

A NON-COMPENSATORY MODEL OF TRANSPORTATION BEHAVIOR BASED ON SEQUENTIAL CONSIDERATION OF ATTRIBUTES

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Abstract—The proposed model of travel choice behavior is based upon an assumption that individuals compare their choice alternatives on a series of attributes ordered in terms of importance; they eliminate from consideration those alternatives which do not meet their expectation on one or more of the characteristics. The process is repeated with adjusted levels of expectation until only one alternative remains. The model thus incorporates a number of psychological decision axioms which have seldom been applied in models aimed at providing transportation planners with useful information from consumer survey data.

Estimates of parameters defining distributions of expectation levels in a population of travelers are generated using a nonlinear optimization technique. The technique is demonstrated to provide estimates which replicate well the choices of travelers in two different contexts: choice of hypothetical concepts of small urban vehicles and choice of destination for shopping trips within an urban area.

INTRODUCTION

Almost every disaggregate travel demand forecasting model is specified as being "linear-in-parameters". To the extent of the authors' literature familiarity, this includes all of the models reported to be behavioral representations of transportation decision-making processes. Notwithstanding are those nonlinear representations of utility which are transformed to linear-in-parameters forms for estimation purposes. Typically, the parameters are coefficients of attributes or features of specific choice alternatives (or generic classes of alternatives), including travel times, costs, conveniences, accessibilities, or transformations of one or more attributes.

In all linear-in-parameters forms the choice process is implicitly assumed to be compensatory. That is, trade-offs among attributes are possible: a change in one or more attributes can be compensated by a change in the opposite direction in one or more other attributes. (Single parameter models are treated herein as special cases.) The present model is proposed as one possible alternative to compensatory models. Admittedly, this model is currently in the development stage; it is a device to test the applicability to transportation contexts of a number of behavioral principles from axiomatic theories of decision-making processes.

The first adopted principle is that of sequential consideration of attributes or features. It is assumed that individuals faced with a choice from among several alternatives will evaluate these alternatives in terms of their attributes, proceeding in a sequential manner from the attribute the individual considers most important to the attribute he or she considers least important.

The sequential consideration principle pervades the human information processing theories of Schroder *et al.* (1967) and Newell and Simon (1972). It is fundamental to the mathematical probability choice theory referred to as Elimination by Aspects (Tversky, 1972a, 1972b), and to predecessor Lexicographic Semiorder Model (Tversky, 1969). The principle is supported by empirical findings in a number of market research studies (e.g. Clarkson, 1963; Alexis *et al.* 1968; Bettman, 1970 and 1971; and Russ, 1971).

The second adopted principle is that of a critical tolerance or threshold level for each attribute. It is assumed that individuals evaluating any alternative on a given attribute will compare the alternative against some standard he or she is willing to accept. All alternatives meeting that standard will be acceptable in terms of the attribute; alternatives not meeting that standard will be rejected.

The critical tolerances principle is closely related to the Satisficing concept of Simon (1955; 1956; and 1959). Thus, the principle potentially can convey many of the dynamic decision-making properties explored in the Satisficing concept, including information search compromise group decisions, changing goal structures and adaptation. Moreover, the critical tolerance principle is also related to the psychological concept of Just Noticeable Differences. This concept, reviewed by Guilford (1954) and Stevens (1962), has been recently introduced by Fishman (1977) to improve the explanatory power of the compensatory binary logit model.

THE POSTULATED DECISION-MAKING PROCESS

Consider a decision maker, n , faced with choosing an alternative from a set, S^n , of N^n desirable alternatives available to the individual. Let S (N elements) denote the universe of such alternatives available to the study population and assume that each of the N alternatives in S can be described by the same set of M descriptive attributes. Each individual may have a different hierarchical ranking of importances associated with these attributes. This ranking, which is assumed to be invariant across alternatives in S^n , is used to determine the sequence of attributes through which the N alternatives are processed. Denote the attribute associated with the i th importance ranking of decision maker n as $j(i)$. Furthermore, define by Λ_{kj}^n the evaluation (rating) by decision maker n of alternative k with respect to attribute $j(i)$.

