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Decisionmaking between multiattribute choice alternatives: a model of spatial shopping-behaviour using conjoint measurements†

H J P Timmermans, R van der Heijden, H Westerveld
Department of Architecture, Building and Planning, Eindhoven University of Technology, PO Box 513, 5600 MB Eindhoven, The Netherlands
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Abstract. In this paper the authors are concerned with the application of conjoint measurement models to predict consumer choice of shopping centres. First, conjoint measurement models are discussed in the context of the development of spatial shopping-models. Next, the conceptual framework underlying the model and conjoint measurement are discussed. The second part of the paper describes an application of the methodology. Conjoint measurement is used to estimate consumer utility functions and a multivariate logit model as an approximation of the unit multivariate normal distribution is used to predict the probability that a consumer will choose a particular shopping centre. The results indicate that the methodology offers a potentially valuable approach to the modelling of spatial shopping-behaviour.

1 Introduction and problem setting

The study of spatial shopping-behaviour continues to be one of the major research themes among geographers. From the late 1950s until the early 1970s the major concern of geographical studies of shopping behaviour was with testing the assumptions of consumer shopping-behaviour underlying classical central place theory (for example, Golledge et al, 1966; Clark and Rushton, 1970) and with the development of spatial interaction models (for example, Lakshmanan and Hansen, 1965; Gibson and Pullen, 1972; Mackett, 1973; Smith et al, 1977). More recently, however, as a result of the unrealistic nature of the distance-minimising postulate of classical central place theory and the criticism about aggregate spatial interaction models, there has been a trend towards developing disaggregate cognitive behavioural models of spatial behaviour which aim at capturing the specific nature of individual decisionmaking processes in a spatial context.

During the 1970s much progress has been made with respect to the identification and estimation of these behavioural models. In particular, nonmetric multidimensional scaling, semantic differential and Likert scales, factor listing, and repertory grid methodology have been suggested for identifying the set of factors upon which consumer choice behaviour appears to be conditional (for example, Downs, 1970; Burnett, 1973; Spencer, 1978; Potter, 1979; Blommestein et al, 1980; Timmermans et al, 1982).

In addition, functional measurement models and conjoint measurement models have been investigated for uncovering the nature of utility functions (for example, Louviere, 1976; Louviere and Wilson, 1978; Prosperi and Schuler, 1976; Schuler, 1979; Schuler and Prosperi, 1978; Timmermans, 1980; 1982). Last, a number of studies have been concerned with developing probabilistic choice models which relate differences in attribute levels or scores on prespecified utility (preference) functions to overt choice probabilities. Examples include Girt's approach (1976) which relates preference scale values to pairwise choice probabilities, the multinomial logit model (for example, McFadden, 1973; Domencich and McFadden, 1975; Richards and

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Ben-Akiva, 1975; Adler and Ben-Akiva, 1976; Koppelman and Hauser, 1978; Recker and Kostyniuk, 1978; McCarthy, 1980; Southworth, 1981; Recker and Schuler, 1981), the nested logit model (McFadden, 1975), the general extreme value model (McFadden, 1978), the multinomial probit model (Daganzo, 1979), and prominence models (Smith and Yu, 1982). Unfortunately, however, very few studies of spatial shopping-behaviour exist that integrate the major developments in each of these research areas into a new and powerful methodology.

In this paper we present a behavioural model of spatial shopping-behaviour, which incorporates several recent developments in the study of human judgement and choice behaviour. Specifically, utility functions are calibrated and tested by using the conjoint measurement approach and a multivariate logit model is used as an approximation of the unit multivariate normal distribution to predict the probability that a consumer will select a particular shopping centre. The model is tested in the context of spatial shopping-behaviour in the city of Eindhoven.

