that a decomposed statistical stress measure would not correct for this problem.

sideration set size of customer i ($CSS_i = \sum_{p=1}^P x'_{ip}$) divided by the number of products (P) available, CSS/P , which represents a natural benchmark for the hit rate—i.e., the hit rate that would result from a random consideration set vector with the same consideration set size and number of products. Only hit rates above this benchmark indicate that the model has identified systematic relationships in the data. A corrected average hit rate that eliminates the effect of the relative size of the consideration set can therefore be calculated in the following way:

$$HR_{corr}(CS) = \frac{HR(CS) - \frac{CSS}{P}}{1 - \frac{CSS}{P}} = \frac{1}{I} \sum_{i=1}^I \frac{\frac{1}{\sum_{p=1}^P x'_{ip}} \sum_{p=1}^P x'_{ip} x''_{ip} - \frac{\sum_{p=1}^P x'_{ip}}{P}}{1 - \frac{\sum_{p=1}^P x'_{ip}}{P}} \quad (5)$$

The expected corrected HR for random data is zero and it can be a maximum of one (perfect recovery of consideration sets).

Similarly, the corrected recovery rate of attribute sets ($HR_{corr}(AS)$) can be computed as follows:

$$HR_{corr}(AS) = \frac{HR(AS) - \frac{ASS}{A}}{1 - \frac{ASS}{A}} = \frac{1}{I} \sum_{i=1}^I \frac{\frac{1}{\sum_{a=1}^A x'_{ia}} \sum_{a=1}^A x'_{ia} x''_{ia} - \frac{\sum_{a=1}^A x'_{ia}}{A}}{\sum_{a=1}^A x'_{ia}} \quad (6)$$

In the following sections, we first compare these five metrics in a simulation context to a classic measure of goodness-of-fit for preference maps: statistical stress. We then illustrate the usefulness of the metrics on an empirical dataset.

3. Monte Carlo simulation

We used a Monte Carlo simulation to test the effects of the number of products, the number of attributes, and the number of consumers on the five metrics and to compare the metrics to a classic measure of stress. The simulation involved the following steps: we first systematically generated *true* preference maps and then distorted these maps through the systematic introduction of different sources of noise (this introduction of noise yielded “design” maps); next, on the basis of these “design” maps, we calculated all relevant distances (x'_{ip} and x'_{ia}). These “design” maps were then submitted to an unfolding procedure to generate the “model” maps, which in turn were used to compute the relevant model-based distances and derived CS and AS memberships (x''_{ip} and x''_{ia}). Figure 1 provides a summary description of the simulation framework.

