



Adaptive Multidimensional Scaling: Brand Positioning Based on Decision Sets and Dissimilarity Judgments

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Abstract

Assessing market structure by deriving a brand positioning map and segmenting customers is essential for supporting brand-related marketing decisions. We propose adaptive multidimensional scaling (ADMDS) for simultaneously deriving a brand positioning map and market segments using customer data on cognitive decision sets and brand dissimilarities. In ADMDS, the judgment task is adapted to the individual customer where dissimilarity judgments are collected only for those brands within a customer's awareness set. Thus, respondent fatigue and unfamiliarity with the brands are circumvented thereby improving the validity of the dissimilarity data obtained, as well as the multidimensional spatial structure derived from them. Estimation of the ADMDS model results in a spatial map in which the brands and derived segments of customers are jointly represented as points. The closer a brand is positioned to a segment's ideal brand, the higher the probability that the brand is considered and chosen. An assumption underlying this model representation is that brands within a customer's consideration set are relatively similar. In an experiment with 200 respondents and 4 product categories, this assumption is validated. We illustrate adaptive multidimensional scaling model on commercial data for 20 midsize car brands evaluated by 212 members of an on-line consumer panel. Potential applications of the method and future research opportunities are discussed.

Keywords Brand positioning · Customer segmentation · Cognitive decision sets · Multidimensional scaling

1 Introduction

Product positioning requires insight into which customers consider the purchase of a brand, and what their perception is of this brand and its competitors. Assessing market structure by segmenting the market and deriving a competitive map of the

brands is an essential tool supporting product positioning. The spatial representation of brands and segments has indeed proven to be very insightful to managers [1]. As a consequence, marketing researchers have gainfully employed multidimensional scaling methods (MDS) for such assessment [2–5].

While popular in the 1980s and 1990s, the utilization of MDS as a tool for perceptual mapping has diminished in this century. The waning popularity of MDS has been due to a number of challenges regarding data collection and analysis. The collection of pair-wise proximity judgments from consumers is costly and burdensome. Respondent fatigue and brand unfamiliarity can have a considerable distorting impact on the way respondents arrive at their dissimilarity judgment. As a result, positioning maps are often non-informative and hard to interpret. Finally, product positioning and competitive market structure studies are based on different types of data that cannot be jointly analyzed by traditional MDS methods. As mentioned in DeSarbo, Grewal, and Scott [6], contemporary approaches for empirical modeling of competitive market structure now take into account both consumer heterogeneity (e.g., market segmentation) and the competitive positioning of products/brands/services. Such analyses are integrated into

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more encompassing managerial frameworks such as the segmentation–targeting–positioning (STP) framework. Here, a firm targets one or more groups or market segments with its offerings and positioning becomes a segment-specific endeavor.

In this paper, we build on developments in the marketing and psychometric literature on MDS-related data collection and analysis methods. In particular, we develop, test, and illustrate an adaptive MDS (ADMDS) procedure that accommodates both large brands sets and brand unfamiliarity by adapting the data collection stage to the individual subject. This is accomplished by restricting the dissimilarity judgments to only those brands included in the awareness set of individual customers (see [7] for an alternative nested spatial decision set model). The adaptive MDS (ADMDS) model is estimated utilizing dissimilarity and consideration set data jointly. We employ the concept of consideration sets in the perceptual mapping procedure as consideration sets play an important role in customer decision making (see [8, 9]). The ADMDS model yields a perceptual map in which the brands and segments of customers are simultaneously estimated and represented as points.

The next section provides an overview on how large sets of brands and unfamiliar brands can be analyzed with MDS methods. Then, we present the adaptive MDS (ADMDS) methodology. An outline of the data collection phase is given, and we describe the proposed ADMDS model structure. In the section that follows, we report on an experimental study examining an important model assumption, namely that brands in a consideration set are relatively similar. The method is illustrated on commercial data for the Dutch car market. Finally, we discuss potential applications of the ADMDS methodology and future research opportunities.

2 Collecting and Scaling Brand Dissimilarities

MDS/positioning studies often entail the collecting of brand attributes, brand (dis-) similarities, consumer preferences, and/or choice data. Obtaining these data through questionnaires typically results in extensive and time-consuming judgments tasks for the respondent. For paired comparisons, the number of brands in the study increases the number of pairs to be compared by respondents quadratically. As a result, a judgment task with a large number of brands can potentially cause respondent fatigue and boredom, and, in addition, customers are usually differentially familiar with a certain brand [10, 11]. As the researcher has to select the brands to be compared a priori, a respondent may still have to compare brands that are unfamiliar to him/her. Hence, this research addressed two problems concerning MDS research: large numbers of brands and unfamiliar brands.

2.1 The Scaling of Large Brand Sets

To construct a meaningful and stable spatial representation of competitive positions within a product category, one typically requires a sizable number of brands. This results in a considerable number of judgments when using the paired comparisons method to obtain brand dissimilarities. As a respondent progresses through such a large judgment task, s/he experiences an increase in fatigue and boredom, which often reduces the reliability and validity of his/her dissimilarity judgments [11–14]. Researchers have used three strategies to prevent or compensate for such undesirable effects of large brand sets.

First, a researcher can use distance-type measures from other sources of data. For example, one can utilize distances calculated from brand attributes. The user must then be confident that all relevant attributes are represented and collected. In addition, there is an allied problem of correlated attributes and weighting. Bijmolt and Van de Velden [15] proposed an attribute-based perceptual mapping procedure with an idiosyncratic brand and attribute sets that alleviate some of these disadvantages. Finally, in recent years, researchers have used a wide range of alternative data sources for perceptual mapping, some of which may accommodate large sets of brands: e.g., transaction and customer network data [16] and product reviews [17].

Second, a researcher may use alternative data collection methods, such as sorting methods [13, 18], which take less time and effort from each respondent [12]. The amount of information obtained from each respondent, however, is also substantially smaller than with paired comparison judgments. As a result, data need to be collected on a relatively large number of respondents to enable the recovery of a meaningful and stable spatial representation.

The third strategy in collecting dissimilarity data for large sets of brands is to confront each respondent with only a subset of the pairs. Before the data collection phase, a researcher may select such a subset at random or according to some blocking design (e.g., [19]). However, the selection of the pairs before data collection results in little to no information on subsets of brands, respondents, and the relation between these two. The subset of brands can also be determined interactively during the judgment task [20]. However, such procedures are deterministic in nature, and the selection of which brands to be compared is based on technical details of the estimation procedure and not on brand or consumer factors that affect the quality of the judgments. In a probabilistic MDS framework, MacKay and Zinnes [21, 22] suggested to split the total set into two subsets: familiar brands versus unfamiliar brands. Next, dissimilarity judgments are collected for all pairs that include at least one familiar brand. However, in their procedure, no differences between respondents are allowed for, whereas respondents generally differ with respect to their familiarity with the brands.