2 Theoretical considerations

As suggested earlier, spatial shopping-behaviour is considered to be the outcome of a subjective decisionmaking process by which consumers combine their separate evaluations of a set of relevant attributes of shopping alternatives into an overall evaluation to arrive at a choice. Several conceptualisations have been proposed for studying this decisionmaking process (for example, Demko and Briggs, 1971; Hudson, 1976; Louviere, 1978; 1979; Louviere and Meyer, 1979). In this paper we summarise the main elements of these conceptualisations and add some new elements and interpretations.

Consider a finite set of N individuals who are in given locations and a finite set (S) of M known shopping alternatives. Each shopping alternative is conceived of as a bundle of objective attributes. Let Ω denote the set of all attributes of the alternatives. A particular shopping centre j may then be described by a vector $X = [X_{j1}, X_{j2}, ..., X_{jk}, ..., X_{jK}]$, where X_{jk} is the level or value for shopping centre j of attribute k. The problem is to derive a model which predicts the probability that a consumer will select a particular shopping centre given the attributes of the shopping centres and the locations of the consumers and shopping centres. It is assumed that such a model may be constructed on the basis of the following set of axioms and assumptions.

Axiom 1. For any type of spatial shopping-behaviour there exists a subset of independent factors or attributes of shopping centres which are systematically related to its occurrence.

These factors may be either quantitative or qualitative in nature. Let the number of influential attributes be K^*. Then, each shopping alternative may be described by the vector of relevant attributes $X = [X_{jk}]$ $(k = 1, 2, ..., K^*;\ K^* < K;\ K^*, K \in \Omega)$.

Axiom 2. For any type of shopping behaviour there exists a subset of shopping alternatives from among which a choice will be made.

This axiom states that a consumer will not necessarily consider all possible shopping alternatives, but rather that he will consider only a subset of alternatives. This subset of alternatives (A: $A \subset S$) is based upon the information level of the consumer with regard to the different shopping alternatives in his environment. Let M_i^* denote the total number of shopping alternatives in the choice set of the ith individual.

Axiom 3. For any factor or influential attribute of the shopping alternatives there exists a corresponding perceived or psychological value.

Let x_{jk} denote this psychological value for an individual of the kth attribute ($k = 1, 2, ..., K^*$) of shopping alternative j ($j = 1, 2, ..., M_i^*$) and x_k is the corresponding quantity for all shopping centres. Then, x_{jk} can be thought of as the utility of alternative j with respect to subset A for an individual. This leads to the following testable assumption:

Assumption 1

$$x_k = f_k(X_k) \; ; \qquad k = 1, 2, ..., K^* , \tag{1}$$

where X_k is the value of the kth attribute of a choice alternative.

Thus, it is assumed that the psychological values are systematically related to the value or the level of the attributes of the shopping centres. Several functions may be used for f_k. Among those usually considered are the following:

$$x_k = a_k + b_k X_k^{c_k} , \tag{2}$$

$$x_k = a_k + b_k X_k + c_k X_k^2 , \tag{3}$$

$$x_k = a_k + b_k \exp(c_k + d_k X_k) . \tag{4}$$

Next, it is assumed that consumers form an overall utility by combining their part-worth utilities x_{jk} ($k = 1, 2, ..., K^*$) according to some algebraic combination rule. The nature of this rule may be uncovered in an experimental setting.

Axiom 4. For any response to a combination of $(X_1, X_2, ..., X_{K^*})$ *which is observed in an experimental setting there exists an algebraic rule by which individuals integrate their part-worth utilities into the observed response measure.*

This axiom implies that

$$h = g(x_1, x_2, ..., x_{K^*}) , \tag{5}$$

where h is the observed response measure.
Several functional forms may be suggested for g. However, as Louviere (1981) has argued, the only forms that have seen serious application or appear to be estimable by tractable procedures are subsets of the general multilinear form:

Assumption 2

$$R = l_0 + l_1 x_1 + l_2 x_2 + l_3 x_3 + l_4 x_1 x_2 + l_5 x_1 x_3 + l_6 x_2 x_3 + l_7 x_1 x_2 x_3 + \epsilon , \tag{6}$$

where ϵ is an error term, $K^* = 3$, and the ls are scaling constants. Specifically, the additive and the multiplicative combination rules are commonly used forms. The additive rule implies that

$$R = l_0 + l_1 x_1 + l_2 x_2 + l_3 x_3 + \epsilon , \tag{7}$$

whereas the multiplicative rule states that

$$R = l_0 + l_1 x_1 \times l_2 x_2 \times l_3 x_3 + \epsilon . \tag{8}$$

These response measures in experimental settings may be linked to real-world decision-making as follows:

Axiom 5. Judgements which are observed in an experimental setting are linearly related to judgements in real-world situations.

