# EXTERNAL ANALYSIS OF PREFERENCES: MULTILEVEL MODELING AND SOME ALTERNATIVES

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**Abstract**

We show how the external analysis of preferences can be done in a multilevel framework. Multilevel analysis accommodates for individual differences in preference formation, by postulating gradual variations in subjects' regression weights according to a normal distribution. The multilevel approach is compared to two other approaches that allow for subject heterogeneity in analyzing preferences. The first is mixture regression analysis, which departs from segments in which subjects have the same regression weights, which are distinct from the weights characterizing the other segments. The second approach is ordinary least squares regression analysis carried out for each subject separately. The multilevel approach is illustrated for data on 847 Dutch consumers regarding their preferences for 7 different meat products. To evaluate the adequacy of the multilevel approach for this data set, this technique is compared to the other approaches on its predictive power with respect to subjects' preferences.

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**1. Introduction**

Preference analysis aims to explain preferences that consumers may have for different products in the market place, that patients may have for different treatments for a disease, that citizens may have for different political candidates in an election, or, in general, that subjects may have for a set of options they can choose from. Preferences are considered to influence actual behavior to a large extent. Establishing the relation between attributes or features of choice options and preferences for these options, has therefore been an important area of investigation, also from a methodological point of view (Green, Carmone & Smith, 1989; Hair, Anderson, Tatham & Black, 1998; Lilien & Rangaswamy, 1998). This approach to analyzing preferences is known as the external analysis of preferences (Green et al., 1989; Schiffman, Reynolds & Young, 1981).

In many empirical studies preferences are expressed on a rating scale. In this paper we will focus on the analysis of such preference ratings. Preference is commonly explained by applying some kind of regression to these preference ratings, where the predictor variables contain information on the objects for which the preferences are expressed. For this reason we will also refer to external preference analysis as preference regression. The information on objects may relate to the perception by subjects of the choice options along different dimensions (e.g. the left-right dimension and the degree of integrity in case politicians are the choice options). These dimensions may be derived from a previous analysis. For instance, one may perform multidimensional scaling for dissimilarity judgements obtained for the same objects, or perform factor analysis or correspondence analysis for attribute judgements gathered for the objects under study (Candel & Maris, 1997; Hauser & Koppelman, 1979; Steenkamp, Van Trijp & Ten Berge, 1994). The dimensions or factors resulting from these analyses are assumed to reflect subjects' dimensions along which the objects are cognitively organized. These variables are considered to be useful in explaining subjects' preferences for the objects under study.

Information on the objects may also be provided by researchers, in that physical parameters of the objects are used as predictor variables. An example is a specification of the nutrients that food products are made up from (that is, the amount of each of relevant substances). Also attributes that explicitly have been presented to the respondents, may be used as predictor variables. The latter is typical for conjoint analysis. Profiles are constructed on the basis of a set of attributes. For example, a television set may be constructed from such attributes as price, brand name, size of screen, and colour reproduction. For the profiles based on these attributes, respondents have to express a preference, which is explained from the utilities attached to the attributes of these profiles. The preference for a television set is thus explained from the utility of its price, the utility of its brand name, the utility of the size of the screen and possibly the utility of other aspects. Commonly the preference for a profile is modeled as the sum of the utilities for each of the attribute levels. Estimates of these utilities may be obtained through regression analysis (Hair et al., 1998; Vriens, 1995).

Two straightforward methods have been used for analyzing the relation between preference and information on the objects' attributes: (1) regression analysis performed across subjects and objects, or (2) regression analysis performed across objects for each subject separately. The first method neglects differences between subjects in preference formation. It is assumed that one subject is a replication of another subject. However, the relation between preference and object information often varies strongly between different subjects. For example, some people weigh quality heavily in choosing among food products, whereas others do not attach that much importance to this attribute (and possibly consider price a much more important aspect). Neglecting this heterogeneity of subjects may lead to regression weights that are misleading for an individual case, and therefore of little practical use. From a statistical point of view, generally this *aggregate regression analysis* will lead to underestimation of the standard errors of the (average) regression coefficients (Bryk & Raudenbush, 1992; Goldstein, 1995). This in turn implies that in general the probability of type I errors will become too large.

The second approach does take care of individual differences by performing a regression for each individual. This *disaggregate regression analysis*, employed by programs such as PREFMAP (Green et al., 1989; Schiffman et al., 1981), may involve some practical problems. In order to obtain precise estimates of the regression weights, many options have to be evaluated by respondents. Furthermore, reducing the number of options may have a detrimental effect upon the power of statistical tests. As an answer to this problem, *mixture regression analysis* (MRA) (Wedel, 1997; Wedel & DeSarbo, 1994) has been developed. This approach assumes that there are distinct classes of subjects, each of which are characterized by different values for the regression weights. Mixture regression analysis aims to find these homogeneous classes. Within these classes, which involve observations on multiple subjects, the regression weights are estimated.

A fourth approach that seems not yet to have been explored in this context, is random effects analysis or *multilevel analysis* (MLA) (Bryk & Raudenbush, 1992; Diggle, Liang & Zeger, 1995; Goldstein, 1995; Snijders & Bosker, 1999). This approach also respects differences between subjects, but assumes that the regression coefficients vary gradually according to a normal distribution. Multilevel modeling may be appropriate when there are no distinctive segments within the population of subjects investigated, or when -as will be explained in the sequel- there are distinct segments that can be captured by covariates that are measured on the subjects.

In this paper we want to show how the multilevel approach can be used in analyzing preferences. Furthermore, we will compare this approach to both mixture regression analysis and the disaggregate regression analysis. The multilevel approach will be illustrated for empirical data on consumers' preferences for meat products. To support the validity of the multilevel model, comparisons with alternative analysis techniques are made concerning the predictive power towards consumers' preferences.

## 2. Multilevel Analysis

In the case of an external analysis of preferences one has information on at least two kinds of entities: subjects ($i = 1,...,N$) and choice alternatives or objects ($j = 1,....,M$). More precisely, the data provide information on subject's $i$ preference for object $j$ at moment $t_{ij}$, $Y_{ij}(t_{ij})$. In addition, we have object scores on a number of variables ($r = 1,...,R$), $X_{ijr}$. These could be observations on a number of variables, but also scores derived from applying a technique such as principal components analysis to observations on these variables. The score of object $j$ on variable $r$, $X_{ijr}$, may vary from one subject to the other.

We first present a general expression from which the multilevel model, which relates $Y_{ij}(t_{ij})$ to the object information, will be developed:

$$Y_{ij}(t_{ij}) = \beta_0 + U_{ij} + E_{ij}(t_{ij}) \ . \qquad (1)$$

As can be seen, the preference for object $j$ is build up from the mean preference, $\beta_0$, a joint effect of person $i$ and object $j$ on preference, $U_{ij}$, and a residual term, $E_{ij}(t_{ij})$, representing the deviation at moment $t_{ij}$. Both $U_{ij}$ and $E_{ij}(t_{ij})$ can be modeled further.