2.2 The Scaling of Unfamiliar Brands

In typical MDS studies, customers are requested to provide judgments on a predefined set of brands, although some of the customers may be unfamiliar with some of the brands. If one or both brands in a pair are unfamiliar to a respondent, s/he will use a strategy to simplify the dissimilarity judgment, for example by using a reference value on the rating scale [11], or by providing almost uniform responses as shown for halo effects in satisfaction ratings [23]. Mano and Davis [24] concluded that low familiarity results in less consistent MDS solutions since the goodness-of-fit of their MDS solution increased with an increase in familiarity. MacKay and Zinnes [21] claim that dissimilarity judgments among familiar brands are more precise. They found that unfamiliar brands drift towards the outside perimeter of the space, whereas familiar brands tend to be located closer to the origin. Thus, brand unfamiliarity affects both the dissimilarity judgments and the resulting MDS solution derived from these judgments. Chatterjee and DeSarbo [25] and DeSarbo, Chatterjee, and Kim [26] demonstrated these effects of brand unfamiliarity upon the derivation of MDS joint spaces obtained from analyses of preference data and ultra-metric trees estimated from proximity judgments. Bijmolt, DeSarbo, and Wedel [10] proposed an MDS method that accommodates such effects of brand unfamiliarity by assuming the dissimilarity judgments to be a familiarity-weighted composition of the distance in the aggregate perceptual map and a reference value on the rating scale. This approach, however, still requires each respondent to judge all familiar and unfamiliar brands which may be a difficult, if not impossible, task. In addition, of all potential judgment strategies that respondents might use, only anchoring to a particular scale value strategy is corrected for in the analysis.

To conclude, the quality of the dissimilarity judgments as well as the perceptual map derived from them is typically affected by large numbers of brands and unfamiliarity with some of the brands. The degree to which fatigue, boredom, and unfamiliarity is indeed problematic will differ depending upon the set of brands being considered as well as the characteristics of the responding respondents. None of the procedures described above takes all these effects satisfactorily into account in collecting and analyzing dissimilarity data. Therefore, we propose a new procedure of adapting the judgment task to the individual respondent and accounting for this data structure in the analysis phase.

3 Adaptive Multidimensional Scaling

3.1 The Data Collection Phase

Respondents typically experience fatigue and boredom while performing a large number of paired comparison dissimilarity judgments and they use certain judgment strategies to arrive at

dissimilarity judgments of unfamiliar brands. Reduction of the task length and complexity can be achieved by adapting the judgment task to the individual respondent, using computer-assisted or web-based interviewing methods. Ideally, such an adapted structure should be accounted for while analyzing the data. Examples of integrated computer-assisted data collection and analysis are the popular Adaptive Conjoint Analysis [27, 28] and the tailored interviewing procedure for the market segmentation on the basis of lifestyles [29].

To construct individually adapted paired comparison tasks, we employ the use of cognitive decision sets including the awareness set, the consideration set, and the choice set [9, 30, 31]. Assume that the researcher wishes to examine a relatively large set of brands, say 20 brands labeled A to T. At the outset of the judgment task, a respondent indicates which of these brands s/he is aware of. Suppose a respondent is aware of 10 of these brands, say A-E, G, H, R, S, and T. This yields the awareness set. Second, for those brands in the awareness set, the respondent indicates which brands s/he would consider seriously when making a purchase and/or consumption decision [32]. Suppose this respondent would consider buying brands A, B, G, and R, and not C-E, H, S, and T. This yields the consideration set, consisting of four brands in this example. Finally, for those brands in the consideration set, the customer indicates which brands s/he would buy, say brands A and B. This yields the choice set (see [7]).

After elicitation of these nested cognitive decision sets, a respondent provides paired comparison dissimilarity judgments for only those brands that are in his/her awareness set, in the example between ten brands, A-E, G, H, R, S, and T. There are two reasons for restricting the paired comparisons to such brands in the awareness set. First, limiting the dissimilarity judgments to brands in the consideration or choice set would introduce a bias in the dissimilarity data as only customers who have a more positive evaluation of the brand provide information on the positioning of that brand. Second, it has been shown that respondents gather and process information when deciding whether or not to consider a brand from the set of brands s/he is aware of [31–34]. Hence, a respondent will have acquired a certain amount of knowledge about the brands in the awareness set which facilitates him/her to make paired comparison dissimilarity judgments between these brands.

3.2 Outline of the Proposed ADMDS Model

From the data collection phase, idiosyncratic nested decision sets and brand dissimilarities are available for each respondent. On the basis of these two sources of data, the respondents are simultaneously grouped into market segments and both the brands and segments will be jointly positioned in the ADMDS map. This builds on MDS methods of DeSarbo and Wu [3], MacKay, Easley, and Zinner [35], and Ramsay [36] which allow for the spatial analysis of multiple types of data

simultaneously. Our ADMDS model is composed of two dependent components: one representing the nested decision sets and one representing the dissimilarity judgments.

Our ADMDS analysis framework fits within the stream of research that has estimated MDS models based on the maximum likelihood principle. Maximum Likelihood Multidimensional Scaling (MLMDS) methods are formulated in a stochastic framework with distributional assumptions for the observed data. As a consequence, MLMDS methods enable researchers to test hypotheses about dimensionality and other confirmatory aspects of the structure being fit [2]. Furthermore, MLMDS methods have been shown to outperform several traditional MDS methods with respect to recovering a “true” brand map [37].

To establish notation for the proposed ADMDS model, let:
 $i, j = 1, \dots, I$: index brands,
 $n = 1, \dots, N$: index customers,
 $s = 1, \dots, S$: index segments,
 $m = 1, \dots, M$: index dimensions, and
 $c = 1, \dots, C$: index nested decision sets.
 For the data, we use the following notation:
 δ_{ijn} the observed dissimilarity between brands i and j for customer n , $\Delta = [[[\delta_{ijn}]]]$, and v_{in} observed set membership of brand i for customer n , $\mathbf{V} = [[v_{in}]]$.

For the ADMDS model specification, we use the following notation:

x_{im} coordinate of brand i on dimension m , $\mathbf{X} = [[x_{im}]]$,
 y_{sm} coordinate of segment s on dimension m , $\mathbf{Y} = [[y_{sm}]]$,
 $w_{im}^{(u)}$ set-related weight of dimension m for segment s ,
 $\mathbf{W}^{(u)} = [[w_{im}^{(u)}]]$,
 $w_{sm}^{(d)}$ dissimilarity-related weight of dimension m for segment s , $\mathbf{W}^{(d)} = [[w_{sm}^{(d)}]]$,
 d_{ijs}^* error-free distance between brands i and j for segment s ,
 u_{is}^* error-free distance between brand i and segment s ,
 u_{is} error-perturbed distance between brand i and segment s , and
 b_{cs} upper boundary of set c for segment s , $\mathbf{B} = [[b_{cs}]]$.