It is assumed that, associated with any given attribute $j(i)$, there is a critical tolerance $C_{j(i)}^n$ between the decision maker n 's evaluation of any alternative on an attribute and some acceptance standard. It is further assumed that this standard can be measured in terms of the percentage difference T_{kj}^n between the individual's evaluation of the alternative that is judged best with respect to attribute $j(i)$ and his or her evaluation of alternative k on attribute $j(i)$.

That is,

$$T_{kj}^n = \frac{\text{Max}_{l \in S_i^n} [\Lambda_{lj}^n] - \Lambda_{kj}^n}{\text{Max}_{l \in S_i^n} [\Lambda_{lj}^n]}, \quad (1)$$

where S_i^n is the set of alternatives still under consideration by individual N at importance level i . The criterion for rejection of an alternative k then is simply

$$T_{kj}^n > C_j^n. \quad (2)$$

Equations (1) and (2) imply that the individual, having assessed the universe of available alternatives, determines a set of tolerances associated with each attribute of the alternatives. These criteria for acceptance are based upon his or her perception of the "best" available. Such a conceptualization is similar to an ideal point model in which the ideal point is a composite of the best features of a set of alternatives. The functional form for T_{kj}^n is chosen to be consistent with the concept of diminishing marginal utility with increasing attribute levels.

In the decision process, these criteria are applied at each stage beginning with the attribute that is most important to the decision maker and proceeding to attributes of lesser importance in order of their importances. Alternatives which fail to meet the criterion for retention at a particular importance level are rejected at that level and removed from further consideration at succeeding levels of importance. The process continues until a single alternative remains and is selected. If this process does not yield a single alternative within the M stages, the decision maker is assumed to adjust (i.e. make more strict) one or more of the critical tolerances and the process is repeated until a single alternative is derived. If at any stage in the process application of the rejection criteria results in the rejection of all alternatives not previously eliminated, the

decision maker is assumed to adjust (i.e. make less strict) one or more of the critical tolerances associated with importance levels at or above that stage.

A schematic of this decision model is shown in Fig. 1. The nomenclature used in this diagram is as previously defined, with the exception that the N superscripts have been omitted and two additional symbols, NR (the number of alternatives in S_i^n) and $R(k)$ (a index which has a value of 1 if alternative k has been rejected, and 0 otherwise), have been defined.

ESTIMATION OF DECISION PARAMETERS

Specification

Consider that for each member n of a sample population of P individuals evaluations A_{ij}^n and corresponding importance rankings i are known for each attribute j for each alternative l in the available choice set S^n of the individual. This is the same type of information employed in most compensatory multi-attribute models (Wilkie and Pessemier, 1973); survey data collection techniques are well developed.

Unknown in the decision process are the critical tolerances $C_{j(i)}^n$ associated with rejection of an alternative. The specific goal of the estimation procedure is to determine mean values of these critical tolerances, $\bar{C}_{j(i)}$, that are generalizable to groups in the population as a whole.

Because the output of the decision model is the identification of a single, chosen alternative, rather than a probability of choice or frequency, it is impossible to employ standard estimation