The joint effect of person $i$ and object $j$, $U_{ij}$, may be decomposed into a person effect, $U^*_{0i}$, expressing that some subjects have a higher preference for the objects under consideration than others. In addition to this effect, we assume each object to have a specific effect upon preference through it's score on a number of variables, $X_{ijr}$. It is assumed that the higher the score of an object on a particular variable becomes, the higher (or lower) the subject's preference will be. The strength of the relation between the score on variable $r$ and preference is represented by a weight $\beta_r$. There is, however, also some individual variation allowed for, in that the $\beta_r$ coefficients are augmented by a subject dependent deviation $U^*_{ri}$. The above leads to the following model for $U_{ij}$:

$$U_{ij} = U^*_{0i} + \sum_{r=1}^{R} X_{ijr}(\beta_r + U^*_{ri}) . \tag{2}$$

This expression shows that next to a main effect of the subject, $U^*_{0i}$, there also is an interaction between subjects and objects. The effect of objects may differ across subjects, due to the object scores, $X_{ijr}$, differing across subjects or due to the regression weights, $U^*_{ri}$, being subject dependent. Substituting Equation 2 into Equation 1, shows that the model can be written as a multilevel model with varying coefficients for the intercept as well as varying regression coefficients for the predictor variables:

$$Y_{ij}(t_{ij}) = (\beta_0 + U^*_{0i}) + \sum_{r=1}^{R} X_{ijr}(\beta_r + U^*_{ri}) + E_{ij}(t_{ij}) . \tag{3}$$

In Equation 3 only $Y_{ij}(t_{ij})$ and $X_{ijr}$ are known quantities. The remaining quantities are parameters, that need to be estimated from the data. Among the parameters, we have $\beta_r$ 's representing effects of the object variables, and the $U_{ri}^*$'s representing individual deviations in these effects. In multilevel analysis these deviations can be modeled further as consisting of nonsystematic and systematic parts. Usually, the nonsystematic parts are assumed to be multivariate normally distributed. The systematic part can be modeled as a linear combination of subject dependent covariates. Let $Z_{ki}$ denote the score of subject $i$ on covariate $k = 1,..., K$. Let $U_{0i}$ and $U_{ri}$ denote the random (nonsystematic) parts of the regression coefficients. We can refine the parameters $U^*_{0i}$ and $U^*_{ri}$ from Equation 3 as:

$$U^*_{0i} = \sum_{k=1}^{K} \beta_{0k} Z_{ki} + U_{0i} , \quad \text{and} \quad U^*_{ri} = \sum_{k=1}^{K} \beta_{rk} Z_{ki} + U_{ri} . \tag{4}$$

In random effects modeling, commonly the random parts $U_{0i}$ and $U_{ri}$ are assumed to be multivariate normally distributed. Modeling the regression weights in terms of subject dependent covariates is important as often one is interested in explaining individual differences in preference formation. An illustrative example is the market researcher who wants to know which type of household, as characterized by a number of variables like income, number of children or family life cycle, strongly weighs health in preferences as regards different meal types.

The model formulated in Equation 3 also applies to object variables of a nonmetric scale level. In this case one can translate the object information into dummy variables, which then take the place of $X_{ijr}$. This usually will be the case for the analysis of data resulting from conjoint analysis. In a conjoint analysis the object profiles often are constructed from nominal or ordinal variables (Hair et al., 1998). Multilevel analysis allows for individual differences in that the weights of the dummy variables, which represent the utilities of the attributes, are randomly distributed according to a normal distribution.

To elaborate upon $E_{ij}(t_{ij})$ in Equation 3, this parameter represents the deviation of the observed preference score from the predicted preference score on moment $t_{ij}$. Commonly, $E_{ij}(t_{ij})$ is considered to be distributed independently across time, according to a normal distribution with constant variance. When preference measurements are taken closely together in time, dependencies in this residual term may occur. In a preference task, psychological processes may be involved that fluctuate but also cohere across time. This may cause a dependency between the preference scores of one subject, which may weaken as their separation in time increases. Well-known options to model such dependencies, are the first-order autoregressive process and the first-order moving average process. The first-order autoregressive process, AR(1) for short, assumes that the value of $E_{ij}(t_{ij})$ still depends by a factor $\phi^k$ on the value at $k$ periods before $t_{ij}$. According to this process, the (auto)correlation of $E_{ij}(t_{ij})$ for two moments that are $k$ periods apart is equal to $\phi^k$. If $\phi$ ranges from -1 to 1, this implies a gradual extinction of the dependency between residual terms across time. The first-order moving average process, abbreviated as MA(1), assumes that the value of $E_{ij}(t_{ij})$ depends to some extent on its value at the period before $t_{ij}$, but only on this value. The value of $E_{ij}(t_{ij})$ is a weighted average of its value at the period before $t_{ij}$ and its increment at time $t_{ij}$. In the case of MA(1) the (auto)correlation for two values that are separated by at least 2 periods equals 0. Both AR(1) and MA(1) assume that the correlation between the residual terms depends only on the time span, and also that the residual scores have a constant mean and variance across time. These properties define these processes as stationary processes. Some multilevel programs (e.g. Hedeker & Gibbons, 1996) allow for testing such autocorrelated errors.

The residual term, $E_{ij}(t_{ij})$, also may capture trend effects of time. This would imply that subjects either begin to like the objects more as they progress in judging these objects (linear trend), or maybe there is an optimum position in the middle of the task at which the preference is highest (curvilinear trend). Note that such trends may be important for aptitude or intelligence tests. For these tasks there may be an increase in the test score as a result of learning over time, or a curvilinear relation between time and the test score due to the test person becoming tired or satiated. In the context of preferences we consider such trends less likely. Modeling the residual term further as a function of time by a polynomial (cf. Snijders, 1996; Van der Leeden, 1998) thus will not be necessary. When different object orders are used, according to a latin square design for example (Maxwell & Delaney, 1990), the empirical significance of these trend effects can be investigated.

Equation 3 implies that the more of a particular attribute an object has, the higher (or lower) the preference for this object becomes. The random effects model in Equation 3 generalizes the *vector model* of preference formation (Green et al., 1989), in that the strength of the relation between preference and the score on the object variable may vary from one subject to the other. The model resembles the Wandering Vector Model (Carroll, 1980; DeSoete & Carroll, 1983). Similar to the Wandering Vector Model, the model in Equation 3 assumes (at least in the absence of systematic variation in the regression weights) that the regression weights of the object scores are normally distributed. Unlike the Wandering Vector Model the model in Equation 3 also allows for stochastic variation in the intercept. This allows for differences between subjects in their preferences for the object set as a whole, which cannot be captured by the object scores $X_{ijr}$ .

The multilevel model in Equation 3 can be easily extended by relating preference to the object information according to a polynomial of degree $n$. A model of degree 2 has some special interest. In this case the multilevel model can be expressed as:

$$(5) \qquad Y_{ij}(t_{ij}) = (\beta_0 + U^*_{0i}) + \sum_{r=1}^{R} X_{ijr}(\beta_r + U^*_{ri}) + \sum_{r=1}^{R} X^2_{ijr}(\gamma_r + V^*_{ri}) + E_{ij}(t_{ij}) \ .$$

This can be considered a stochastic extension of the *ideal point model* (Green et al., 1989). In the ideal point model, for each variable there is an optimum position, called the ideal point. The more the object is removed from this ideal point the smaller the preference for this object becomes. It is also possible to have an anti-ideal, which is a point of minimal preference. The more an object is removed from this anti-ideal, the larger the preference becomes. For the model in Equation 5, the optimum position for subject $i$ on variable $r$ is given by:

$$(6) \qquad -\frac{(\beta_r + U^*_{ri})}{2(\gamma_r + V^*_{ri})}.$$

The sign of the second derivative of the preference function in Equation 5, corresponding to the acceleration, indicates whether the optimum is an ideal or an anti-ideal. The score on variable $r$ in Equation 6 is an ideal when $(\gamma_r + V^*_{ri}) < 0$, and is an anti-ideal when $(\gamma_r + V^*_{ri}) > 0$.