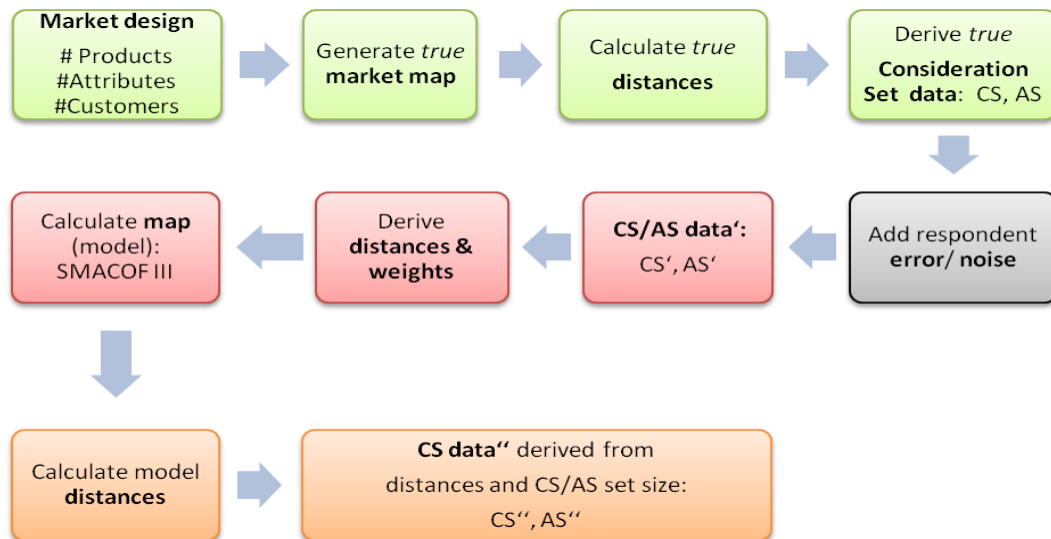


Figure 1 – Monte Carlo simulation framework

The first step in the Monte Carlo study was to establish the *true* environment (upper line in Figure 1). To match typical multidimensional scaling studies, we specified two different numbers of products (10, 20 products), four different numbers of consumers (50, 100, 200 and 400 consumers), and two different numbers of attributes (10, 20 attributes) and generated for each combination a two-dimensional preference map that was used as the *true* map in the simulation⁶. Each of the components (consumers, products, and attributes) on the map was represented as an ideal point (i.e., a distance map). We calculated the *true* distances between all objects (products, attributes, and consumers) on each of the randomly generated maps. These distances served as a basis for identifying, for each consumer i on the map, *true* product and attribute consideration sets. A *true* product consideration (attribute) set consisted of the CSS_i products (attributes) with the shortest distances from a given consumer's ideal point. To use realistic numbers, we systematically varied CSS and ASS for both sets (using two, four, and six products or attributes). These numbers are consistent with previous research reporting that consumers typically have between two and six products (or brands) in their consideration sets (e.g., Aurier, Jean, & Zaichkowsky, 2000). The number of attributes was also consistent with previous research on conjoint research that suggests how respondents have difficulty handling an excessive number of attributes (e.g., Pullman, Dodson, & Moore, 1999). We used six products and attributes as an upper limit to ensure that the consideration (attribute) sets were not larger than the total number of products (attributes) included in the simulation (ten in the minimum case).

⁶ In order to guarantee consistent representations of the objects and their relative distances, we initially (before introducing noise) ordered these objects uniformly on an ellipse (such a formation has been shown to best reflect ranking data in unfolding models (Van Deun et al. 2007)).

In a second step, to reflect actual error in the data collection process (which, in an empirical study, may happen due either to clerical errors or to consumer uncertainty or memory deficiencies), we systematically introduced noise into the data. The true consideration (attribute) sets were used as inputs after being exposed to noise (0%, 25%, 50%, and 75%). For a noise level of 25%, for example, we randomly chose 25% of the cells from the consideration set matrix X' and set those cells with probability CSS/P to one (zero otherwise). To reflect varying degrees of noise for individual products and attributes (typically, less well known products and/or attributes are assessed with more uncertainty than known products or attributes; see for instance Chapman & Staelin (1982)), we introduced noise for either 50% or 100% of the products/attributes. Our noise manipulations therefore reflect the fact that uncertainty may be found in (some of) the products or attributes (or of course in both). They are a combination of the level of noise in the consideration (attribute) sets and the proportion of products (attributes) affected. Explicitly varying the proportion of products (attributes) affected by noise allowed us to test whether disaggregated measures of $r(P2P)$ and $r(A2A)$ were able to detect product and attribute-specific noise.

Overall, we used a full factorial design without replication and manipulated a total of nine factors (number of products, attributes, and consumers; consideration set and attribute set size; noise levels of consideration and attribute sets, number of products affected by noise, number of attributes affected by noise) for a total of $(2 \times 2 \times 4 \times 3 \times 3 \times 4 \times 4 \times 2 \times 2) = 9,216$ different “design” maps for three different types of input data⁷.