3.3 Modeling Nested Decision Sets

On the basis of the nested structure of the decision choice sets, one can represent both brands and respondents as points in a multidimensional space [7, 8]. We formulate a mixture unfolding model [38–41] to estimate segment-specific ideal points. Alternatively, the segments could be represented by ideal vectors [42, 43]. As the vector model is a special case of the ideal point model, a segment-specific ideal vector can be represented in our model through an ideal point far outside the area of the brand points. Note that in the application

presented later in this paper, the segments ideal points are relatively close to the brands (see Fig. 1), which is in contradiction with a vector model representation.

Formulating a mixture model to estimate segment-specific parameters, instead of individual-specific ones, reduces the number of parameters substantially, and results in more insightful representations. Furthermore, mixture MDS methods derive a segmentation of the respondents and a competitive positioning map of the brands simultaneously, which is preferred over traditional sequential analyses given the interdependence that exists in managerial brand positioning decisions on these two issues. Although it has been argued that continuous distributions of preference parameters are preferable over a discrete one as imposed by the mixture model approach [44, 45], research has revealed that the extent to which these two approaches differ is an empirical issue depending upon the nature of the heterogeneity contained in samples [46].

Let there be a latent distance, u_{is} , which is defined by perturbing an error free distance u_{is}^* by a multiplicative error:

$$u_{is} = u_{is}^* \tau_{is}, \tag{1}$$

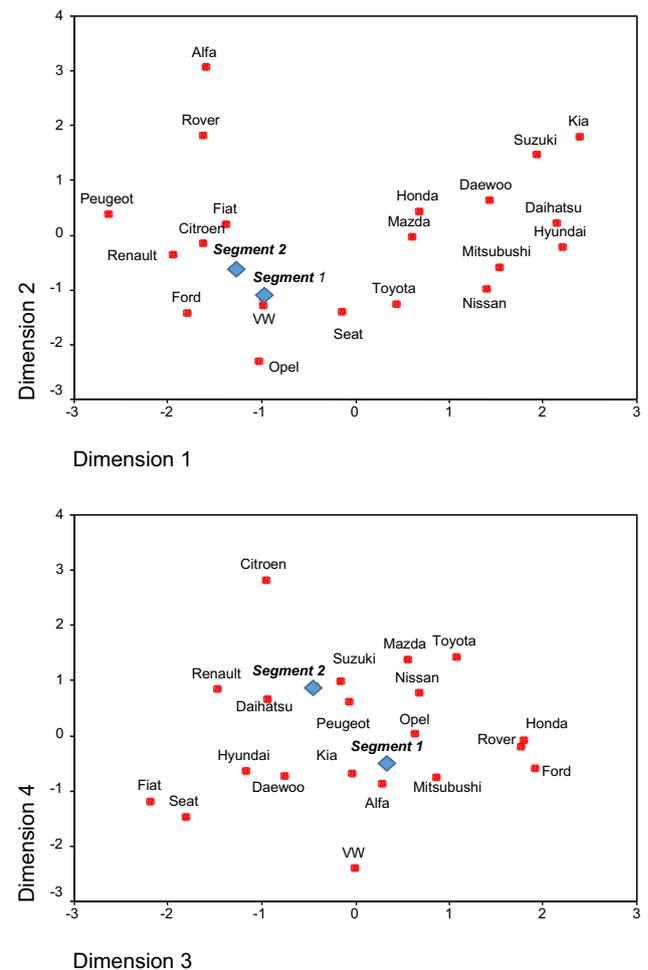


Fig. 1 Perceptual map of midsize car brands obtained with the adaptive MDS model

where $\log \tau_{is}$ is assumed to be normally distributed with zero mean and variance $\sigma_{\tau,s}^2$. The multiplicative error model, and hence the lognormal distribution for the distances, is chosen for three reasons. First, distances are non-negative by nature. Second, it has frequently been observed that the error variance of proximities increases with the size of the proximities [47]. Finally, there is some empirical evidence that the lognormal distribution adequately represents paired comparisons on rating scales [48] and consideration set data [32].

We assume that each segment has a unique location in the M -dimensional map. The error free weighted Euclidean distance, u_{is}^* , between the spatial locations of segment s and brand i is defined as:

$$u_{is}^* = \sqrt{\sum_{m=1}^M w_{sm}^{(u)} (x_{im} - y_{sm})^2}. \tag{2}$$

The segment-specific dimensional weights $w_{sm}^{(u)}$ are constrained to be nonnegative. For identification purposes, the following constraints are imposed upon these weights: $\sum_{m=1}^M w_{sm}^{(u)} = M$, for $s = 1, \dots, S$.

Recall, each respondent has indicated which brands s he is aware of, considers to purchase, and would choose. Brand familiarity is generally affected by market share, distribution, and the advertising budget of the brand, and thereby indirectly related to utility-based measures such as consideration and choice [49–51]. We, therefore, do not assume awareness to directly affect the perceptual map and segments but use it only as a selection mechanism in determining which brands are compared on the dissimilarity scale. Consideration and choice, however, are assumed to be based on the perceived attribute values of the brands [32, 34]. Therefore, we assume that brands in the consideration and choice set of a respondent are relatively similar, and thus that brands in these sets are located relatively close to the corresponding ideal point. We define an observed set indicator membership variable v_{in} with the following interpretation:

- $v_{in} = 1$: respondent n considers to buy, and chooses brand i ;
- $v_{in} = 2$: respondent n considers to buy, and but does not choose brand i ;
- $v_{in} = 3$: respondent n does not consider to buy brand i .

The relation between the set membership data, v_{in} , and the latent distances, u_{is} , conditional upon respondent n belonging to segment s , is defined as:

$$v_{in} = \begin{cases} 1 & \text{if } b_{0s} \leq u_{is} < b_{1s} \\ 2 & \text{if } b_{1s} \leq u_{is} < b_{2s} \\ 3 & \text{if } b_{2s} \leq u_{is} < b_{3s} \end{cases}, \tag{3}$$

where the following inequality restrictions hold: $-\infty = b_{0s} < b_{1s} < b_{2s} < b_{3s} = \infty$, and one fixes one cutpoint and the mean of the utility function to zero for identification but leaves the scale of the latent utility as a free parameter (Eq. 4). Next, the probability $p_{icn|s}$ that respondent n indicates brand i to belong to set c , conditional upon respondent n belonging to segment s , is given by

$$\begin{aligned} p_{icn|s} &= P_s(v_{in} = c) \\ &= P(b_{c-1,s} \leq u_{is} < b_{c,s}) \\ &= \Phi\left(\frac{\log b_{c,s} - \log u_{is}^*}{\sigma_{\tau,s}}\right) - \Phi\left(\frac{\log b_{c-1,s} - \log u_{is}^*}{\sigma_{\tau,s}}\right), \end{aligned} \tag{4}$$