In multilevel modeling the nonsystematic parts of the regression weights in Equation 5 are assumed to be normally distributed. In case there is no systematic variation, this implies that $U^*_{0i}$, $U^*_{ri}$ and $V^*_{ri}$ are normally distributed. Furthermore, whenever the regression coefficient for the linear term, $U^*_{ri}$, is normally distributed, and there is no random variation in the regression coefficient for the quadratic term, that is, $V^*_{ri} = 0$, it follows from Equation 6 that the multilevel model specifies a normally distributed ideal point along each variable $r$.

Several stochastic ideal point models have been proposed in the literature (e.g. DeSoete, Carroll & DeSarbo, 1986; Zinnes & MacKay, 1992) that resemble the model in Equation 5. These define preference as a decreasing function of the distance between ideal point and object, assuming a normally distributed ideal point. When translating these models to a model for preference ratings, starting from given object scores, we obtain a variant of the random effects model as presented in Equation 5. More precisely, it can be shown that a non-normally distributed intercept ($U^*_{0i}$) results, normally distributed regression coefficients for the linear terms ($U^*_{ri}$) and nonrandom and identical regression parameters for the quadratic terms ($\gamma_r = \gamma$ and $V^*_{ri} = 0$). The reader is referred to the appendix for details. Since in multilevel analysis, all random coefficients are assumed to be normally distributed, the model in Equation 5 (assuming there are no systematic parts in the coefficients $U^*_{0i}$, $U^*_{ri}$ and $V^*_{ri}$) can be considered only an approximation of a distance model with a normally distributed ideal. On the other hand, the multilevel model as presented in Equation 5, specifies a curvilinear relation between object variables and preference, and this relation can vary randomly across subjects. As such this model may be tested for empirical significance.

Multilevel modeling provides estimates of the variances and covariances of the random regression coefficients. The variances can be tested for statistical significance, which indicates whether intersubjective variation is present. In addition, it is possible to estimate for each subject the individual regression parameters through empirical Bayes estimation. For speical variants of the multilevel model, Bayes estimates have been shown to minimize the expected mean squared error (Bryk & Raudenbush, 1992; Snijders, 1999). Although biased, Bayes estimates are superior because of their low variance. Empirical Bayes estimates, as obtained in multilevel analysis, can be considered approximations of these Bayes estimates (Carlin & Louis, 2000). For large samples one may expect empirical Bayes estimates also to minimize the mean squared error, so that the resulting mean squared error will be lower than the mean squared error of ordinary least squares estimates, as obtained in separate preference regressions for each individual. This in turn, may lead one to expect that also better predictions concerning the dependent variable can be obtained through empirical Bayes estimates. Indeed Bryk and Raudenbush (1992) illustrate the better predictive performance of the empirical Bayes estimates in an empirical study on the growth of children's vocabulary size. In the present application we examine whether multilevel analysis yields better predictions of subjects' preferences than disaggregate regression analysis does. In the empirical part of the paper we will address this issue.

In the next section, we consider an alternative approach to preference regression, known as mixture regression analysis.

## 3. Mixture Regression Analysis

An alternative approach to incorporating subject heterogeneity in preference regression has received a lot of attention in the domain of marketing. In this area many techniques have been developed to cluster relatively homogeneous entities such as customers or companies into segments. Identification of such segments is assumed to be useful in devising effective marketing strategies. In the domain of preference regression, a technique has been developed that clusters subjects into segments that have similar weights in the relation between object preference and the scores of these objects on a number of variables. This technique is known as mixture regression analysis (Wedel & DeSarbo, 1994; Wedel & Kamakura, 1997).

Formally, we can define mixture regression as follows. Let the homogeneous clusters or segments be denoted by $s$ (=1,...,$S$), let the set of persons in cluster $s$ be denoted by $G_s$, and let the prior probability of subject $i$ belonging to segment $s$, be denoted by $\pi_s$. Furthermore, let the density of score $Y_{ij}(t_{ij})$ for a subject belonging to segment $s$ be denoted by $g(Y_{ij}(t_{ij})|i \in G_s)$. The density of the observed scores for subject $i$ on $M$ objects given a vector $\phi$ of model parameters, can now be defined as:

$$(7) \qquad f(Y_{i1}(t_{i1}),...,Y_{ij}(t_{ij}),...,Y_{iM}(t_{iM}) \mid \phi) = \sum_{s=1}^{S} \pi_s \prod_{j=1}^{M} g(Y_{ij}(t_{ij})|i \in G_s) \ .$$

In the case of preference regression for preference ratings, $g(Y_{ij}(t_{ij})|i \in G_s)$ is commonly defined by the normal density. So the density for all preference scores of a subject is a mixture of normal densities, with as mixing weights the prior probabilities of belonging to each of the segments. For a subject belonging to segment $s$, we thus have for the subject's score on the preference variable at $t_{ij}$:

$$(8) \qquad Y_{ijs}(t_{ij}) = \beta_{0s} + \sum_{r=1}^{R} X_{ijr}\beta_{rs} + E_{ijs}(t_{ij}) \ ,$$

where $E_{ijs}(t_{ij})$ is normally distributed within each segment $s$. This expression can be considered the mixture regression analogue of the expression for the random effects model as given in Equation 3. Notice that within each segment, there is no variability allowed for in the regression coefficients; the regression weights are fixed. There is, however, for each subject and object combination some variability which is captured by a normally distributed error term. Note that an extension of Equation 8 can be made, similar to the extension made in multilevel analysis, by adding squared object scores to the model (cf. Equation 5). This would constitute an ideal point extension of the mixture regression model.

Next to the prior probability, $\pi_s$, also for each subject $i$ the posterior probability of belonging to segment $s$, $\pi_{is}$, can be calculated. Applying Bayes' theorem, we have

$$(9) \qquad \pi_{is} = \frac{\pi_s \prod_{j=1}^{M} g(Y_{ij}(t_{ij}) \mid i \in G_s)}{\sum_{s=1}^{S} \pi_s \prod_{j=1}^{M} g(Y_{ij}(t_{ij}) \mid i \in G_s)} \ .$$

The posterior probabilities can be used to assign subjects to a segment (namely to the segment for which the posterior probability is largest) and thus to the corresponding set of regression weights. These weights could be used in predicting subject's preferences. This approach seems to be appropriate whenever subjects have posterior probabilities that clearly favor one segment. In the case of more mixed results, one would like to consider the posterior probabilities for all segments in predicting subjects' preferences. In the latter case one could predict a subject's preferences by weighting the preferences predicted for each segment by the subject's posterior probability of belonging to this segment.