⁷ One requirement for testing the metrics in a simulation context was the need to integrate the *true* consideration set and attribute set data as an integral part of the simulation. Because preference maps based on similarities do not include such information, we did not test the metrics for such maps. We instead tested the metrics for three types of input data: binary, ranking, and rating data (where rankings and ratings are obtained in a two-step procedure, first asking consumers to select relevant products and attributes, then to rank or rate these products and attributes). Because the patterns of results were similar for all input data, we only report the results for binary data. Detailed results for ranking and rating data may be obtained directly from the authors.

The next steps in the simulation consisted of the generation of preference maps on the basis of the (noisy) data obtained through the “design” maps (see Figure 1). Following classic multidimensional unfolding procedures, we first calculated a distance matrix based on the input data⁸. This distance matrix then served to generate a “model” map using the SMACOF III unfolding procedure⁹ (see Borg and Groenen (2005) for more detail on the procedure followed). To allow for a meaningful representation of the complete information on the maps, a weighting procedure was retained. Following the classical MDS/unfolding procedure, we assessed the value of stress on these maps (squared stress). We then computed the metrics proposed in the previous section using the distances calculated from the “design” and “model” preference maps.

To ensure metric validity, we used a hold-out procedure to calculate out-of-sample metrics. To compute the product-to-product, attribute-to-attribute, and product-to-attribute correlation coefficients, we split the data sample into two equal-size parts: the first half of the (generated) customers served to derive the map configuration; the second (hold-out) half served to correlate consideration (attribute) sets for the hold-out customers with the competitive structure (consideration set overlaps) derived from the map configuration. In order to calculate the corrected out-of-sample hit rates for products ($HR_{corr}(CS)$) and attributes ($HR_{corr}(AS)$), we further eliminated the impact of a subset of two product and two attribute valuations per customer from the iterative majorization procedure by setting the respective weights of the SMACOF III procedure to zero. After estimation, these hold-out valuations for each customer were used to calculate the corrected out-of-sample hit rates.

⁸ In an initial analysis, we compared a variety of distance measures to one another (Euclidian, Hamming, Jaccard, and correlation-based distances). As the distance measures used had no interaction effects with the factors of interest, we report the analyses based on the most commonly used distance measure in MDS studies, the Euclidian distance.

Results of Monte Carlo simulation

We conducted the analysis in three steps. First, we assessed the extent to which sstress and the proposed metrics were affected by noise¹⁰. Of particular interest in this step of the analysis was the extent to which the different metrics were able to differentiate between various types of noise. Second, we investigated the sensitivity of the different metrics to the factors manipulated in the simulation. Finally, we explored the ability of disaggregated product-to-product and attribute-to-attribute recovery rates to detect noise associated with a single product or attribute.

Correlations between metrics and noise components. Because all metrics in the simulation could only assume values between -1 and 1, we min-max (into the interval [0;1]) and logit transformed the metrics before entering them into the correlation analyses. As a first result (Table 2), we found sstress to be a good measure of goodness-of-fit and to be affected by noise (r ranging from .261 to .522 with the average noise introduced in the product and attribute consideration sets). The analysis indicates that the proposed metrics were also able to detect noise and that they could additionally distinguish between different types of noise. Product-focused metrics (product-to-product recovery rates and consideration set recovery rates) had respective correlations of -.791 and -.735 with the average noise in the consideration sets but only correlations of -.068 and -.070 with the average noise in the attribute sets; in contrast, attribute-focused metrics (attribute-to-attribute recovery rates and attribute set recovery rates) had respective correlations of -.796

⁹ Preference maps for consideration set data could be derived by use of Levine's (1979) pick-any procedure (cf. Kim et al., 1999). However, since we also conduct simulations for ranking and rating data (cf. Holbrook and Moore (1984)), we chose the SMACOF III algorithm for all three data types considered.