It follows that the competing rules are described as

$$U_j = Z_0 + Z_1 x_{j1} + Z_2 x_{j2} + Z_3 x_{j3} , \tag{9}$$

and

$$U_j = Z_0 + Z_1 x_{j1} \times Z_2 x_{j2} \times Z_3 x_{j3} , \tag{10}$$

where the Zs are scaling constants.
Last, this overall utility measure, U_j, must be functionally related to overt choice probabilities. To derive this relationship between overall utility and choice probability it is assumed that an individual's expressed overall utility is composed of a fixed component ($\bar{U}_j$) and a random component ϵ_j:

$$U_j = \bar{U}_j + \epsilon_j . \tag{11}$$

Assuming utility-maximising behaviour implies that the jth alternative will be chosen if

$$U_j > U_{j'} , \qquad \text{for all } j' \neq j \quad (j' = 1, 2, ..., M_i^*) . \tag{12}$$

If we designate the differences between utilities as $\mu_{jj'} = U_j - U_{j'}$, it follows that the probability that alternative 1 will be chosen can be written as

$$\begin{aligned} p(U_1 > U_2, U_3, ..., U_{M_i^*}) &= p(\bar{U}_1 + \epsilon_1 > \bar{U}_2 + \epsilon_2, \bar{U}_3 + \epsilon_3, ..., \bar{U}_{M_i^*} + \epsilon_{M_i^*} \\ &= p[(\mu_{12} > 0) \cap (\mu_{13} > 0) \cap ... \cap (\mu_{1M_i^*} > 0)] . \end{aligned} \tag{13}$$

Depending upon the assumptions regarding the distribution of the error terms various model forms arise. If it is assumed, following Thurstone's judgemental model (1927), that the joint distribution of, for example, ϵ_j and ϵ_q is bivariate normal with means 0 and 0, variances σ_j^2 and σ_q^2, and correlation coefficient ρ_{jq}, then the distribution of U_j and U_q will be bivariate normal with means $\bar{U}_j$ and $\bar{U}_q$, variances σ_j^2 and σ_q^2, and correlation coefficient ρ_{jq}.

The distribution of μ_{jq} is univariate normal $\mathrm{N}(\mu_{jq}, \sigma_{jq}^2)$, where

$$\bar{\mu}_{jq} = \bar{U}_j - \bar{U}_q , \tag{14}$$

and

$$\sigma_{jq}^2 = \sigma_j^2 + \sigma_q^2 - 2\rho_{jq}\sigma_j\sigma_q . \tag{15}$$

Then, the probability that an individual will choose j is given by

$$p(j\!: j, q) = \frac{1}{(2\pi\sigma_{jq})^{1/2}} \int_0^\infty \exp\left[-\tfrac{1}{2}\frac{(y-\bar{\mu}_{jq})^2}{\sigma_{jq}}\right] \mathrm{d}y . \tag{16}$$