Mixture regression analysis (MRA) and multilevel analysis (MLA) make different assumptions regarding the nature of heterogeneity in subjects' regression weights. MLA starts from gradual variations in subjects' regression weights according to a normal distribution. MRA on the other hand assumes segments in which subjects have regression weights distinct from regression weights characterizing the subjects in other segments, and there is no variation within each of the segments. Note that the covariates in a multilevel analysis (see Equation 4) may be able of capturing some of the abrupt changes in the regression weights as they are modeled in mixture regression analysis. This however critically depends on the availability of covariates that indeed capture these differences in the regression weights. To the extent that the assumptions of one or the other technique are satisfied more, this technique will give a more adequate analysis of subjects' preferences. The validity of these techniques is an empirical issue. There are also developments combining both techniques (see Verbeke & Lesaffre, 1996). This would be a viable alternative when abrupt changes in subjects' regression coefficients are present and on top of that the regression coefficients change gradually according to a normal distribution. By comparing MRA and MLA for a real data set, we aim to evaluate the validity of each of these models and also want to obtain insight into the fruitfulness of employing a combined technique as proposed by Verbeke and Lesaffre (1996).

## 4. Empirical Illustration

### 4.1. Data set and procedure

The data concern judgments as given by 847 consumers for seven different kinds of meat products. The data were gathered in 1997 by a market research firm among members of a

Dutch consumer panel. The respondents are mainly responsible for meat purchases in their household, and are supposed to be representative of the target group in the Dutch population. The study was carried out to obtain insights into the cognitive dimensions underlying consumers' preferences for meat (Schifferstein, Candel & Van Trijp, 1998).

Seven meat products were included in the study: pork, beef, chicken, veal, lamb, minced meat and fish. These products were evaluated by the respondents on a set of attributes, which were assumed to reflect the major perceptions that consumers have regarding meat products. The attributes were selected on the basis of an extensive study of the literature (Steenkamp & Van Trijp, 1998) as well as qualitative interviews with consumers. Table 1 displays an overview of the attributes that were selected for this study. The attributes were scored on 5-point rating scales with labeled end points. Product preference was measured on three evaluative 5-point rating scales. The end poles were labeled with respectively "pleasant - unpleasant", "attractive - unattractive" and "good - bad". Overall preference was measured for each of the seven products by taking for each subject the mean score on these three evaluative scales.

Yeah-saying tendencies were accommodated for by changing the end labels of both the attribute and preference scales randomly. To accommodate for order effects, different versions of the questionnaire were used. These versions differed in the order of the products and the order of the attributes. The product orders were constructed according to a latin square design (Maxwell & Delaney, 1990). There were two orders for the attributes: a basic order and its reverse.

### 4.2. Uncovering perceptual dimensions for meat

The perceptual dimensions assumed to underlie the preferences for meat were uncovered by principal components analysis (PCA) of the attribute judgements. The attribute judgements as given by each of the subjects for the seven meat products under study were first organized into a two-way matrix: the subject-product combinations were located in the rows and the attributes in the columns. As shown by Kiers (1991), PCA on such a matrix in fact generalizes the analysis techniques for three-mode data known as PARAFAC and TUCKALS-3. Since we encountered no interpretational difficulties with this more complex analysis, the above approach was adapted.

*Table 1.* Correlations between product attributes and VARIMAX rotated components (correlations larger than 0.4 are printed bold).

| | *Principal component* | | | |
|---|---|---|---|---|
| | Sensory Quality | Con-venience | Special | Natural Production |
| *Attribute* | | | | |
| Tender | **.7877** | .2130 | .0408 | .0716 |
| Good quality | **.6623** | .2464 | .2851 | .2010 |
| Tastes good | **.5760** | **.5080** | .3170 | .0431 |
| Goes with few dishes | .2190 | **.7835** | .2112 | -.1080 |
| Easily available | .0968 | **.7365** | -.2108 | -.0393 |
| Simple preparation | .3717 | **.6157** | -.2633 | -.0167 |
| Suitable for special occasions | .3173 | .1188 | **.7061** | -.0232 |
| Cheap | .1491 | **.4373** | **-.6733** | -.0856 |
| Lean | **.4030** | -.0559 | **.5770** | .1514 |
| Healthy | .2844 | .1833 | **.5336** | **.4583** |
| A premium product | .1202 | -.3074 | **.5140** | .0607 |
| Suitable for guests | .3427 | .2175 | **.4582** | .0137 |
| No hormones | .0539 | -.0257 | .0262 | **.8200** |
| Produced animal friendly | -.0704 | -.0739 | .0673 | **.7998** |
| Produced environ-mentally friendly | .1011 | -.0001 | .0900 | **.6029** |
| No additives | .3758 | -.0453 | .1589 | **.5378** |
| Produced hygienically | .2873 | .0999 | .1628 | .3347 |

In applying PCA a four-component solution was chosen, based on the scree-plot criterion as well as the interpretability of the resulting components (Hair et al., 1998). After VARIMAX rotation, these components explained 16.3%, 14.7%, 14.2% and 13.5% of the variance respectively, and could be interpreted as sensory quality, convenience in use, special and natural production. The interpretation is based on the attributes that correlate strongly with the components (see Table 1 for an overview). The resulting components, for which we obtain individual-specific product scores, will act as predictor variables in the preference regression. The component scores are standardized across products and subjects, implying that for each component the score zero can be interpreted as the "average" product.

**4.3. Mixture regression analysis**

To explain consumer preference from products' scores on the components uncovered by PCA, a mixture regression analysis was performed assuming a mixture of normal distributions. The program GLIMMIX version 1.0 (Wedel, 1997) was employed, in which model estimates are obtained according to an EM algorithm. To accommodate for local optima, for each number of segments multiple analyses with random starting values were done. Each time the smallest value for the information criteria AIC, CAIC and BIC and the corresponding solution were stored (Wedel & DeSarbo, 1994). These information criteria are based on the likelihood function and penalize for the number of model parameters. The latter property allows for a comparison between nonnested models on the basis of these statistics.

We compared a mixture regression model with only linear terms to a model also having a quadratic term: the squared product scores summated across the four components. This led to a significant improvement of the log likelihood (e.g. for four segments: $\Delta\chi^2 = 63.94$, $\Delta df = 1$ , $p < 0.001$) as well as to a decrease in the information indices (e.g. for four segments: $\Delta CAIC = 29.62$). Allowing the squared scores to have different coefficients for each of the dimensions, did not result in a better fit (e.g. for four segments we have: $\Delta\chi^2 = 19.24$, $\Delta df = 12$ , $p > 0.05$, and $\Delta CAIC = -100.16$). Therefore the results for the analysis including a single regression coefficient for the quadratic term, will be reported upon.

Examining the values of AIC, CAIC and BIC for one up to six segments, BIC and CAIC achieve their minimum for a solution with four segments. Within the range of one to six segments, AIC does obtain a minimum value. Since CAIC and BIC have been shown to be superior for determining the number of segments (Wedel & Kamakura, 1997), we pick the four-segment solution. To examine the separation of these segments the entropy measure $E_s$ (Wedel & Kamakura, 1997) is calculated. This turns out to be 0.48, indicating that the segments are only weakly separated.[1]

Interpreting the regression coefficients of the dimensions is a difficult issue. Because of the quadratic term in the preference model, the sensitivity of preference to changes in the dimensions, as expressed by the derivative of the preference function with respect to the dimension under consideration, depends on the location on the dimension. The sensitivity or "importance" of a dimension thus also depends on the score on that dimension. The regression coefficients for the dimensions reflect the importance of the dimension on the zero location, which, because the dimensions are standardized across subjects and products, can be considered the location of the "average" product. In comparing the importances of the dimensions, we will consider this average product.