¹⁰ Note that because sstress improves as it gets closer to 0, while the proposed metrics improve as they get closer to 1, improvements in sstress are indicated through negative coefficients, whereas improvements in the other metrics are indicated through positive coefficients.

and $-.735$ with the average noise in the attribute sets but only correlations of $-.062$ and $-.070$ with the average noise in the consideration sets. The metric that focused on both attribute and product information was, like *sstress*, unable to detect differences between the various sources of noise given the averaged levels. Hence, we conclude that $r(P2A)$ will provide more specific information than *sstress* only when considering individual product-to-attribute relationships. This first analysis therefore indicates that the proposed metrics can be used to calculate goodness-of-fit and yield specific information on the sources of badness-of-fit, which *sstress* does not provide.

Table 2: Correlations between metrics and noise

Noise on	Metrics (logit transformed)					
	<i>sstress</i>	$r(P2P)$	$r(A2A)$	$r(P2A)$	HR_{corr} (CS)	HR_{corr} (AS)
Products	.522	-.791	-.062	-.500	-.735	-.070
Attributes	.522	-.068	-.796	-.542	-.070	-.735

Note: all correlation coefficients were significant at $p < .01$

Effects of simulation factors on metrics. In a second step, we conducted a series of regression analyses to assess the impact of the factors manipulated in the simulation study on the various metrics. As in the analyses above, we used logit transformations of the metrics for the regression analyses. Table 3 lists the regression coefficients obtained for the regression analyses and the adjusted coefficients of determination.

Table 3 – Results of regression analyses

	Metrics (logit transformed)					
	Stress	r(P2P)	r(A2A)	r(P2A)	HR _{corr} (CS)	HR _{corr} (AS)
Constant	-2.812**	2.818**	2.777**	2.372**	4.924**	4.942**
Number products	.016**	-.057**	-.021**	-.042**	-.088**	-.011*
Number attributes	.016**	-.018**	-.050**	-.035**	-.009	-.082**
Number consumers	.000**	.005**	.005**	.005**	.000	.000
CS size	-.051**	.284**	.087**	.183**	.324**	.063**
AS size	-.051**	.084**	.286**	.192**	.048**	.310**
CS noise	.009**	-.091**	-.007**	-.044**	-.105**	-.010**
AS noise	.009**	-.008**	-.091**	-.048**	-.010**	-.106**
Adjusted R²	.724	.725	.726	.687	.586	.582

Note: * $p < .05$, ** $p < .01$, analyses based on 9216 maps

We first focused our attention on the effects of the number of products, attributes, and consumers on the various metrics. Increasing numbers of products and attributes generally led to worse levels of stress and also negatively affected consideration set and attribute set recovery (with a positive effect on stress and a negative effect on the other metrics); this is intuitively logical because the graphical representation process becomes increasingly difficult as more (potentially asymmetrically related) objects need to be represented on the maps. Increasing numbers of products and attributes, however, had only a moderate impact on product-to-product, attribute-to-attribute, and product-to-attribute recovery rates. The analyses also show that increasing numbers of consumers improved stress and the proposed metrics; this seems reasonable because the multidimensional scaling procedure then had more information on which to base its approximation. The effects of consideration set and attribute set size on the metrics were quite consistent across

all three sources of data (binary, ranking, and rating data). Increasing the size of these sets systematically improved the metrics, that is, sstress was reduced and the recovery rates improved as consideration set and attribute set size increased. Note however that sstress reacted particularly strongly to set size when using rating and ranking based data.

In line with the results from the first analysis stage, sstress appeared to be influenced by noise (that is, noise was detrimental to sstress) but was equally affected by product-centered and attribute-centered noise. In contrast, the metrics proposed were much more strongly affected by noise that was consistent with their content—namely product-to-product and consideration set (attribute-to-attribute and attribute set) recovery rates were influenced by noise introduced in the products (attributes). Therefore, the metrics proposed seem able to detect specific sources of noise.

Overall, the metrics proposed therefore appear to behave as expected. Like stress, they are generally affected positively by increasing sample size and negatively by increasing the numbers of objects represented on the maps. In addition, unlike stress, they are able to differentiate between different sources of noise.