Similarly, a multivariate normal density function describes the choice probabilities between M_i^* alternatives, depending upon the values of $\bar{\mu}_{jj'}$ and $\sigma_{jj'}$ ($j' = 1, 2, ..., M_i^*$; $j' \neq j$). If, however, it is assumed that all variances are equal, it follows that, given alternatives j, q, and r:

$$\begin{aligned} \rho_{jq,jr} &= \frac{\sigma_j^2 - \sigma_j\sigma_q\rho_{jq} - \sigma_j\sigma_r\rho_{jr} + \sigma_q\sigma_r\rho_{qr}}{\sigma_{jq}\sigma_{jr}} \\ &= \frac{\sigma_j^2 - \sigma_j\sigma_q\rho_{jq} - \sigma_j\sigma_r\rho_{jr} + \sigma_q\sigma_r\rho_{qr}}{(\sigma_j^2+\sigma_q^2 - 2\sigma_j\sigma_q\rho_{jq})^{1/2}(\sigma_j^2 + \sigma_r^2 - 2\sigma_j\sigma_r\rho_{jr})^{1/2}} \\ &= \frac{\sigma^2(1-\rho-\rho+\rho)}{[2\sigma^2(1-\rho)]^{1/2}[2\sigma^2(1-\rho)]^{1/2}} = \tfrac{1}{2} . \end{aligned} \tag{17}$$

Bock and Jones (1968) have suggested that the generalised multivariate logistic distribution is a useful approximation to the multivariate normal distribution. To use this function it is necessary to adjust the scales of the variates to fit the normal distribution. This is accomplished by using $\pi/(3)^{1/2}$ times the unit normal deviates as logistic deviates. Hence, the following assumption is tested:

Assumption 3. The probability that a consumer will choose shopping alternative j from among M_i^* alternatives is approximated by

$$p(U_1 > U_2, U_3, ..., U_{M_i^*}) = p(\mu_{12} > 0) \cap (\mu_{13} > 0) \cap ... \cap (\mu_{1M_i^*} > 0)$$
$$= \left[1 + \sum_{\substack{j'=1 \\ j' \neq j}}^{M_i^*} \exp\left(-\frac{\pi}{(3)^{1/2}} \frac{\mu_{jj'}}{\sigma_{jj'}}\right)\right]^{-1} . \qquad (18)$$

These axioms and assumptions imply that overt spatial choice behaviour is predicted by a multivariate logistic distribution in which parameters are derived directly from measurements of consumers' evaluations of shopping centre attributes.

3 Conjoint measurement

To operationalise the above model, it is necessary to have measurements of the relationship between consumers' part-worth utilities and the value or level of the attributes of the shopping centres. In addition, the nature of the combination rule by which consumers combine these part-worth utilities into an overall utility measure must be uncovered. Several measurement procedures exist for this purpose. In this study, conjoint measurement has been used.

Conjoint measurement is concerned with simultaneously measuring the joint effect of two or more independent variables on the ordering of a dependent variable (Luce and Tukey, 1964; Krantz, 1964; Krantz and Tversky, 1971). The approach is based on the notion that it may be possible to measure the relative effects of two or more independent variables even though their individual effects may not be measured properly. In its most commonly used form conjoint measurement involves first specifying a measurement model which describes the way in which the individual effects are combined into an overall effect. Subsequently, the part-worth utilities of the attribute levels are derived such that the ordering of the choice alternatives as predicted by the measurement model is as nearly monotonic with the observed rank ordering of the choice alternatives as possible. Usually this is accomplished by forming factorial combinations of attribute levels which are presented to the respondents as choice alternatives. Respondents are then asked to rank these choice alternatives according to their overall utility. The goodness of fit of the scaling solution is indicated by a measure called stress:

$$S = \left[\frac{\sum_{s \neq t}^{n} (d_{st} - \hat{d}_{st})^2}{\sum_{s \neq t}^{n} (d_{st} - \bar{d})^2}\right]^{1/2} , \qquad (19)$$

where

S is the stress measure;

d_{st} is the Euclidean interpoint distance between the (s, t)th pair of points;

$\hat{d}_{st}$ is a set of values, chosen to be as close to the d_{st} as possible, subject to being monotone with the observed dissimilarities.

The most appropriate measurement model may be identified by comparing these stress values for different measurement models, the lowest value indicating the best model. Alternatively, an axiomatic approach may be used for diagnosis and testing of different measurement models (Krantz and Tversky, 1971). Emery and Barron (1979), however, have shown that the numerical approach appears to be at least as efficacious as the axiomatic approach.