Inspecting the regression coefficients in Table 2 indicates that the four segments can be characterized as follows. The modal segment, comprising of 34% of the respondents, finds sensory quality and convenience most important in evaluating the products. The next largest segment (26% of the respondents) especially values sensory quality and the special dimension, and can be characterized as the exclusivity segment. The smallest segment (18%) finds convenience most important and thus can be interpreted as a convenience segment. A segment comprising 22% of the respondents is similar to the modal segment. However, for this segment the sum of the squared object scores has a positive regression weight (although only marginally significant), indicating there is an anti-ideal point along all dimensions. It can be verified that this anti-ideal is below the range of product scores along these dimensions. Consequently, this segment can be characterized as having an increasing and positively accelerated preference curve along each dimension for the range of products under consideration. The other segments on the other hand, are characterized by a negative regression coefficient for the quadratic term, implying an ideal point, which can be shown to

[1] Let $p_{is}$ be the estimated posterior probability of subject $i$ (=1,...,$N$) belonging to segment $s$ (=1,....,$S$). The entropy measure $E_s$ is now defined as (Wedel & Kamakura, 1997):

$$E_s = 1 + \sum_{i=1}^{N}\sum_{s=1}^{S} \frac{p_{is} \ln p_{is}}{N \ln S},$$

which takes on values between 0 and 1. The more each subject has a posterior probability favoring one segment, the more $E_s$ approaches 1.

lie above the products' scores along each of the dimensions. This means that the other segments are characterized by increasing but negatively accelerated preference curves over the domain of product scores.

*Table 2.* Overview of regression weights (and t-values) for the 4-segment solution of a mixture regression analysis.

| Dimension | Segment 1 (34 %) | Segment 2 (26 %) | Segment 3 (22 %) | Segment 4 (18 %) |
|---|---|---|---|---|
| Sensory quality | 0.475 (16.90) | 0.409 (14.17) | 0.444 (12.31) | 0.406 (11.58) |
| Convenience | 0.329 (12.31) | 0.220 (7.72) | 0.275 (7.88) | 0.463 (13.80) |
| Special | 0.259 (11.08) | 0.345 (14.57) | 0.212 (6.95) | 0.184 (6.28) |
| Natural | 0.178 (6.54) | 0.129 (4.49) | 0.169 (4.93) | 0.292 (8.89) |
| Sum of squared dimensions | -0.034 (-4.00) | -0.017 (-1.96) | 0.019 (1.69) | -0.033 (-3.05) |

**4.4. Multilevel analysis**

To perform the external analysis of preferences through multilevel analysis, we use the program MIXREG (Hedeker & Gibbons, 1996). MIXREG allows for the estimation of normally distributed random effects, at the same time assuming autocorrelated error terms. It uses marginal maximum likelihood estimation, and employs both the EM algorithm and a Fisher-scoring solution. Estimation of the individual random effects is possible by an empirical Bayes procedure. For more details on the estimation procedures implemented in MIXREG, the reader is referred to Hedeker and Gibbons (1996).

First, we analyze the data according to a model including a random intercept and random regression coefficients for each of the dimensions as resulting from the PCA. To test for the ideal point extension of this model, also the squared object scores summated across the four dimensions, were included as an additional term. Since letting the regression coefficient for this term be random resulted in convergence problems, the program MIXREG was rerun with a constant regression coefficient. This resulted in a significantly better fit ($\Delta\chi^2 = 40.55$, $\Delta df=1$, $p <$

0.001), pointing to a curvilinear relation between preference and the scores on the dimensions. Letting the squared scores have separate regression weights for each dimension, did not result in a better fit ($\Delta\chi^2 = 4.27$, $\Delta df = 3$, $p > 0.20$). Also time-related covariates reflecting the order in which the products were judged, were included in the analyis model. This enabled us to devise a test for both linear and curvilinear trend effects of time on preference. As expected, including these covariates did not improve the model fit: $\Delta\chi^2 = 2.97$, $\Delta df = 1$, $p > 0.05$ for linear trends, and $\Delta\chi^2 = 0.03$, $\Delta df = 1$, $p > 0.80$ for curvilinear trends. The parameter estimates for this basic model are displayed in the left part of Table 3.

Next, a number of background variables on the households were added to the model and tested for significance. These variables were: a variable indicating single-person versus multiperson status of the household, age of the housewife, and geographical location of the household. Geographical location consisted of five categories (three largest cities in the West, remainder of the West, North, East and South), and was included in the analysis through 4 dummy variables, South being the reference category. These covariates were used both to describe the variable, nonrandom part of the intercept, the variable, nonrandom parts of the regression coefficients of each of the perceptual dimensions as well as the variable, nonrandom part of the regression coefficient for the sum of squared dimension scores. We trimmed the model down by successively deleting nonsignificant covariates from the model. The parameter estimates for the final model are given in the right part of Table 3. This model significantly improves the basic model ($\Delta\chi^2 = 78.69$, $\Delta df = 18$, $p < .001$). In the final model, the age of the housewife effects the weight attached to the sum of squared product scores, such that the older the housewife becomes the less negative the weight becomes. Geographical area turns out to be related to the weight attached to two dimensions underlying preference. Households in the West and North more heavily weigh the special dimension than households in the South. Households in the three largest cities in the West and households in the East weigh natural production more than households in the South of the Netherlands. Of course, since these results are post-hoc, cross-validation is called for. Additionally, we investigated whether there are temporal dependencies between the preference judgements, that can be described by a stationary process. MIXREG allows for testing different variants of such processes. We tested for an AR(1) process and for a MA(1) process. Both analyses did not improve the model fit: $\Delta\chi^2 = 0.003$, $\Delta df = 1$, $p > 0.95$ for AR(1), and $\Delta\chi^2 = 0.002$, $\Delta df = 1$, $p > 0.95$ for MA(1).

*Table 3.* Results from multilevel analyses in which covariates are added.

| Variable | Parameter | Without covariates<br>Estimate ( S.E.) | With covariates<br>Estimate (S.E.) |
|---|---|---|---|
| *Fixed part* | | | |
| Intercept | $\beta_0$ | 3.528 (0.010) | 3.649 (0.044) |
| Sensory quality | $\beta_1$ | 0.418 (0.010) | 0.502 (0.031) |
| Convenience | $\beta_2$ | 0.308 (0.010) | 0.446 (0.029) |
| Special | $\beta_3$ | 0.262 (0.008) | 0.270 (0.029) |
| Natural production | $\beta_4$ | 0.184 (0.011) | 0.091 (0.036) |
| Sum of squared dimensions | $\gamma_1$ | -0.019 (0.003) | -0.037 (0.009) |
| Age housewife | $\beta_{01}$ | | -0.006 (0.006) |
| Geographical area: | | | |
| - Cities in the West (vs. South) | $\beta_{02}$ | | -0.025 (0.030) |
| - Remainder West (vs. South) | $\beta_{03}$ | | -0.058 (0.025) |
| - North (vs. South) | $\beta_{04}$ | | 0.031 (0.034) |
| - East (vs. South) | $\beta_{05}$ | | -0.012 (0.027) |
| Age housewife x Sensory quality | $\beta_{11}$ | | -0.012 (0.004) |
| Age housewife x Convenience | $\beta_{21}$ | | -0.020 (0.004) |
| Age housewife x Special | $\beta_{31}$ | | -0.007 (0.004) |
| Age housewife x Natural | $\beta_{41}$ | | 0.009 (0.004) |
| Special x Geographical area: | | | |
| Cities in the West | $\beta_{32}$ | | 0.076 (0.027) |
| Remainder West | $\beta_{33}$ | | 0.046 (0.022) |
| North | $\beta_{34}$ | | 0.087 (0.030) |
| East | $\beta_{35}$ | | 0.019 (0.024) |
| Natural x Geographical area: | | | |
| Cities in the West | $\beta_{42}$ | | 0.092 (0.034) |
| Remainder West | $\beta_{43}$ | | 0.014 (0.028) |
| North | $\beta_{44}$ | | 0.027 (0.037) |
| East | $\beta_{45}$ | | 0.056 (0.030) |
| Age housewife x sum of squared dimensions | $\gamma_{11}$ | | 0.003 (0.001) |
| *Random part* | | | |
| Intercept | $\sigma^2(U_0)$ | 0.028 (0.004) | 0.028 (0.004) |
| Sensory quality | $\sigma^2(U_1)$ | 0.018 (0.004) | 0.018 (0.004) |
| Convenience | $\sigma^2(U_2)$ | 0.020 (0.004) | 0.019 (0.003) |
| Special | $\sigma^2(U_3)$ | 0.014 (0.003) | 0.013 (0.003) |
| Natural production | $\sigma^2(U_4)$ | 0.022 (0.004) | 0.020 (0.004) |
| Residual | $\sigma^2(E_{ij})$ | 0.221 (0.006) | 0.220 (0.006) |
| - 2 log likelihood | | 8495.61 | 8416.92 |