where Φ is the cumulative standard normal distribution function. DeSarbo, Lehmann, Carpenter, and Sinha [7] and DeSarbo, Park, and Rao [52] proposed similar frameworks for modeling ordered successive category measurements. Defining an indicator variable z_{icn} which takes the value 1 when brand i is classified in set c by respondent n , and 0 otherwise. Then, the conditional likelihood function of the set membership data of respondent n can be written as:

$$L_n^{(u)} = \prod_{i=1}^I \prod_{c=1}^3 P_{icn|s}^{z_{icn}} \tag{5}$$

3.4 Modeling the Dissimilarity Data

Dissimilarity data δ_{ijn} are collected for respondent n for those pairs (i, j) of which both brand i and brand j are included in the awareness set of respondent n . These dissimilarity data are described through a weighted Euclidean distance model akin to the CLASCAL method proposed by Winsberg and De Soete [53]. We define the error-free-weighted Euclidean distance between the brands i and j for segment s as follows:

$$d_{ijs}^* = \sqrt{\sum_{m=1}^M w_{sm}^{(d)} (x_{im} - x_{jm})^2}. \tag{6}$$

Here, M elements of x_{im} are fixed for identification. The dimensional weights $w_{sm}^{(d)}$ are constrained to be nonnegative, and the following identification constraints are imposed:

$$\sum_{s=1}^S w_{sm}^{(d)} = S, \quad \text{for } m = 1, \dots, M..$$

It is assumed that the observed dissimilarities δ_{ijn} constitute the error-free distances and a multiplicative error component. Thus, conditional on respondent n belonging to segment s ,

$$\delta_{ijn} = d_{ijs}^* \varepsilon_{ijn} \quad (7)$$

where $\log \varepsilon_{ijn}$ is assumed to be normally distributed with zero mean and variance $\sigma_{\varepsilon,s}^2$.

Then, assuming independence across dissimilarity judgments [47], the conditional likelihood of the dissimilarity data as provided by respondent n , given segment s , can be written as:

$$L_{n|s}^{(d)} = \prod_{i,j} \varnothing \left(\frac{(\log \delta_{ijn} - \log d_{ijs}^*)}{\sigma_{\varepsilon,s}} \right) \quad (8)$$

where \varnothing is the standard normal density function and $\prod_{i,j}$ indexes those dissimilarities observed for respondent n . Thus, we do not impute values for the non-observed dissimilarities for respondent n , but include only observed brand pairs i,j in the likelihood function (8).

3.5 Estimating the Joint Model

Both set membership data and the dissimilarity data contain information about the locations of the brands

as contained in \mathbf{X} . In making use of all information available to obtain estimates of the configuration, the set membership data and the dissimilarity data model-components are estimated simultaneously. The joint conditional likelihood for respondent n conditional upon belonging to segment s equals:

$$L_{n|s}^{(ud)} = L_{n|s}^{(u)} L_{n|s}^{(d)} \quad (9)$$

where it is assumed that the dependence of the dissimilarity and the decision set data is captured by the parameters in the model. Assuming that respondent n has an unknown prior probability λ_s of belonging to segment s , the unconditional likelihood for respondent n can be expressed as a finite mixture of S conditional likelihood functions [41, 54]:

$$L_n^{(ud)} = \sum_{s=1}^S \lambda_s L_{n|s}^{(ud)} \quad (10)$$

where the prior probabilities obey the constraint:

$$\sum_{s=1}^S \lambda_s = 1 \quad ..$$

The complete log-likelihood of all the data of N respondents is:

$$\log L^{(ud)} = \sum_{n=1}^N \log \left[\sum_{s=1}^S \lambda_s \left[\prod_{i,j} \varnothing \left(\frac{(\log \delta_{ijn} - \log d_{ijs}^*)}{\sigma_{\varepsilon,s}} \right) \times \prod_{i=1}^I \prod_{c=1}^3 \left[\Phi \left(\frac{\log b_{cs} - \log u_{is}^*}{\sigma_{\tau,s}} \right) - \Phi \left(\frac{\log b_{c-1s} - \log u_{is}^*}{\sigma_{\tau,s}} \right) \right]^{z_{icn}} \right] \right] \quad (11)$$

The log-likelihood depends on the following model parameters: the $I \times M$ matrix \mathbf{X} of brand coordinates, the $S \times M$ matrix \mathbf{Y} of segment coordinates, the $S \times M$ matrix $\mathbf{W}^{(u)}$ of set-related dimensional weights, the $S \times M$ matrix $\mathbf{W}^{(d)}$ of dissimilarity-related dimensional weights, the $S \times 2$ matrix \mathbf{B} of set boundaries, the $S \times 1$ vector $\underline{\lambda}$ of segment proportions, the $S \times 1$ vector $\underline{\sigma}_T$ of dispersion parameters, and the $S \times 1$ vector $\underline{\sigma}_\varepsilon$ of dispersion parameters. However, the total number of parameters in the model is reduced by M for centering indeterminacy of \mathbf{X} and \mathbf{Y} , by M for the constraint on the dissimilarity-related weights for fixing the size of \mathbf{X} versus $\mathbf{W}^{(d)}$ for each dimension, by S for the constraint on the set-related weights for size indeterminacy between \mathbf{B} and $\mathbf{W}^{(u)}$ for each segment, and by 1 for the constraint on the segment proportions. Hence, the

effective number of free parameters K in the model equals $(I + 3S - 2)M + 4S - 1$. The equality and inequality constraints on the parameters are imposed by introducing the appropriate Lagrangian multipliers and appending these equations to the function to be optimized. Model estimates are obtained with the constrained maximum likelihood module in GAUSS.

The proposed ADMDS method may often converge to a local optimum since the parameter estimates are derived iteratively and the model structure is highly non-linear. Using rational starting values, however, reduces the chance to obtain such sub-optimal solutions. Rational starting values for \mathbf{X} are obtained by metric MDS [55]. An initial segment structure is obtained by performing K-means clustering on the nested set data. From these starting values for $\underline{\lambda}$, \mathbf{Y} , and \mathbf{B} are derived. Finally, initial values for $\mathbf{W}^{(u)}$, $\mathbf{W}^{(d)}$, $\underline{\sigma}_T$, and $\underline{\sigma}_\varepsilon$ are set to 1.

3.6 Assessing Model Fit

Within any iteration after parameter estimates have been obtained, the posterior probability λ_{ns} that respondent n belongs to segment s can be computed, using Bayes’ rule, as [54]:

$$\lambda_{ns} = \frac{\widehat{\lambda}_s \widehat{L}_{n|s}^{(ud)}}{\sum_{s=1}^S \widehat{\lambda}_s \widehat{L}_{n|s}^{(ud)}} \tag{12}$$

where $\widehat{L}_{n|s}^{(ud)}$, Eq. (9), corresponds to the conditional likelihood of respondent n given segment s and the current parameter estimates. Hence, the posterior probabilities λ_{ns} provide a probabilistic classification of the N respondents into S segments. One may form non-overlapping segments by assigning each customer to that latent class for which the posterior probability is the largest [54]. These posterior probabilities are particularly useful for segment profiling.