One of the major problems of factorial designs is that too many attributes would represent an unreasonable ranking-task for a respondent. Hence, Johnson (1974) has suggested a procedure, called trade-off analysis, which may be used when many attributes are involved. This procedure involves presenting pairs of attributes to respondents who are requested to rank the stimulus combinations of each pair with respect to their overall utility. Next a starting matrix ($\mathbf{P}_1$) of part-worth utilities is randomly generated; the subscript 1 indicates the utilities for the first iteration. Given some specific combination rule, a vector Y of overall utilities for each pair of attributes is constructed. For a pair of attributes k and k' this vector can be described as

$$Y = (Y_{11}, Y_{12}, ..., Y_{1L_{k'}}, Y_{21}, Y_{22}, ..., Y_{2L_{k'}}, ..., Y_{L_kL_{k'}}) ,$$

where L_k is the number of attribute levels for attribute k, and $L_{k'}$ is the number of attribute levels for attribute k'. This vector Y is compared with the vector D, consisting of the observed rank orders, on the basis of two measures:

$$\frac{Y_m}{Y_n} - 1 , \tag{20}$$

and

$$\frac{D_m}{D_n} - 1 , \tag{21}$$

where m and n are cells.

These measures are calculated for each pair of attributes, and the goodness-of-fit measure at each iteration is calculated as

$$\phi_r = \sum_{m,n} \beta_{mn} \left[\left(\frac{Y_m}{Y_n}\right) + \left(\frac{Y_n}{Y_m}\right) - 2\right] \Big/ \sum_{m,n} \left[\left(\frac{Y_m}{Y_n}\right) + \left(\frac{Y_n}{Y_m}\right) - 2\right] , \tag{22}$$

where

ϕ_r is the goodness-of-fit measure at iteration r;

m, n are cells in vector Y; and

$$\beta_{mn} = \begin{cases} 1 & \text{if sign} \left(\frac{Y_m}{Y_n} - 1\right) \neq \left(\frac{D_m}{D_n} - 1\right) , \\ 0 & \text{otherwise.} \end{cases}$$

A good scaling solution is indicated by a low ϕ-value. At each next iteration the matrix of the part-worth utilities is calculated as:

$$\mathbf{P}_{r+1} = \mathbf{P}_r - \phi_r \mathbf{G}_r , \tag{23}$$

where

$\mathbf{P}_r$ is a $K^* \times L$ matrix of part-worth utilities at iteration r, with L denoting the maximum number of attribute levels;

$\mathbf{G}_r$ is a $K^* \times L$ gradient matrix at iteration r, each of whose elements is the partial derivative ϕ with respect to the corresponding elements of $\mathbf{P}_r$.

This gradient matrix is computed proportional to

$$\mathbf{G}_r = \frac{\partial \phi_r}{\partial \mathbf{P}_r} . \tag{24}$$

This process continues until after two successive iteration steps the drop in the ϕ-measure is below some initially specified criterion value. As with simple conjoint measurement the best combination rule may be identified by comparing the scaling solutions cf different combination rules, the lowest ϕ-value indicating the best combination rule.

4 Test of the model

4.1 *The study area*

The model was tested in the District of Woensel, a part of the city of Eindhoven. Within this area, twelve shopping centres can be identified. Apart from these twelve shopping centres, the city centre was also included in the choice set. Thus, in total thirteen shopping centres were included in the analysis. These centres differ considerably in terms of size and in terms of their locational, morphological, and functional attributes.

4.2 *The identification of the relevant attributes*

A first step in testing the model is to identify the factors which are influential to the decisionmaking of consumers. Kelly's repertory grid methodology (1955) and the factor-listing approach were employed to identify these factors. In its most common form, the repertory grid methodology requires a subject to name elements which fulfil certain roles for him. Alternatively, these elements may be selected by the researcher and this was the method used in this study. Next, the subject is presented with triads of elements and asked to name a construct on the basis of which two of these elements are alike and thereby different from the third. This process continues until after several consecutive presentations the subject is unable to provide any additional constructs.