### 4.5. Interpretation of the analysis results

In interpreting the results from the multilevel analysis we are especially interested in the sensitivity of preference to changes in the dimensions underlying the consumers' perception of meat products. First, one should note that the regression coefficients for the perceptual dimensions each vary significantly across subjects, as evidenced by the significant variances of these coefficients ($p < 0.001$). On the other hand, the variances are rather small relative to the mean coefficients, so that the mean coefficients are indicative of the sensitivity of preferences to changes on these dimensions. This average sensitivity can be read from the partial derivatives of the preference regression model (with mean coefficients) with respect to each of the corresponding dimensions. To facilitate the interpretation, below we give the expressions for these derivatives for each of the four dimensions (cf. Table 3):

| | |
|---|---|
| Sensory quality: | 0.502 - 0.012 Age + (0.006 Age - 0.074) Sensory quality |
| Convenience: | 0.446 - 0.020 Age + (0.006 Age - 0.074) Convenience |
| Special: | 0.270 - 0.007 Age + 0.076 Cities West + |
| | 0.046 Remainder West + 0.087 North + 0.019 East + |
| | (0.006 Age - 0.074) Special |
| Natural: | 0.091 + 0.009 Age + 0.092 Cities West + |
| | 0.014 Remainder West + 0.027 North + 0.056 East + |
| | (0.006 Age - 0.074) Natural |

As can be seen, due to the quadratic term in the multilevel model, for each of the dimensions the sensitivity depends on the score on the underlying dimension. We will consider the sensitivity for the dimensions for the average location of the products across all respondents (= score 0). For this score, a person living in the South of the Netherlands and belonging to the youngest category (age = 1), the partial derivatives for sensory quality, convenience, special and natural are respectively: 0.490, 0.426, 0.263, and 0.100. So, for a youngster living in the South of the Netherlands, when considering the centroid of the perceptual space, sensory quality and convenience are the most important dimensions, whereas special and natural are least important. As another example, for the centroid, a person living in the Eastern region, belonging to the highest age category (age = 11), has the following importances for sensory quality, convenience, special and natural respectively: 0.370, 0.226, 0.212, and 0.246. Hence for an aged person living in the East, sensory quality stands out as the most important dimension, whereas convenience, special, and natural production are of equal (but lower) importance. Note that both persons described above have a pattern of importances that does not fit in nicely with one of the patterns of importances characterizing the segments as uncovered by mixture regresion analysis (see Table 2). Assuming that the two importance patterns discussed are representative for a reasonable number of consumers, this makes comparing MLA and MRA on their validity for analyzing preference, a relevant issue.

On the basis of the empirical Bayes estimates for the regression coefficients, we are also able to verify that all subjects have ideal points along each of the dimensions. Furthermore, in the case of sensory quality, convenience and special nearly all subjects have ideal points that are above the range of their component scores. Consequently, for these dimensions the subjects have increasing but negatively accelerated preference curves: the more, the better, albeit that some kind of satiation seems to occur. For the natural dimension on the other hand, a small number of the subjects (5%) has an ideal score amidst their component scores. For a minority of the subjects there thus seems to be some optimal amount of natural production when choosing among different types of meat. Note that these preference functions are not in line with the preference functions characterizing the segments uncovered by mixture regression analysis. Here we also had positively accelerated preference functions and for none of the segments the optimum position was among the product scores along the dimensions. This calls again for comparing MLA and MRA on their validity as models of preference.

### 4.6. Evaluation of the multilevel model's predictive power

We evaluate the predictive power of the estimated multilevel model. The model could be used to develop an optimal product from consumer point of view, by using a grid-search technique. In this procedure the perceptual space is scanned systematically and for each point in the space the preference is calculated (see e.g. Kim et al., 1999). The usefulness of this procedure depends on the predictive power of the model with respect to consumers' preferences. In evaluating the predictive power we distinguish between the set of products on which the model is estimated, the estimation set (pork meat, beef, veal, lamb, minced meat, chicken and fish in our study), and the set of products not involved in model estimation, the validation set. The validation set can be used for testing the model's predictive power. In our analysis a meat replacing product was part of the validation set. To obtain a larger validation set, one can reanalyze the data starting from the total set of products, leaving one product out. We did two such re-analyses with respectively the product veal and chicken left out.

*Table 4.* Improvement in the mean squared error of prediction (MSEP) of the multilevel model relative to alternative analysis models.

| Comparison model | Intercept only | Disaggregate Regression | Aggregate Regression | Mixture Regression |
|---|---|---|---|---|
| *Validation set:* | | | | |
| Meat replacer | 66.0 % | 93.6 % | 3.4 % | 8.5% |
| Veal | 51.3 % | 97.0 % | 11.0 % | 14.3% |
| Chicken | 75.0 % | 99.5 % | 7.1 % | 15.6% |

To evaluate the predictive power for the three validation products, the mean squared error of prediction (MSEP) was calculated as a measure of the badness-of-prediction. Let $\hat{Y}_{ij}(t_{ij})$ be the predicted preference score for subject $i$ and object $j$ according to a particular model, then the MSEP for object $j$ is defined as follows:

$$MSEP_j = \frac{\sum_{i=1}^{N} (\hat{Y}_{ij}(t_{ij}) - Y_{ij}(t_{ij}))^2}{N} . \tag{10}$$

Comparing the MSEP of the multilevel model to the MSEP of a model, in which the preferences are predicted by the average preference score across all products in the estimation set (the intercept only model), substantial improvements are found. As can be seen in the first column of Table 4, the improvements in MSEP relative to this primitive model are rather substantial (varying between 51.3% and 75%). At one end we can predict preference by the intercept only model, at the other end we can perform separate least squares regressions for each individual (disaggregate regression analysis) and use the results for predictions. Since we expect the latter to lead to regression coefficients with a larger mean squared error of estimation compared to the empirical Bayes estimates of multilevel analysis, we expect multilevel analysis to lead to more adequate predictions (see Bryk & Raudenbush, 1992). The results in the second column of Table 4 support this expectation. The relative improvements in MSEP run from 93.6% to 99.5%. It appears that the number of products, seven in this study, is too small for the disaggregate regression analysis to come up with stable estimates that are useful in predicting product preference.