When applying the ADMDS method to empirical data, the actual number of dimensions and segments is unknown and has to be inferred from the data. We make such inferences by estimating the model for varying number of dimensions, M , and the varying number of segments, S , and compare the alternative model specifications on the basis of various goodness-of-fit statistics.

The fit measures for the adaptive MDS procedure fall into several categories. First, model fit can be assessed by comparing the observed data with predicted values. For the dissimilarity data, the congruence coefficient CC , proposed by Borg and Leutner [56], is reported per segment. This coefficient is defined as follows:

$$CC = \frac{\sum_{n=1}^N \sum_{i,j} (\delta_{ijn} d_{ijn})}{\sqrt{\sum_{n=1}^N \sum_{i,j} (\delta_{ijn})^2 \sum_{n=1}^N \sum_{i,j} (d_{ijn})^2}} \tag{13}$$

where d_{ijn} denotes the estimated distance between brands i and j for customer n after being classified to the segment with the highest posterior probability, λ_{ns} , and $\sum_{i,j}$ indexes those pairs

observed for respondent n . A high value of CC , close to the maximum of 1, corresponds to a good fit.

For the cognitive decision set-data, set memberships (v_{in}) are compared with the estimated probabilities $p_{icn|s}$. Each respondent is assigned to a segment and the probability that a particular brand belongs to a particular decision set can thus be computed. The overall probability, averaged across all observed set memberships, reflects model fit. Furthermore, averages computed per brand, per segment, and/or per

respondent are used for diagnostic purposes. Second, the model fit can be assessed with information criteria that penalize the likelihood function obtained by the number of parameters estimated. As recommended in DeSarbo, Manrai, and Manrai [39] for latent class MDS models, we use CAIC = $-2\log L^{(ud)} + (\log(T) + 1)K$ [39, 57]), where T denotes the total number of nested sets and dissimilarity observations, which is highly similar to BIC but slightly more conservative, as CAIC = BIC + K . When comparing alternative model formulations for the same data set, lower CAIC and BIC indicate a relatively better fit. Third, model fit can relate to the extent to which the respondents can be classified into the segments. The estimated proportion of classification error equals: $CE = \sum_{n=1}^N (1 - \max_s \lambda_{ns}) / N$. Relating this to assigning all respondents to the largest segment yields an R^2 -type measure, namely the reduction of classification error:

$$R_{CE}^2 = \frac{(1 - \max_s \lambda_s) - CE}{(1 - \max_s \lambda_s)} \tag{14}$$

In addition to CE and R_{CE}^2 , the following entropy statistic ES is computed to investigate the separation between segments [40]:

$$ES = 1 + \left(\frac{\sum_{n=1}^N \sum_{s=1}^S \lambda_{ns} \log \lambda_{ns}}{N \log S} \right) \tag{15}$$

ES is bounded between 0 and 1, where a value close to 1 indicates that the derived segments are well separated.

4 Consideration Set Composition

4.1 Focusing or Keeping Broad Options?

The proposed ADMDS model entails the joint representation of consideration sets and brand dissimilarities in a single spatial representation. As mentioned in the previous section, the underlying assumption is that brands within a consideration set are relatively similar. However, empirically this may or may not be the case. If a respondent focuses on a particular ideal brand s/he is looking for, the consideration set will be homogeneous in composition, because the brands considered are similar to that particular ideal brand. Alternatively, a respondent might decide to keep options across a broad range open for consideration [58, 59] in order to circumvent missing an alternative brand that is substantially better than the others or to reduce potential satiation once the brands chosen are

actually consumed. Using a sorting task for brand similarity, Desai and Hoyer [60] examined the number of clusters that brands in the consideration set are derived from. This allowed them to assess the effects of various situational factors on the composition of consideration sets. However, whether brands in the consideration set are relatively similar or dissimilar has not been addressed in the literature [9]. Therefore, to investigate the validity of our model assumption, we assess the relative similarity of brands within the consideration set in an experimental study. In addition, we study whether the results depend on the product category and whether consumer involvement and expertise are important moderators.

4.1.1 Study Design

Four product categories were selected for the investigation that varies broadly, namely durables (compact cars), fast-moving consumer goods (shower gel), retail outlets (clothing shops), and services (radio stations). For each product category, the ten largest brands in terms of market share were included in the study. The recruitment of 200 respondents was done using a “mall intercept” method at and around a major university campus. 83% of the respondents were students. Each respondent filled in a questionnaire for one of the product categories. Each respondent was randomly assigned to one product category, with a maximum of 50 respondents per product category. If a respondent indicated that the product category seemed irrelevant to him or her, and s/he was reassigned to another product category.¹

First, respondents rated the perceived dissimilarity for each pair of brands (45 pairs) on a nine-point scale (1 = highly similar to 9 = highly dissimilar). Next, each respondent was presented with a number of unrelated questions, which took about 5 min. Then, the list of ten brands and a general description of a decision situation were provided. The instructions indicated what brands they would consider. For example, for clothing shops, the question was: “Suppose you go shopping for clothing. Which of the following stores would you consider to visit for that purpose?” Then, each respondent rated seven items, three on expertise and four on involvement. All items started with “Compared to other people...” and had to be rated on a seven-point scale ranging from “less than others” and “more than others”. For expertise, we used for example: “... I know a lot about clothing shops.” For involvement, we used for example: “... clothing shops are important to me.”

¹ Due to the reassigning of respondents the percentage of students differs between product categories: compact cars 67%, clothing shops 84%, radio stations 90% and shower gel 98% ($\chi^2 = 18.99$; d.f. = 3; $p < 0.01$). However, being a student or not is not related to our expertise and involvement classifications ($\chi^2 = 0.26$; d.f. = 1; $p = 0.61$ and $\chi^2 = 0.12$; d.f. = 1; $p = 0.73$, respectively). Furthermore, students do not differ significantly from the other respondents in the dependent variable, the relative dissimilarity ($F = 0.07$; d.f. = 1182; $p = 0.79$). Therefore, all respondents are studied simultaneously.

Finally, the questionnaire contained several questions on socio-demographic variables.

The three expertise items and the four involvement items form two reliable scales (Cronbach’s $\alpha = 0.81$ and $\alpha = 0.92$, respectively). Hence, averaged item scores are used as measures of expertise and involvement. Median splits for expertise and involvement are used for each product category separately. As anticipated, expertise and involvement are not independent. However, because the low/high and high/low combinations contain 22 and 23 observations, the effects of both expertise and involvement can still be assessed accurately.