Although this procedure might be used in a totally disaggregate approach, in the present study the repertory grid methodology was employed to elicit the most frequently named constructs on the basis of which consumers appear to discriminate between shopping centres. Twenty respondents were asked to participate in the repertory grid session. The personal constructs were elicited by randomly presenting triads of shopping centres to these subjects. To ascertain that all shopping centres were presented at least twice to the subjects, nine initial triads were constructed such that this requirement was fulfilled. Subjects only considered a particular triad if they possessed knowledge about all three shopping centres constituting the triad. It appeared that in total 236 constructs were specified by the subjects. Among the most frequently mentioned constructs were the number of shops, location relative to home, and parking facilities. These three constructs were used in the following stages of the analysis.

4.3 *The conjoint measurements*

To capture the nature of the combination rules ninety-one randomly selected respondents were invited to participate in the survey. These respondents were asked to provide utility scores on a set of hypothetical stimuli. These stimuli consisted of twenty-seven hypothetical shopping centres, each describing a three-attribute profile. The attributes used were those that were most frequently mentioned in the repertory grid test: size, distance, and parking facilities. Each attribute was varied over three levels: size varied between small, medium, and large number of shops; distance varied between 15, 30, and 45 minutes; and parking varied between 4, 12, and 20 minutes search time to find a free parking lot. The levels of the three attributes were combined into 3 x 3 x 3 factorial design to yield the twenty-seven hypothetical stimulus combinations. Each stimulus combination was printed on an index card. Prior to presentation these cards were randomised. Each subject was then asked to sort the twenty-seven stimulus combinations in three categories of overall utility. They were instructed to evaluate the hypothetical shopping centres on the basis of their utility for buying clothing. Next, each subject was asked to rank the index cards within each category from most preferred to least preferred. In addition, each subject was asked to ascertain that the resulting rank ordering of the hypothetical shopping centres was correct. Otherwise, shifting cards across categories was allowed.

The result of this sequential procedure is thus a strict rank order of the twenty-seven hypothetical shopping centres for each subject. Last, Roskam's UNICON algorithm (Roskam, 1974) was applied individually to each subject's ranking of the twenty-seven hypothetical stimulus combinations. The multiplicative and the additive combination rules were both tested as representations of the way in which these subjects apparently combined the three attributes.

The results of the analysis indicated that the scaling solutions were satisfactory. The highest stress-value was 0.020, the mean stress-value was 0.004. All part-worth utility scales were monotonic in the expected direction. It was found that the multiplicative combination rule provided the best solution for fifty-nine respondents, whereas the additive combination rule gave the best description of the way in which respondents combined their part-worth utilities into an overall utility measure in thirty-two cases. Thus, it may be concluded that the multiplicative rules provide the best results for the total sample, but, also, that different consumer groups occur in the sample. Various consumer groups may be distinguished on the basis of the combination rule they use to trade off between attributes.

4.4 *The prediction of choice behaviour*

The final step in the analysis concerned the prediction of the choice of the shopping centres, given the derived utility values. Equation (18) shows that it is assumed that a generalised logistic function gives a good description of the probability that a consumer will choose a particular shopping centre. To test this model, it is necessary to calculate mean utilities and standard deviations of the utility measure for each shopping centre. Therefore, each shopping centre was defined in terms of the attribute levels which were used in the conjoint measurement. Next, the mean and the standard deviations for each shopping centre were calculated on the basis of the part-worth utilities which were derived in the conjoint measurements. The logit model then provided an independent prediction of the probability that a particular shopping centre would be chosen. These predicted probabilities were subsequently compared with observed relative frequencies of patronages. It was found that the logit model accounted for 91.9% of the variance in the destination totals. Hence, it might be concluded that the logit model, calibrated on the basis of utility measurement of hypothetical shopping centres, gives a satisfactory prediction of real-world shopping-choice-behaviour.