Disaggregated analyses. To check the consistency of the metrics, we also independently computed, at a disaggregated level, the product-to-product (attribute-to-attribute) correlations for each product (attribute). For this analysis, we chose only those designs whose added noise level was positive and for which there existed variation in the level of noise added between the products and attributes (i.e., 50% of the variables were outset to the respective noise level). These disaggregated metrics should therefore be a good reflection of noise. Across all products, we recorded correlation coefficients of .80 (.80) with the actual noise added, thereby demonstrating

a good ability to detect noise for single products (attributes). This indicates that noise can be properly identified at the individual product and attribute level and that the product (attribute)-level metrics can be used to reflect noise in the focal product (attribute).

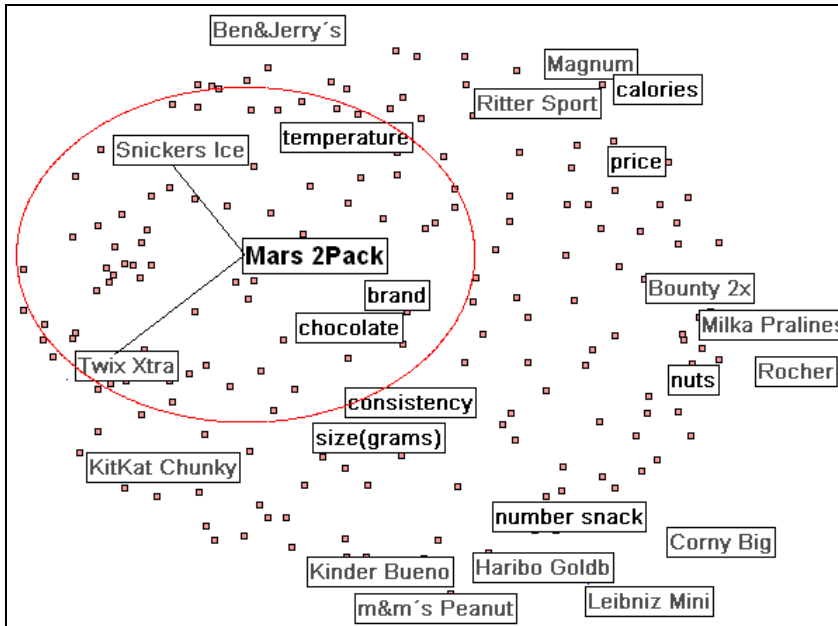
4. Illustration of the metrics with an empirical dataset

To further illustrate the use of the metrics, we applied them to an empirical dataset on sweet snacks, with 15 products and 9 attributes. Data were collected from 209 German consumers through a computer-based survey. Study participants first indicated which products and attributes they considered in their purchase decisions regarding sweet snacks; they then ranked these attributes and products accordingly. These rankings were used as the basis for the development of the preference map. Consideration and attribute set sizes could therefore differ for different consumers.

Figure 2a depicts the preference map obtained for the general market consideration map. Table 6a summarizes the out-of-sample fit metrics for this map. To facilitate interpretation, we adopted the convention recommended by DeSarbo, Grewal & Wind (2006) for displaying a focal product's competition boundary with a circle¹¹ to indicate distances from the focal product where consideration set probabilities are equal to 50%. The circle size depends on two factors: (1) the better the hit rate for the focal product, the smaller the circle; and (2), the greater the total number of customers who consider the focal brand, the larger the circle. Circle size is therefore not

¹¹ Because the SMACOF III algorithms do not directly yield the circle size (radius), we determined the radius ex post by applying a Logit Model with the distances between customer locations and the focal product as independent

an appropriate fit measure by itself, but it elegantly indicates the focal product's relevant area on the map.