To study the relative dissimilarity of the brands considered, a deviation measure is computed for each respondent, obtained by subtracting the average dissimilarity judgment for pairs of brands both belonging to the consideration set from the average of all other dissimilarity judgments. For example, suppose a respondent considers to buy brands A to D, the average of the six dissimilarities A-B, A-C, A-D, B-C, B-D, and C-D is subtracted from all other dissimilarity judgments by this respondent. Hence, a positive (negative) value indicates that dissimilarities within the consideration set are relatively small (large), and so the respondent considers similar (dissimilar) brands.²

4.1.2 Results

ANOVA was used to test whether brands in the consideration set are more or less dissimilar compared with the other brands, using the measure of relative dissimilarity described above as dependent variable, and expertise, involvement, and product category as explanatory factors. Table 1 presents the results of the ANOVA model and Table 2 presents the average of the relative brand dissimilarity, across experimental groups. Importantly, all relative dissimilarity scores in Table 2 are positive, and the intercept of the ANOVA model (Table 1) is positive and highly significant. The average relative dissimilarity is positive (1.02) and significantly larger than zero ($t = 8.84$; d.f. = 186; $p < 0.01$). To examine the size of this effect, we compute the mean and standard deviation of all dissimilarity judgments of each respondent. Averaging across respondents yields: for compact cars 5.24 and 1.59, for shower gels 5.21 and 1.80, for radio stations 5.85 and 2.05, and for clothing shops 5.51 and 1.83. Considering these means and standard deviations and the range of the scale (1 to 9), we consider an effect size of 1.02 for the relative dissimilarity very large. Hence, respondents tend to use a focusing strategy: the brands included in the consideration sets are substantially more similar compared to the other brands.

² The measure is not defined for 13 respondents having consideration set size of 0 or 1, which are therefore left out from further analyses.

Table 1 Analysis of variance assessing the brand similarity composition of consideration sets

Factor	Sum of squares	d.f.	F value	p value
Intercept	191.73	1	78.18	< .001
Expertise	.08	1	.03	.860
Involvement	.12	1	.05	.828
Product category	23.35	3	3.17	.026
Product category × expertise	4.33	3	.59	.623
Product category × involvement	3.02	3	.41	.746

There are significant differences in the relative dissimilarity between product categories (Table 1; $p = .026$). For clothing shops, the consideration sets are less focused compared to the other three product categories (0.45 versus 1.10 to 1.41 for the other three categories; Table 2). However, even for clothing shops, the consideration sets are relatively homogeneous: the relative dissimilarity measure of 0.45 is significantly larger than zero ($t = 2.33$; d.f. = 47; $p = .024$). As shown in Table 1, none of the main or interactive effects of expertise or involvement are significant (p values ranging from .623 to .860). Thus, the extent to which the focusing strategy is used is not affected significantly by expertise and involvement.

Hence, we conclude that consideration sets contain relatively similar rather than dissimilar brands that addresses the research question raised by Roberts and Lattin [9] and provides support for the assumptions of our ADMDS model regarding consideration sets and brand dissimilarities.

5 A Commercial Marketing Application

We illustrate the proposed ADMDS procedure on data from a commercial positioning study of the Dutch market of midsize

Table 2 Average relative brand dissimilarity within consideration sets*

	Product category			
	Compact cars	Shower gel	Radio stations	Clothing shops
Expertise				
Low	.82	1.71	0.97	.43
High	1.40	1.13	1.22	.47
Involvement				
High	.75	1.57	1.01	.54
Low	1.45	1.24	1.17	.37
Total	1.13	1.41	1.10	.45

*Positive values indicate that brands are relatively similar within consideration sets

cars, conducted in the mid 1990s. Data have been collected in a nationwide representative online consumer panel, the Center Data Telepanel, consisting of about 1500 households. Through the online system, the pairs of brands presented to a particular respondent can quickly be constructed (and randomized) online after the nested decision set questions have been answered. Twenty car manufacturers/brands selling one or more midsize models were used in the study. Throughout the questionnaire, each manufacturer/brand was identified by the brand name followed by the midsize model(s) in brackets. At the start of the interview, each respondent was presented this list of 20 brands and the respective models. They were asked to check whether or not someone within the household owns one or more of these cars, and if so whether that car was manufactured in the last 5 years. Respondents not meeting these conditions did not belong to the target population and were therefore deleted from further interviewing. For each midsize car owned by the household, the person using the car most often completed the questionnaire. In total, 212 usable questionnaires were obtained.

Data on perceptions, preferences, behavior with respect to cars, and socio-demographic background variables were obtained from each respondent. Respondents were asked to indicate from a list of 20 car brands which they were familiar with, which they would consider buying, and which they would buy if a purchase would actually be made. Only brands identified in the previous step were given as options in the next step, e.g., only car brands that are known to a respondent were given as options to be considered. Next, paired comparisons on a seven-point dissimilarity scale were made for those brands included in the awareness set. Here, to reduce the workload for the respondents, a maximum of 20 pairs per respondent were utilized and a random selection of pairs was made in case the actual number exceeded this. Note that traditional dissimilarity data collection procedures are not suitable for this positioning study as these would require 190 paired comparisons, a number that is prohibitively large and would invoke enormous respondent fatigue and boredom.

The awareness set size varies between 5 and 20, with an average of 16.86. These numbers are 1, 12, and 2.71 respectively for the consideration set. Hence, most respondents know relatively many car brands but consider only a few. This pattern has high face validity and compares to numbers

presented in Hauser and Wernerfelt [32] and DeSarbo and Jedidi [8]. Most respondents were unfamiliar with a subset of the brands, and brand familiarity and consideration vary substantially across respondents. In addition, there was high variability in awareness, consideration, and choice across brands (see Table 3), with VW and Opel at the high extreme and Kia at the low extreme.

We estimate our ADMDS model on the basis of the nested decision sets and dissimilarity judgments of the 212 respondents. To correct for differences in scale use, we first linearly transformed the dissimilarity judgments to have a minimum of 1 and a maximum of 7 for each individual respondent and preprocessed the data for each individual so that the dissimilarities have an average value of 4 for each respondent. As a result, the mean and variance of the dissimilarities are similar in magnitude across respondents.

We obtained estimates for two models: (1) the full model including all dimensional weights, and (2) a restricted model with the dimensional weights restricted to 1. Furthermore, to determine the most appropriate number of segments and dimensions, analyses have been performed for all combinations of $S = 1, \dots, 5$ segments and $M = 1, \dots, 5$ dimensions. Hence, in total 50 sets of parameter estimates are obtained for the ADMDS model. We base model selection on the minimum CAIC criteria (see Table 4).