4.5 *Disaggregation*

A disadvantage of the analysis is that the calculation of mean utilities might mask differences in the underlying individual utility measures. Thus, differences in the decisionmaking process might not be accounted for, and this might lead to inaccurate predictions of choice proportions. Hence, to test whether a disaggregate approach yields a better prediction of the proportions of the shopping centres a number of relatively homogeneous groups of individuals were developed. This implies that it is assumed that individuals with the same combination rule and similar part-worth utilities will reveal similar choice behaviour.

Ward's clustering algorithm (1963) was used to develop the relatively homogeneous groups of individuals. The input for this clustering algorithm consisted of the derived part-worth utility values of each attribute. The clustering algorithm aggregates individuals on the basis of similarities in their part-worth utility values by minimising the increment to the pooled within-group sum of squares at each stage of the clustering process. The clustering process was conducted separately for the individuals who apparently used a multiplicative combination rule in the conjoint measurements and for those who used an additive rule.

The results of the grouping analysis suggested that for each combination rule two groups of individuals may be distinguished. Groups A and B employed a multiplicative combination rule, and were composed of twenty-nine and thirty respondents, respectively. Groups C and D apparently used an additive combination rule, and contained twenty-one and eleven respondents, respectively. The relative importance of an attribute for each group may be defined as the proportion of the total variation in the scale weights accounted for by that particular attribute. The results are given in table 1.

Table 1 shows that size was the most important attribute for individuals of groups B and D, whereas for individuals in groups A and C distance was the most important attribute.

The assessment of the predictive ability of the disaggregate approach implies that the mean and the standard deviation of the overall utility value of the shopping centres should be calculated separately for each group. Then, the logit model can be used to predict the choice behaviour of each group. Last, the frequency distributions of patronage totals for each group may then be summed to calculate overall predicted proportions of choice, which may be compared with observed proportions. In doing this, it turned out that the disaggregated model accounted for 95.5% of the variance in the patronage totals of the shopping centres. Thus, it may be concluded that the disaggregate approach yielded a better result than the approach based upon calculating mean utilities for the total sample.

Table 1. Relative importance of the attributes to the groups A–D.

Group	Attributes		
	size	parking	distance
A	0.25	0.31	0.45
B	0.58	0.17	0.25
C	0.22	0.11	0.67
D	0.54	0.29	0.17

5 Conclusions and discussion

In this paper we have presented an approach to the study of spatial shopping-choice-behaviour. The approach was tested in the context of a study of spatial shopping-behaviour in Eindhoven. The results of the study support the approach. First, it was found that conjoint measurements can yield interpretable estimates of part-worth utilities of attributes of spatial alternatives. Second, it was found that respondents' decisionmaking in a hypothetical context bears some systematic relationship with decisionmaking in real-world contexts. Utility scores obtained in hypothetical situations were shown to be applicable to the prediction of observed choice proportions in real-world situations. Last, this research has demonstrated that the external validity of the approach is high. Different samples were used to identify the influential factors and to estimate part-worth utilities, and to measure patronage totals. It appears that the results obtained for one sample can be used successfully for the analysis of an entirely different sample.

By demonstrating that spatial choice-behaviour can be predicted successfully from scores in hypothetical settings, the present study offers a potentially valuable approach to the study of spatial choice-behaviour. That is, the approach does not necessitate the calibration of the parameters of a model on the basis of statistical associations between aggregate environmental factors and observed choice probabilities. Hence, it might be argued that the parameters of the model are not influenced by the spatial structure of the study area, a characteristic so typical of aggregate spatial interaction models. In addition, the approach offers much potential to test the reliability and the internal and external validity of the results of each stage in the model building process. Also, whereas in the present analysis choice proportions have been predicted on the basis of consumer groups, a totally disaggregate approach could be employed in which measurement errors are used for the standard deviations. It is hoped, therefore, that future research will address these issues and compare the predictive ability of this approach with that of competing models.

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