$sstress=.150$, $r_{P2P}=.634$, $r_{A2A}=.562$, $r_{P2A}=.485$, $HR_c(CS)=.527$, $HR_c(AS)=.253$

Figure 2a: Representation of general Sweet Snack market structure

The general snack market map yields a relatively high $sstress$ value of .150 (see the bottom of Figure 2a). A more detailed observation of the metrics at the product and attribute levels enables us to identify specific sources of problems in the map representation (Table 4a). For instance, the metrics indicate that the map provides a relatively good representation of Rocher's competitors and their customers but a poor representation of Rocher's relevant attributes. In contrast, some other products' competitive relationships, such as Ritter Sport Nougat ($r(P2P)=.222$) or M&M's Peanut ($r(P2P)=.337$), appear to be quite poorly represented on the general market map. Focus-

variables and product considerations as the dependent variable. The radius for the focal product is then calculated as minus the constant of the Logit Model divided by the distance parameter.

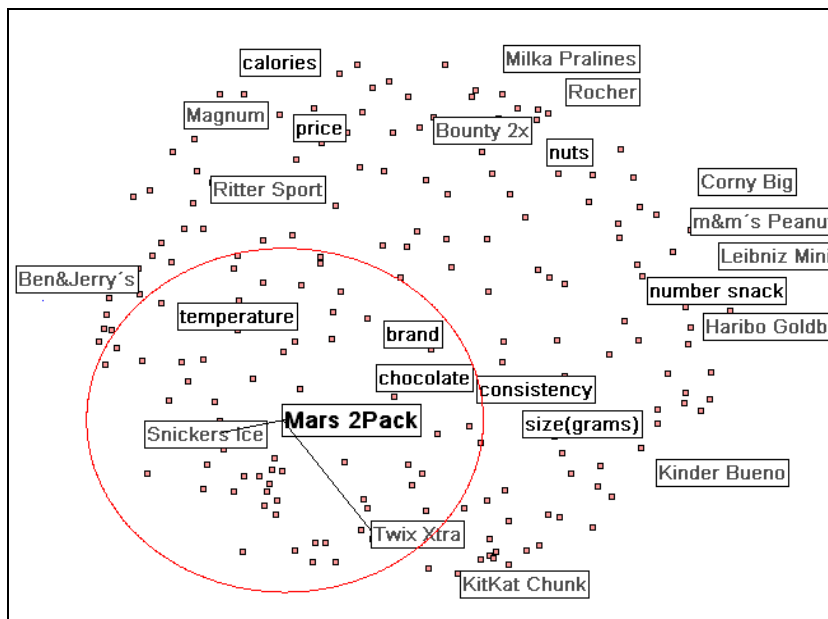
ing on the attributes, an observation of the attribute-to-attribute correlations ($r(A2A)$) suggests that the attributes brand name, chocolate taste, consistency, size (grams), and temperature (frozen) appear well represented on the map, whereas we see considerable error in the representations of nut content and price.

To even better illustrate the use of the metrics, we decided to focus more specifically on a specific brand and chose Mars 2Pack for this purpose. Table 4a shows that Mars 2Pack's competitive relationships ($r(P2P)=.672$), as well as its links to relevant attributes ($r(P2A)=.794$) are reasonably well represented on the general market map (Figure 2a). The metrics also indicate a reasonable consumer representation of Mars 2Pack ($HR_{corr}(CS)=.621$), thereby suggesting that managers can also use this map to identify relevant consumer characteristics. An observation of the map indicates that the attributes chocolate and brand name (and to a lesser extent temperature (availability of frozen product)) are mapped close to Mars 2Pack, and that Snickers Ice and Twix Xtra appear to be the relevant competitors.