Table 3 Descriptive statistics for the automobile brands

Manufacturer/ brand	Percentage of respondents		
	Aware	Consider	Choice
Alfa	80.2	4.2	1.4
Citroën	92.0	20.3	10.4
Daewoo	74.1	9.4	3.8
Daihatsu	67.5	3.8	0.5
Fiat	93.4	8.5	3.3
Ford	98.1	14.6	6.1
Honda	92.5	13.2	2.4
Hyundai	78.8	9.0	2.8
Kia	38.7	0.5	0.0
Mazda	85.4	13.7	4.2
Mitsubishi	88.7	9.4	1.4
Nissan	90.1	10.8	2.8
Opel	99.5	31.1	18.4
Peugeot	96.4	17.0	2.8
Renault	91.5	26.9	11.3
Rover	65.1	8.0	1.9
Seat	82.5	7.5	2.8
Suzuki	80.7	5.2	0.9
Toyota	92.5	20.8	6.1
VW	99.1	37.3	16.5

Table 4 Model fit (CAIC) for $S = 1, \dots, 5$ and $M = 1, \dots, 5$ *

Number of dimensions (M)	Number of segments (S)				
	1	2	3	4	5
1	19,143	18,980	18,877	17,869	18,008
Without dimensional weights					
2	12,406	12,967	13,113	12,962	13,179
3	11,888	11,820	11,799	11,787	<i>11,764</i>
4	<i>11,706</i>	11,737	<i>11,552</i>	<i>11,781</i>	11,835
5	11,764	<i>11,595</i>	11,745	11,869	11,942
With dimensional weights					
2	12,156	12,544	12,708	12,705	12,893
3	11,706	11,600	11,897	11,965	12,435
4	<i>11,540</i>	11,534	<i>11,808</i>	<i>11,942</i>	<i>12,067</i>
5	11,737	11,669	11,898	12,073	12,230

*Minimum values in each column (per model type) are indicated in italics, the best model overall ($S=2$, $M=4$, with weights) is indicated in boldface. Minimum values for BIC (in each column and overall) are obtained in exactly the same cells as for CAIC

The “best” solution with dimensional weights for $S=2$ segments and $M=4$ dimensions yields the lowest CAIC and BIC value and is therefore deemed most appropriate. The other model fit criteria generally indicate good to excellent model fit. The congruence coefficient CC for the dissimilarity data is very high: 0.920. For the nested set data, the overall average correct set membership probability is 0.784 and varies between 0.498 and 0.957. The latent classes are reasonably well separated, as indicated by the reduction of classification error R_{CE}^2 of 0.760 and the entropy statistic ES of 0.721. Furthermore, all model fit criteria improve only very slightly or not all if the number of segments or dimensions are increased which supports our model selection.

Figure 1 and Table 5 contain the parameter values obtained with ADMDS for $S=2$ and $M=4$. The estimated values of the parameters are hard to interpret directly, as many are interrelated. For example, the estimated threshold values b_{cs} should be compared with the distances between brands and ideal points, according to Eq. (3). Therefore, we present the perceptual map in Fig. 1, which shows the relative competitive positions of the 20 midsize car manufacturers/brands. Country-of-origin has a clear impact on the brand map, where the right-hand side of dimension 1 contains the Japanese and Korean brands and the left-hand side contains the European and American brands. For example, the French car brands (Renault, Peugeot, and Citroën) and the Italian brand, Fiat, are tightly clustered in the plot of the first two dimensions. To support the interpretation of the dimensions, we correlate the brand coordinates of each dimension with average attribute scores for the brands (each respondent rated the attributes for two brands familiar to him/her). The price, safety,

Table 5 Parameter estimates for ADMDS model with $S=2$ and $M=4$ with weights

Parameters		Segments (s)	
		1	2
Proportion	λ_s	.674	.33
Dissimilarity-weights	$w_{sm}^{(d)}$		
Dimension 1		.825	1.175
Dimension 2		1.059	.941
Dimension 3		1.057	.943
Dimension 4		1.004	.996
Set-weights	$w_{sm}^{(u)}$		
Dimension 1		1.251	1.382
Dimension 2		1.162	1.083
Dimension 3		1.268	1.026
Dimension 4		.320	.509
Set boundaries	b_{cs}		
Choice ($c=1$)		.637	.533
Consideration ($c=2$)		.825	1.407
Dissimilarity-related error dispersion	σ_ε	.825	.965
Set-related error dispersion	σ_τ	.588	.463

sportiness, and design attributes have a significant negative correlation ($p < 0.01$) with the first dimension (-0.73 , -0.67 , -0.68 , and -0.69 , respectively). Hence, brands on the left-hand side are perceived as more expensive, safer, sportier, and having a nicer design than brands on the right-hand side. Brands scoring low on dimension 2 are perceived as more long-lasting (correlation is -0.54 ; $p = 0.01$), with the highest average ratings for durability for VW (5.33) and Opel (5.03). The attribute operation cost has a negative correlation with the third and fourth dimensions, correlations being -0.41 ($p = 0.07$) and -0.38 ($p = 0.10$) respectively. Furthermore, the reliability attribute correlates 0.37 ($p = 0.10$) with dimension 3. These perceptions match the higher reliability and lower repair costs which have indeed been published in various consumer reports for Toyota, Mazda, and Nissan, whereas the opposite holds for Seat and Fiat. Compared to the first three dimensions, the fourth dimension turns out to be somewhat harder to interpret because is less strongly related to the attribute information available. However, it separates French (Citroen) from German (VW) brands and has some correlation with operation cost. The fourth dimension may thus capture another aspect of reliability, durability, and maintenance differences between French and German brands. Although interpretations based on the map itself induce an additional burden for the researcher, it also constitutes an advantage over attribute-based perceptual mapping [61] where the perceptual map is necessarily restricted to a pre-specified set of attributes.

Interviews with industry experts could further support our interpretation of the fourth dimension (it may also refer to some perceptual esthetic quality of differences between French and German brands such as styling). Thus, the ADMDS approach may reveal insights for product design and brand positioning which would not become apparent in an attribute-based perceptual mapping procedure.

Segments 1 and 2 comprise 67% and 33% of the respondents, respectively (Table 5). For the brand dissimilarity perceptions, respondents from segment 2 weight the first dimension (1.18), reflecting country-of-origin, price and design, more heavily, whereas respondents from segment 1 weight the durability (1.06), reliability (1.06), and repair costs (1.00) (dimensions 2 to 4) more heavily. The set-related weights show that the fourth dimension is largely neglected by both derived segments (weights respectively 0.32 and 0.59) while considering and choosing a brand, while respondents in segment 1 weigh dimension 1 (1.25) and 3 (1.27), and respondents in segment 2 weigh dimension 1 (1.38) more heavily.