Since we are also interested in the added value of random subject heterogeneity, we compare the multilevel model against the predictions made by a regular aggregrate regression analysis, where no random variability of the regression coefficients is allowed for. This illustrates the effect of additional intersubject variability on top of the consumer background variables included as covariates in the regression model. Table 4 shows moderate, but consistent improvements in MSEP (ranging from 3.4% to 11.0 %). The random variation in the regression coefficients appears to add moderately, but consistently across the set of products, to the predictive value of the model.

Finally, the predictions made by mixture regression analysis are compared to the predictions made by multilevel analysis. The results from mixture regression analysis can be used in predicting consumer preference, by weighting the preferences within each of the four segments with subject's posterior probability of belonging to each of these segments. (Since the posterior probabilities for most subjects did not favor one of the segments, this may be considered a better strategy than predicting subjects' preferences by the preferences of the segments for which their posterior probability is largest). As can be seen in Table 4, for all three products of the validation set, the predictions resulting from mixture regression were worse than the multilevel predictions. (This also turned out to be the case when subjects' preferences were predicted by the preferences of the segments for which their posterior probabilities were largest).

An explanation for the multilevel model having a better predictive power than the mixture regression model may be that the variation in the regression coefficients is not so much of a discrete nature, that is, characterized by abrupt changes in their values, but rather of a gradual nature as captured by the normal distribution. A way of checking this is by adding the segment memberships (that is, the posterior probabilities) resulting from mixture regression analysis as covariates to a multilevel analysis without any other covariates. To explain that this analysis enables a test as to whether there are abrupt changes in the regression weights, assume a situation, where for each subject the posterior probabilities are 1 for one segment and 0 for the others. In this case the posterior probabilities act as indicator variables, indicating to which segment a subject belongs. The regression weights obtained for these indicators in a multilevel analysis thus can capture abrupt changes in the regression weights corresponding to differences in the segments (see Equation 4). In the more general case that the posterior probabilities vary between 0 and 1, the regression weights reflecting the segment related changes, are no longer multiplied by indicator variables but by posteriors expressing the degree of segment membership. By adding the posterior probabilities as covariates to a multilevel analysis, we are thus able to test whether there are abrupt changes in the regression weights on top of the continuous changes as modeled by multilevel analysis. This analysis did not show an improvement in model fit ($\Delta\chi^2 = 9.34$, $\Delta df = 18$, $p > 0.90$). Remember that we also found that the segments from mixture regression analysis are weakly separated. These results point to the regression weights not changing abruptly from one segment to the other. Subsequently setting the regression coefficients fixed in the multilevel analysis leads to a significant decrease in model fit ($\Delta\chi^2 = 271.712$, $\Delta df = 15$, $p < 0.001$). The latter result supports that there is substantial variation in the regression coefficients, which, however, seems to be of a more gradual nature.

**5. Conclusions and Discussion**

Multilevel modeling was introduced as a technique to perform an external analysis of preferences, in which explicit care is taken of individuals' differences in preference formation. The technique was contrasted with several competing techniques, that is, mixture regression analysis, and disaggregate regression analysis. In the empirical illustration multilevel analysis appears to outperform the predictions made by the disaggregate regression analysis, and also turns out to outperform the predictions made by mixture regression analysis. Particularly the suitability of multilevel analysis vis-à-vis mixture regression analysis seems to be largely an empirical matter. Whether gradual variations in the regression coefficients as assumed in multilevel analysis, lead to better explanations of the data compared to the abrupt changes in the regression coefficients as assumed in mixture regression analysis, can only be ascertained after applying both analysis techniques to numerous relevant data sets. Note however, that through the availability of appropriate covariates, multilevel analysis, like mixture regression analysis, may be capable of modeling abrupt changes in the regression coefficients. To the degree that abrupt changes in the regression weights are present, which can not be captured by including appropriate covariates in a multilevel analysis, an approach like the one developed by Verbeke and Lesaffre (1996) would become a relevant alternative. For the present data however, no such indications were found.

In the empirical illustration it was also tested whether autocorrelated errors corresponding to either a first-order autoregressive process or a first-order moving average process, significantly improved the MLA analysis. This turned out not to be the case. A reason for not finding such dependencies across time may be that the preference judgements for the different products were sufficiently separated in time. Between the preference judgments for two different products, a subject had to give various attribute judgements on the products. This may have minimized the dependencies across time. Another explanation may be that, since the attribute judgements and the preference judgements for a particular product were grouped together in the questionnaire, both types of data may be subject to the same psychological influences. Since the attribute judgements are assumed to influence preference via the corresponding principal components, these possibly also explain serial correlations between preferences that otherwise might have been explained by autocorrelated residual terms. If, for instance, we would have related subjects' preferences to physical product parameters (which are constant across time), we possibly might have found significant improvements in model fit due to letting the residual terms be autocorrelated.

The present study discussed mixture regression, without considering techniques that also incorporate subject dependent covariates in the model. Relating subjective differences in the regression coefficients to covariates in a single analysis however is not the sole benefit of random effects modeling. Mixture regression models have been proposed in which the covariates determine the prior probabilities of belonging to the segments, each of which are characterized by a distinct set of regression coefficients. These mixture models are, however, not included in GLIMMIX version 1.0 (Wedel & Kamakura, 1997). A program that does provide the possibility to incorporate such concomitant variables is the Latent GOLD program version 2.0 (Vermunt & Magidson, 2000a; Vermunt & Magidson, 2000b).

The multilevel approach suggested in the present paper can also be applied to the analysis of other types of data expressing subjects' preferences. Subjects could, for instance, make choices from each pair of alternatives that can be constructed from the $M$ alternatives. The resulting data can be analyzed according to a random effects binomial logit model. For such a logit formulation, MlwiN (Goldstein et al. , 1998) or the program MIXNO (Hedeker, 1998) could be employed to estimate the regression parameters. Within the context of mixture regression analysis, GLIMMIX (Wedel, 1997) or the program Latent GOLD (Vermunt & Magidson, 2000a; Vermunt & Magidson, 2000b) can be employed to obtain information on potential discrete segments and corresponding posterior probabilities. These programs allow for analyzing data according to a mixture of binomial distributions. So, also in the case of choice data, programs are available that enable the application of the approaches that have been compared in the present paper.