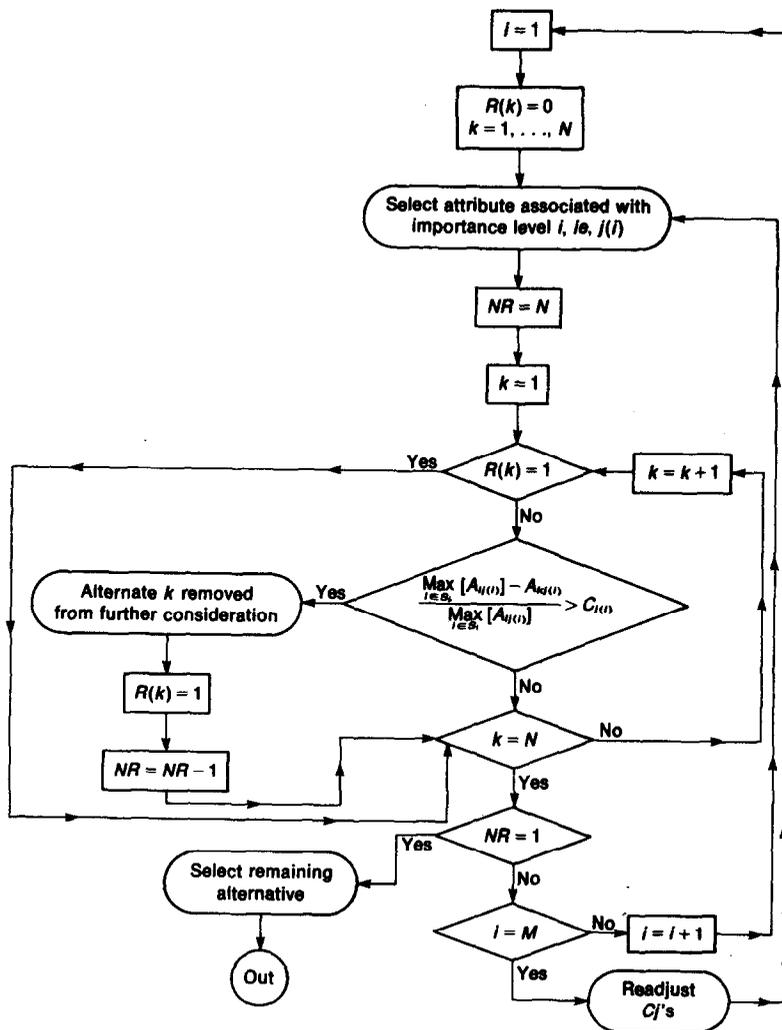


Fig. 1.

techniques such as maximum likelihood or least square error in the estimation of the critical tolerances. Rather than assuming that the values of the critical tolerances are invariant over the cross-section of individuals surveyed, with the objective of the estimation one of minimizing the difference between observed and predicted behaviors (as is the case in these standard estimation techniques), it is assumed that: (1) For a sample population, the probability that a particular value of critical tolerance is associated with evaluations along attribute j is distributed according to some unspecified uni-modal distribution with mean $\bar{C}_{j(i)}$ and standard deviation $\sigma_{j(i)}$. (2) Subject to certain random individual differences in preferences in his or her determination of subjective value (see Torgenson, 1958) the individual will employ a value of critical tolerance $C_{j(i)}^n$ that is as close as possible to the population mean $\bar{C}_{j(i)}$.

In this estimation procedure, it is assumed that the decision process itself is invariant over the cross-section, which implies that the predicted and observed behaviors must be identically equal to each other.

The objective then is to determine estimates of the mean values of the critical tolerances $C_{j(i)}$ ($i, j = 1, \dots, M$) such that the standard deviations $\sigma_{j(i)}$ of the distributions of the individual tolerances $C_{j(i)}^n$ ($i, j, \dots, M; n = 1, \dots, P$) are minimized, subject to the constraint that every decision maker is assigned his or her observed choice.

Because of well-known difficulties associated with optimization problems involving multiple objective functions it is assumed that a reasonable measure of achieving the stated objective is contained in minimizing the weighted mean of the standard deviations $\sigma_{j(i)}$ for $i, j = 1, \dots, M$; i.e.

$$\text{Min}_{C_{j(i)}^n} \left[Q = \frac{1}{M^2} \sum_{i,j=1}^M w_{j(i)} \sigma_{j(i)} \right] \quad (3)$$

where $w_{j(i)}$ = weight assigned to the case in which attribute j is associated with importance level i .

While scant justification for this assumption exists from a behavior-theoretic standpoint, except for the case in which it is assumed *a priori* that the dispersions are equal (similar to a Thurstone Case V assumption; see, e.g. Torgenson, 1958), substantive benefits are derived from this form in application of the model as a predictive tool. First, it can be reasonably expected that, in the sequential decision process, the vast majority of choice decisions will occur at stages in the decision process associated with attributes that have the higher importance rankings. The weighting factors in the objective function specified by eqn (3) allow the forecaster to bias the estimation such that sharp definition of the critical tolerances associated with these important attributes will be achieved. In addition, the policy maker can adjust eqn (3) to emphasize the importance of policy-sensitive variables in the decision process over which he/she can exercise control.