Table 4a: Product- and attribute-specific metrics for general market structure

	$r(P2P)$	$HR_{corr}(CS)$	$r(P2A)$	Attribute	$r(A2A)$	$HR_{corr}(AS)$
Ben & Jerry's	.823	.621	.215	Brand	.977	.008
Bounty 2x	.555	.583	.359	Calories	.410	.642
Corny Big Schoko	.434	.281	.199	Chocolate	.902	.187
Haribo Goldbears	.620	.432	.404	Consistency	.912	.304
Kinder Bueno	.544	.528	.589	Number snacks	.453	.135
Kit Kat Chunky	.921	.674	.849	Nuts	.000	.282
Magnum	.715	.329	.474	Price	.000	.287
Mars 2Pack	.672	.621	.794	Size (grams)	.790	.221
Milka Pralinés	.700	.360	.000	Temperature	.610	.208
Leibniz Minis	.601	.615	.791	Average Metrics	.562	.252
M&M's Peanut	.337	.322	.558			
Ritter Sport Nugat	.222	.571	.310			
Rocher	.701	.638	.000			
Snickers Ice	.759	.604	.897			
Twix Xtra	.909	.731	.839			
Average Metrics	.634	.527	.485			

To get even better insights into this particular product's representation and to account for asymmetric representations, we calculated a weighted preference map for Mars 2Pack (Figure 2b). To calculate the focal product's map, we rescaled the weighting matrix entries for the products (attributes) according to their relative relevance to Mars 2Pack (i.e., by their overlaps with the focal product divided by the total number of overlaps between the focal product and the other products (attributes), CSO and $CSASO$). Stress had a slightly improved (lower) value of .141 for the map weighted in favor of Mars 2Pack.



$sstress=.141$, $r_{P2P}=.647$, $r_{A2A}=.534$, $r_{P2A}=.468$, $HR_c(CS)=.537$, $HR_c(AS)=.192$

Figure 2b. Representation of sweet snack market focusing on *Mars 2Pack*

Table 4b: Product- and attribute-specific metrics for map focusing on *Mars 2Pack*

Product	$r(P2P)$	$HR_{corr}(CS)$	$r(P2A)$	Attribute	$r(A2A)$	$HR_{corr}(AS)$
Ben & Jerry's	.864	.567	.038	Brand	.967	.070
Bounty 2x	.459	.635	.000	Calories	.239	.415
Corny Big Schoko	.434	.255	.355	Chocolate	.847	.103
Haribo Goldbears	.604	.482	.404	Consistency	.912	.140
Kinder Bueno	.772	.632	.685	Number snacks	.439	.282

Kit Kat Chunky	.961	.718	.849	Nuts	.000	.228
Leibniz Minis	.765	.657	.752	Price	.000	.255
Magnum	.720	.406	.474	Size(grams)	.790	.184
Mars 2Pack	.695	.604	.896	Temperature	.610	.048
M&M's Peanut	.000	.191	.686	Average Metrics	.534	.192
Milka Pralinés	.689	.499	.000			
Ritter Sport Nugat	.240	.542	.169			
Rocher	.695	.573	.000			
Snickers Ice	.894	.554	.917			
Twix Xtra	.918	.740	.795			
Average Metrics	.647	.537	.468			

Table 4b reports the disaggregated metrics obtained following this weighting procedure. The calculation of the alternative market map with higher weights for the brands and attributes that have relevance to Mars 2Pack suggests an improvement in the representation of Mars 2Pack and of relevant attributes ($r(P2A)=.896$). Based on these metrics, a communication strategy highlighting Mars 2Pack's chocolate taste and brand image seems reasonable. The focal representation of Mars 2Pack (Figure 2b) also leads to a more consistent competitive representation of Snickers Ice ($r(P2P)=.894$) as compared to the general market map ($r(P2P)=.756$), and to an excellent competitive representation of Twix Xtra ($r(P2P)=.918$). The metrics therefore suggest that the relationships between Mars 2Pack and these two competitors are indeed well represented on the weighted map, and that Snickers Ice's and Twix Xtra's actions should be carefully tracked. Overall, the metrics allow for a precise identification of the sources of problems and can serve as a filter for deciding which information from the map to trust. Moreover, the overlap metrics can be used to calculate more suitable representations of the focal brand(s).