**Appendix**

We show that the preference of subject $i$ for object $j$ on moment $t_{ij}$, $Y_{ij}(t_{ij})$, as defined according to a distance model of preference with a normally distributed ideal, leads to a regression model with random coefficients. Let $d_{ij}$ denote the Euclidean distance between subject's $i$ ideal and object $j$ in an $R$-dimensional space defined by the objects' attributes. The dimension is indicated by $r = 1,...,R$. Let $I_{ir}$ be the ideal position of subject $i$ along dimension $r$, and let $X_{ijr}$ be object's $j$ position on dimension $r$ as perceived by subject $i$. We can now formulate the distance-based preference model as

(A1) $$Y_{ij}(t_{ij}) = \gamma d_{ij}^2 + \beta_0 + E_{ij}(t_{ij}),$$

which can be elaborated as

(A2) $$Y_{ij}(t_{ij}) = \gamma \sum_{r=1}^{R} (I_{ir} - X_{ijr})^2 + \beta_0 + E_{ij}(t_{ij})$$

(A3) $$= \gamma(\sum_{r=1}^{R} I_{ir}^2 + \sum_{r=1}^{R} X_{ijr}^2 - 2\sum_{r=1}^{R} I_{ir}X_{ijr}) + \beta_0 + E_{ij}(t_{ij}),$$

which, after the following substitutions

(A4) $$U^*_{0i} = \gamma\sum_{r=1}^{R} I^2_{ir} \quad , \quad \beta_r + U^*_{ri} = -2\gamma I_{ir}$$

can be written as:

(A5) $$Y_{ij}(t_{ij}) = \beta_0 + U^*_{0i} + \sum_{r=1}^{R}(\beta_r + U^*_{ri})\, X_{ijr} + \gamma\sum_{r=1}^{R} X^2_{ijr} + E_{ij}(t_{ij}) \; .$$

It is easy to see that this is a random coefficient model. Since $I_{ir}$ is normally distributed, $U^*_{ri}$ is also normally distributed, whereas $U^*_{0i}$ is non-normally distributed. The quadratic terms each have nonrandom regression weights that are identical for each of the dimensions (i.e. $\gamma$).

**Literature**


Bryk, A.S. & Raudenbush, S.W. (1992). *Hierarchical linear models: Applications and data analysis methods*. Newbury Park: Sage.

Candel, M.J.J.M. & Maris, E. (1997). Perceptual analysis of two-way two-mode frequency data: Probability Matrix Decomposition and two alternatives. *International Journal of Research in Marketing*, *14*, 321-339.

Carlin, B.P. & Louis, T.A. (2000). *Bayes and empirical Bayes methods for data analysis*. Boca Raton: Chapman & Hall.

Carroll, J.D. (1980). Models and methods for multidimensional analysis of preferential choice (or other dominance) data. In E.D. Lantermann & H. Feger (Eds.), *Similarity and choice* (pp. 234-289). Bern: Huber.

DeSoete, G. & Carroll, J.D. (1983). A maximum likelihood method for fitting the wandering vector model. *Psychometrika*, *48*, 553-566.

DeSoete, G., Carroll, J.D. & DeSarbo, W.S. (1986). The wandering ideal point model: A probabilistic multidimensional unfolding model for paired comparisons data. *Journal of Mathematical Psychology*, *30*, 28-41.

Diggle, P.J., Liang, K-Y & Zeger, S.L. (1995). *Analysis of longitudinal data*. Oxford: Clarendon Press.

Goldstein, H. (1995). *Multilevel statistical models*. London: Arnold.

Goldstein, H., Rasbash, J., Plewis, I., Draper, D., Browne, W., Yang, M., Woodhouse, G., Healy, M. (1998). *A user's guide to MlwiN*. Multilevel Models Project, Institute of Education, University of London.

Green, P.E., Carmone, F.J., Jr. & Smith, S.M. (1989). *Multidimensional scaling. Concepts and applications*. Boston: Allyn and Bacon.

Hair, J.F., Jr., Anderson, R.E., Tatham, R.L. & Black, W.C. (1998). *Multivariate data analysis*. Upper Saddle River, NJ: Prentice-Hall.

Hauser, J.R. & Koppelman, F.S. (1979). Alternative perceptual mapping techniques: Relative accuracy and usefulness. *Journal of Marketing Research*, *16*, 495-506.

Hedeker, D. (1998). *MIXNO: A computer program for mixed-effects nominal logistic regression.* University of Illinois: University of Illinois at Chicago, Division of Epidemiology and Biostatistics.

Hedeker, D. & Gibbons, R.D. (1996). MIXREG: A computer program for mixed-effects regression analysis with autocorrelated errors. *Computer Methods and Programs in Biomedicine*, *49*, 229-252.

Kiers, H.A.L. (1991). Hierarchical relations among three-way methods. *Psychometrika*, *56*, 449-470.

Kim, J., Chatterjee, R., DeSarbo, W.S. & Bijmolt, T.H.A. (1999). Incorporating context effects in multidimensional scaling of 'pick-any-N' choice data. *International Journal of Research in Marketing*, *16*, 35-56.

Lilien, G.L. & Rangaswamy, A. (1998). *Marketing engineering: Computer-assisted marketing analysis and planning*. Reading, MA: Addison-Wesley.

Maxwell, S.E. & Delaney, H.D. (1990). *Designing experiments and analyzing data*. Belmont, CA: Wadsworth.

Schifferstein, H.N.J., Candel, M.J.J.M. & Van Trijp, J.C.M. (1998). A comprehensive approach to image research: An illustration for fresh meat products in the Netherlands. *Tijdschrift voor Sociaal-Wetenschappelijk Onderzoek van de Landbouw, 13,* 163-175.

Schiffman, S.S., Reynolds, M.L. & Young, F.W. (1981). *Introduction to multidimensional scaling: Theory, methods and applications*. New York: Academic Press.

Snijders, T.A.B. (1996). Analysis of longitudinal data using the hierarchical linear model. *Quality and Quantity*, *30*, 405-426.

Snijders, T.A.B. & Bosker, R.J. (1999). *Multilevel analysis. An introduction to basic and advanced multilevel modeling*. London: Sage.

Steenkamp, J.E.B.M. & Van Trijp, J.C.M. (1988). *Sensorische vleeskwaliteit en bereidingsgewoonten vers vlees*. Rijswijk, The Netherlands: Produktschap voor Vee en Vlees.

Steenkamp, J.E.B.M., Van Trijp, J.C.M, & Ten Berge, J.F.M. (1994). Perceptual mapping based on idiosyncratic sets of attributes. *Journal of Marketing Research*, *31*, 15-27.

Van der Leeden, R. (1998). Multilevel analysis of repeated measures data. *Quality and Quantity*, *32*, 15-29.

Verbeke, G. & Lesaffre, E. (1996). A linear mixed-effects model with heterogeneity in the random-effects population. *Journal of the American Statistical Association*, *91*, 217-221.

Vermunt, J.K. & Magidson, J. (2000a). Latent class cluster analysis. In: J.A. Hagenaars & A.L. McCutcheon (Eds.), *Advances in latent class analysis*. Cambridge: Cambridge University Press.

Vermunt, J.K. & Magidson, J. (2000b). *Latent GOLD 2.0 user's guide*. Belmont, MA: Statistical Innovations, Inc.

Vriens, M. (1995). *Conjoint analysis in marketing. Developments in stimulus representation and segmentation methods*. Doctoral dissertation, University of Groningen, The Netherlands.

Wedel, M. (1997). *GLIMMIX 1.0 user's manual*. Groningen: ProGAMMA.

Wedel, M. & DeSarbo, W.S. (1994). A review of recent developments in latent class regression models. In R.P. Bagozzi (Ed.), *Advanced methods of marketing research* (pp.352-388). Oxford: Blackwell.

Wedel, M. & Kamakura, W.A. (1997). *Market segmentation: Conceptual and methodological foundations*. Dordrecht: Kluwer.

Zinnes, J.L. & MacKay, D.B. (1992). A probabilistic multidimensional scaling approach: Properties and procedures. In G. Ashby (Ed.), *Multidimensional models of perception and cognition* (pp. 35-60). Hilldale, NJ: Lawrence Erlbaum.

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