In terms of individual tolerances, the objective stated in eqn (3) can be restated as

$$\text{Min}_{C_{j(i)}^n} \left\{ Q = \frac{1}{M^2} \sum_{i,j=1}^M \frac{w_{j(i)}}{(P_{ij} - 1)^{1/2}} \left[\sum_{n \in N_{ij}} C_{j(i)}^n - \frac{1}{P_{ij}} \sum_{q \in N_{ij}} (C_{j(i)}^q)^2 \right]^{1/2} \right\} \quad (4)$$

where N_{ij} = set of individuals assigning importance level i to attribute j , and where P_{ij} is the number of individuals in the set N_{ij} . The problem becomes one of satisfying eqn (4) subject to

$$0 \leq C_{j(i)}^n \leq 1, n = 1, \dots, P_{ij} \text{ and } i, j = 1, \dots, M \quad (5)$$

and to the requirement that the choice determined by the decision model be the same as the observed choice for each individual in the sample population. This latter constraint can be represented mathematically in the following manner:

Let k^* denote the chosen alternative and let \hat{S}_i^n denote the set of alternatives still under consideration by individual n at importance level i . Then the condition that the chosen alternative k^* must not be eliminated at any stage is given by

$$C_{j(i)}^n > \frac{\text{Max}_{l \in \hat{S}_i^n} [\Lambda_{lj}^n] - \Lambda_{k^*j}^n}{\text{Max}_{l \in \hat{S}_i^n} [\Lambda_{lj}^n]} \text{ for all } i. \quad (6)$$

The remaining condition then is that all non-chosen alternatives must be eliminated at some level; or,

$$C_{j(i)}^n < T_{kj}^n \quad \text{for all } k \neq k^* \text{ and for at least one value of } j. \quad (7)$$

Introducing a dichotomous variable

$$\eta_{ik}^n = \begin{cases} 1, & C_{j(i)}^n < T_{kj}^n \\ 0, & C_{j(i)}^n \geq T_{kj}^n \end{cases} \quad \text{for all } j, k \neq k^*,$$

then condition (7) requiring elimination of non-chosen alternatives can be stated as

$$\sum_{i=1}^M \eta_{ik}^n \geq 1, \quad \eta_{ik}^n \geq \eta_{il}^n \quad \text{for all } k \neq k^*, l > i, \quad (8)$$

where it is assumed that the importance levels are numbered consecutively by decreasing order of importance.

Procedure

A heuristic algorithm was developed to determine the solution to the nonlinear constrained optimization problem specified by eqns (4)–(6) and (8). The algorithm is basically a constrained method of steepest descent.

An initial feasible solution is generated by first ordering, for each observation, the attributes according to stated importances. At each importance level a value of the critical tolerance $C_{j(i)}^n$ ($0 \leq C_{j(i)}^n \leq 1$) is assigned such that the chosen alternative just passes the test for retention; all other alternatives which do not pass the retention test are removed and the process continued until only one alternative remains. Observations for which more than one alternative remains after the process is completed are discarded, since a non-chosen alternative exhibits an ordinal utility greater than or equal to the chosen alternative. This is inconsistent with any rational choice mechanism except those explicitly employing random disturbances or perception thresholds.

This initial feasible solution is improved by the method of steepest descent, constrained to meet the conditions specified by eqns (5), (6) and (8), until a local minimum is achieved.

No attempt is made to defend the efficiency of this algorithm. Rather, it represents an initial attempt by the authors to implement a solution to the rather complex constrained nonlinear optimization problem posed by the decision model. Questions regarding the relationship between the local minima cannot be answered analytically. While one test of the heuristic would be to generate various starting positions and compare resulting minima, the only general procedure for generating an initial feasible solution appears to be that proposed. Other possible initial solutions depend on the nature of the data and can be achieved by modification of the original initial solution. One such modification was accomplished on one of the two data sets used in the initial tests of the model. Results indicated a close correspondence between the final solution generated from the two different initial solutions.

Additionally, it would appear that concerns regarding the global nature of the optimum achieved are largely academic. For use as a planning or predictive tool, the primary concern is one of specifying the critical tolerances at a level consistent with planning objectives and data reliability. If the dispersions of the critical tolerances are sufficiently small to allow accurate forecasting, given data limitations, then it makes little difference if the solution is sub-optimal or optimal.