5. Conclusions

Our objective in this paper was to develop metrics that would help managers identify specific sources of representation inaccuracy in preference maps. Using consideration set and attribute set measures as an external criterion, we developed five metrics to help achieve five major objectives: to identify the accuracy of the (asymmetric) representation of competitors, attribute combinations, product-attribute associations and of the relevant (groups of) consumers. The metrics are intuitive and simple to implement and, compared to existing practices, only require two simple additional measures, namely consideration and attribute sets. The added cost is therefore kept to a minimum (in fact, consideration sets are often gathered when companies develop preference maps on the basis of consideration set information or through a two-stage process in which study participants first select the relevant products and attributes and then rank or rate these products and attributes) and the benefits are substantial because these metrics can be used to statistically determine which map is better suited for a given purpose. As the metrics are expressed as recovery rates or correlation coefficients, they could easily be compared across preference maps to help managers choose the map that best represents the market depending on their perspective. Note that because the metrics are sensitive to the numbers of products, attributes, consumers, and set sizes represented, direct metrics comparisons should only be done between maps representing the same objects (as illustrated in the comparison of the sweet snack market's standard and weighted maps)¹².

A key benefit of the proposed metrics is their ability to identify sources of noise—that is, to detect whether noise stems from lack of knowledge about the products in the market, about rele-

vant attributes, or both. Statistically, the measures appear better able to detect noise in the data than sstress; therefore the added benefit won through interpretable metrics does not come at the expense of goodness-of-fit. Furthermore, because the proposed metrics can also be computed at the product or attribute level, they can be used to identify the goodness-of-fit of the representation of individual products or attributes, thereby also providing information about asymmetric competitive relationships. Such information appears to be of high managerial relevance because managers can use the metrics to decide whether the map information concerning their focal products (or some attributes of particular interest to them) can be trusted. This may be a meaningful contribution because there is ample behavioral evidence that, for unfamiliar products or attributes, consumers often construct preferences on the spot (e.g., Dhar & Simonson, 2003; Slovic, 1995). Hoeffler (2003), for instance, stresses the difficulty of obtaining reliable preference measures for really new products because consumers are not able to adequately make trade-offs between unknown features. However, to date little help has been available for identifying the products or attributes for which such a phenomenon actually occurs and the proposed metrics appear particularly valuable in that respect.

To limit complexity in the simulation study, a number of decisions were made that may impact the generalizability of the results obtained for that study. First, because the implementation of the study necessitated the inclusion of both consideration and attribute set data, we did not include similarity-based preference maps. Even though the metrics could be computed for similarity-based maps (the only requirement for the calculation of the metrics is the availability of self-reported consideration and attribute sets), we cannot conclude that they would perform well in identifying sources of noise for such maps. We were however able to show that the metrics per-

¹² Note however that this is not unique to our metrics: indeed, our simulation study suggests that sstress is also af-

form well in identifying specific sources of noise across binary, ranking, and rating data. Second, while the number of products, attributes, and consumers were chosen to be realistic, the consideration and attribute set sizes may be seen more critically because the simulation did not allow these sizes to vary across consumers. However, the noise manipulations should diminish this concern because the addition of noise into the consideration and attribute sets resulted in variation in the level of certainty for the introduction of a given product (attribute) in a set, thereby incorporating some variation across consumers. Moreover, our empirical application to the sweet snack market did allow for varying set sizes.

The present research focuses on the development of disaggregated and interpretable metrics to help assess the fit of specific preference maps. As shown in the empirical illustration, the metrics can also be used to help generate reweighted maps. The next step would be to integrate the metrics to the map development process. Ideally, the metrics could be used as criteria to develop preference maps that maximize the recovery rates that are deemed to be strategically most important for specific types of decisions (for instance, a focus on attribute-attribute recovery for new product decisions).

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