With respect to the first joint space plot of dimensions 1 and 2, the ideal point of segment 1 is located very close to VW, and the ideal point of segment 2 is fairly close to the French car brands. In looking at the joint space plot of dimensions 3 and 4, segment 1 appears to prefer the Opel, Alfa, and Kia while segment 2 leans more towards the Suzuki and Daihatsu brands. The consideration set boundary is substantially wider for segment 2 than for segment 1. This points to larger consideration sets for consumers in segment 2 which is corroborated when we compute the set membership probabilities using Eq. (4) for each segment (Table 6). For segment 1, the consideration probability is small for most brands except for Opel (27.8%) and VW (33.8%), whereas for segment 2 this probability is in the range 10 to 20% even for brands located far from the segment ideal point. But in this segment, Renault (52.1%), Citroen (44.8%), and Peugeot (37.0%) have a large probability of being considered. Daihatsu, for example, is positioned far from both segment ideal points (Fig. 1) with respect to the first two dimensions, but close to segment 2 with respect to the third and fourth dimensions; it has a probability of being considered of 13.1% in segment 2 and only 2.6% in segment 1. Contrary to the consideration set boundaries, the choice set boundaries (b_{1s}) are quite similar across the segments. Hence, differences in the brands that are chosen are largely caused by the position of the segment ideal. For example, looking at Daihatsu again, the choice probabilities converged to 1.2 and 1.7% for segments 1 and 2, respectively. The top-3 brand choice probabilities for segment 1 are as follows: VW (0.23), Opel (0.18), and Ford (0.08), and for segment 2: Renault (0.17),

Table 6 Predicted consideration and choice probabilities

Brand	Segment 1		Segment 2	
	Consideration probability	Choice probability	Consideration Probability	Choice Probability
Alfa	.019	.008	.133	.017
Citroën	.076	.040	.448	.128
Daewoo	.039	.019	.162	.023
Daihatsu	.026	.012	.131	.017
Fiat	.048	.024	.280	.056
Ford	.138	.081	.237	.043
Honda	.059	.030	.175	.026
Hyundai	.027	.012	.122	.015
Kia	.015	.007	.090	.010
Mazda	.100	.055	.273	.054
Mitsubishi	.062	.032	.155	.022
Nissan	.071	.037	.183	.028
Opel	.278	.183	.324	.072
Peugeot	.083	.045	.370	.091
Renault	.084	.046	.521	.170
Rover	.036	.017	.174	.026
Seat	.078	.041	.252	.047
Suzuki	.021	.010	.120	.015
Toyota	.130	.074	.256	.048
VW	.338	.232	.273	.054

Citroën (0.13), and Peugeot (0.09), which reveals the important behavioral differences between the two segments that have direct managerial implications.

Assume, for example, the position of the brand manager of Daihatsu. What should his/her strategy be? Obviously, to make further in-roads with both segments, some decision needs to be made with respect to the brand's positioning on the first two dimensions. One possible strategy derived from the inspection of the joint

space four-dimensional map in Fig. 1 and the segment level choice and consideration probabilities in Table 6 might be to team up with VW or Ford to make a sportier and higher quality brand for this mid-size market (much like Toyota, Isuzu, and Suzuki had joint ventures with GM in the early 2000's to produce GEO branded automobiles) that may make greater in-roads especially into segment 1. Thus, the new Daihatsu brand could have been marketed towards segment 2.

6 Conclusions

In this paper, we develop, test, and illustrate an adaptive MDS (ADMDS) procedure for simultaneous segmentation and positioning. This approach first enables positioning research-based not only on dissimilarity judgments of brands by respondents but also on their awareness, consideration, and choice of these brands. This renders the ADMDS approach more meaningful for the development of positioning strategies. The procedure deals with two important problems encountered in MDS research, namely the scaling of large brands sets and the problem with differential lack of brand familiarity. This is accomplished by adapting the data collection stage to the individual respondent. The procedure uses a nested decision set framework for making brand choices: awareness, consideration, and choice. Information contained in the brand dissimilarities as well as in the nested decision sets is reflected in the derived estimates of the ADMDS model. In the illustrative application to commercial data, adaptive MDS represented a complex data set comprising a large brand set parsimoniously with four dimensions and two segments. Importantly from a marketing perspective, the dimensions have a clear interpretation and the segments differed considerably in their choice behavior.

An important assumption of the joint representation of the consideration sets and the brand dissimilarities is that brands within a consideration set are relatively similar. The question on the similarity composition of consideration sets has been raised previously [9] but has remained unanswered. We found that across a wide range of product categories that brands within a consideration set are indeed relatively similar, indicating that customers focus, rather than broaden, their options at this stage. Further research should be done to assess the effects of other moderator variables and using other samples of customers, product categories, and brands. Furthermore, in some situations, this assumption might be violated. For example, for some product categories, multiple brands are purchased for variety seeking, separate usage occasions, and/or multiple consumers in a household. In those cases, the MDS model could be extended by capturing multiple ideal points per segment [62].

In the application presented in this paper, we used a decompositional approach [61] to perceptual mapping as directly observed dissimilarity judgments were collected and analyzed. In a compositional approach, perceptions are studied via attribute ratings of brands. These attributes can be pre-specified or unrestricted and individual-specific [63]. From both kinds of attribute ratings, however, dissimilarities between brands can be derived for each respondent. In the compositional approach to positioning research, one may also restrict the data collection to an individual-specific subset of brands [15, 64] which may even be advisable since there too the number of judgments asked from respondents increases

rapidly with the number of brands, quickly reaching the limit of what is feasible from the perspective of respondent burden. The ADMDS model proposed in this paper can be applied to analyze the incomplete matrices of derived dissimilarities and can thus be applied to compositional data as well.

Future research could extend the modeling approach presented in this paper. For example, the model specification by being adapted by representing each segment by means of a vector instead of an ideal point, or allowing segments not to use all dimensions of the perceptual map [65]. Next, one could examine whether the current and alternative model specifications fit various types of nested data and dissimilarity data. In addition, performance in terms of recovery of ‘true’ known parameter values and stability of the model estimates could be examined under a wide range of circumstances in a Monte Carlo analysis, varying factors like the number of brands and underlying dimensions. Furthermore, to facilitate targeting of the segments, the latent class memberships could be modeled as functions of concomitant variables (see [41]) to enhance interpretation (including socio-demographics). This would enhance the ability to perform predictive validation analyses with a holdout sample in being able to predict segment membership for respondents not included in the calibration stage. Various naïve benchmark models could be examined and compared with the proposed ADMDS method on both simulated and actual data. Finally, reparameterization options to constrain the derived brand coordinates to be linear functions of known attributes (see [6]) could aid in the interpretations of the dimensions, as well as provide a basis for testing model predictions on holdout brands and/or new brands not yet on the market.

The adaptive data collection task, in which the set of brands is reduced sequentially, is based on the awareness, consideration, and choice set framework. The ADMDS model can be applied also to alternative nested sets of brands, assuming that dissimilarity judgments are made only for those brands in one of the smaller sets. One may also consider the sequence of brand sets as frequently used in advertising research: completely unfamiliar, aided recall, unaided recall, top-of-mind awareness. In addition, the nested structure could be limited to familiar versus unfamiliar brands or pick-any choice data. These other applications enable positioning research based on a wide range of consumer behaviors that may be relevant in different contexts. Finally, a potentially interesting area of application is decision making in business-to-business markets [66] where the final choice of suppliers is often made after specification of a short list and an even smaller set of firms invited to make a quotation. Applying the adaptive MDS model to such nested decision structures and similarities between competitors on the short lists would yield positioning maps as well as insights in the competitive structure between suppliers and segmentation of industrial buyers.

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