A further simplification which was used to facilitate initial testing of the model involves the specification of the critical tolerances $C_{j(i)}^n$ as a function of the importance level i . It was assumed in these initial applications of the model that the values of $C_{j(i)}^n$ are independent of the importance level i decision maker n associates with attribute j :

$$C_{j(i)}^n = C_j. \quad (9)$$

Such an assumption can be empirically tested. Results of such a test on one data set are reported herein.

In addition, the weights $w_{j(i)}$ in eqn (4) were assumed equal to unity. The objective function then reduces to the special case:

$$\text{Min } Q = \frac{1}{M} \sum_{j=1}^M \sigma_j, \quad (10)$$

or,

$$\text{Min}_{C_j^a} Q = \frac{1}{M} \sum_{j=1}^M \frac{1}{\sqrt{(P-1)}} \sum_{n=1}^P \left[\left(C_j^n - \frac{1}{P} \sum_{q=1}^P C_j^q \right)^2 \right]^{1/2}. \quad (11)$$

Support for this assumption is provided in arguments originally proposed by Thurstone (1959). Briefly, if the σ_j ($j = 1, \dots, M$) are independent and identically distributed (or simply independent provided that the third absolute moment of σ_j about its mean is finite) then the sum of these distributions is asymptotically normal (Cramer, 1957, p. 216) and eqn (10) represents an estimate of the mean of the standard deviations.

INITIAL TESTS WITH TWO DATA SETS

Data descriptions

The sequential elimination model was tested using two data sets, each representing a different transportation choice context. Both data sets encompassed attitudinal data in the form of decision makers' ratings of choice alternatives with respect to their satisfactions on a comprehensive list of attributes. The model is not limited to this type of data, however. Attribute measures such as perceived times and costs in minutes and dollars are equally relevant for use in the model. The present data sets were chosen simply on the basis of convenience.

Data Set I involved individuals' choices among hypothetical new concepts of small, special purpose urban vehicles. These concepts are described in Krishnan and Golob (1977). They are aimed at limited travel purposes within urban areas and could be restricted in terms of range, speed or where they could be used. Evaluations and rankings of alternative concepts and attribute importance ratings were obtained through a nationwide mail-panel survey of 1565 households. The evaluations were in the form of seven-point semantic differentials for seventeen attributes. For reasons of simplicity, only nine of these attributes were employed in the test of the sequential model. These nine attributes were determined to be perceived in a less ambiguous fashion than the remaining eight.

Data Set II involved travelers' choices of stores for grocery shopping purposes. The data were collected from a mail survey sent to a random sample of 1500 households in Buffalo, New York (Kostyniuk, 1975). From the 337 returned questionnaires a total of 132 with sufficiently complete data for this study were extracted. Other returned questionnaires not used in this analysis either had missing data on one or more of the attributes or were cases in which the individual indicated only one alternative. For each household, descriptions of grocery stores frequently visited and attitudes toward these stores were solicited. The attitudinal data included importance ratings on a set of ten attributes and evaluations of up to four frequently visited stores with respect to each of the attributes. The evaluations were once again in the form of seven-point semantic differentials. The attributes measuring ease of getting to/from the store were combined into a single attribute because of extremely high correlations between these two variables, leaving a final total of nine attributes. This combination was done merely for convenience. Correlations among attributes used in the model specification, in general, have no effect on the model estimation because of the assumed hierarchical (sequential) choice process.

Parameter estimates

Random subsamples of 153 and 144 individuals from Data Set I were selected for estimation of parameters and tests of goodness-of-fit, respectively. The parameter estimates for Data Set I

are displayed in Table 1. The algorithm converged to the solution of Table 1 using the initial solution determination defined in the Procedure Subsection of this paper. In addition, a second initial solution was formulated by a data-specific modification of the original initial solution. The algorithm converged to a second optimal solution very close to the first optimal solution. The final solutions differed by an average mean critical tolerance across all attributes of 0.004. The standard deviations of the distributions of the critical tolerances are all small, with a mean standard deviation of 0.023. The assumption $\sigma_j = \sigma$ ($j = 1, \dots, M$) is supported by the small standard deviation about this mean of standard deviations; 0.011.

It is not possible to compare "utility weights" obtained with compensatory approaches to an equivalent measure in this model since, by definition, the model is non-compensatory and involves only an ordinal ranking of importances. However, some correspondence between these model constructs was noted in the estimation.

The Data Set I results of Table 1 were compared with parameter estimates from a compensatory multi-attribute choice model. A multinomial logit model was calibrated for the sample of 1 199 Data Set I respondents with complete data using the same nine attributes. An inspection of the maximum likelihood estimators of the attribute coefficients revealed that the three attributes with coefficients significantly different from zero at the 0.01 one-tailed confidence level, as determined by asymptotic t -statistics, are precisely the three attributes with the highest mean critical tolerance and median important rank: "vehicle size", "perceived safety" and "flexibility of use".

Since the critical tolerances associated with the rejection of an alternative are specified in terms of attribute levels of the alternative perceived as the best relative to that attribute, attribute levels causing rejection of an alternative vary with the corresponding level of the best alternative available. The nature of variation typifies the principle of diminishing returns. Hence, it is not appropriate to draw general conclusions based on the magnitudes of the critical tolerances; such conclusions must be based both on the critical tolerances and the specific ratings of the alternative in question and the "best" available. An inspection of the data revealed that attributes with the higher median importances generally had lower ratings than those deemed less important. Thus, for the majority of individuals in the sample, the larger critical tolerances associated with the more important attributes actually represent small tolerable scale deviations at the levels they were most frequently evaluated. This result calls for further investigation.

The results from estimation of model parameters for Data Set II are shown in Table 2. A random subsample of 80 decision makers were used, leaving a hold-out sample of 52 for goodness-of-fit tests. Convergence was achieved, and the results indicate smaller tolerances associated with convenience features of the stores and higher tolerances associated with quality features. The standard deviations of the distributions of the tolerances are once again all small (the mean standard deviation is 0.075), and χ^2 tests in all cases reject the hypothesis that the distributions are uniform at the 0.01 level. The standard deviation of the distribution of standard deviations of the mean tolerances is also small (0.049), supporting the assumption $\sigma_j = \sigma$ ($j = 1, \dots, M$) as in the case of Data Set I.

Results for Data Set II are consistent with those for Data Set I with respect to cor-

Table 1. Data set I: Estimated attribute tolerances in sequential decision model (attributes in order of decreasing median importance rank)

Attribute	Critical tolerance	
Vehicle size	0.164	0.039
Perceived safety	0.103	0.027
Flexibility of use	0.081	0.034
Parking	0.024	0.012
No. of Passengers	0.015	0.012
Fuel economy	0.032	0.010
Ability to be seen	0.053	0.027
Seating comfort	0.064	0.035
Cargo space	0.022	0.015

Table 2. Data Set II: Estimated attribute tolerances in sequential decision model (attributes in order of decreasing median importance rank)

Attribute	Critical tolerance	
	Mean	Std. deviation
Meat quality	0.165	0.113
Produce quality	0.215	0.092
Ease of finding things	0.087	0.065
Variety of items	0.210	0.103
Reasonable prices	0.185	0.101
Ease of returns	0.109	0.075
Crowding	0.137	0.063
Convenient hours	0.084	0.032
Accessibility	0.117	0.031

response between estimated mean critical tolerances and median importance ranks. With one notable exception, once again attributes with higher median importances tend to exhibit greater mean critical tolerances; the attribute "Ease of Finding Things" is an apparent anomaly.

Analyses reported by Recker and Kostyniuk (1978) include estimates of multinomial logit choice models for Data Set II. As in the case of Data Set I, parameter estimates from such a compensatory choice model are consistent in a general sense with parameter estimates for the present noncompensatory model. The group of four attributes found to be most effective in explaining store choice through the logit formulation are precisely those attributes found to have the highest critical tolerances: "Meat Quality", "Produce Quality", "Variety of Items" and "Reasonable Prices". This result further emphasizes the need for additional research.

Goodness-of-fit

Model goodness-of-fit for Data Set I was tested by applying the estimated mean critical tolerances shown in Table 1 to a hold-out sample of 144 individuals. Using these mean critical tolerances, the choices of 71.5% of the individuals in the hold-out sample were predicted correctly. The correct prediction ratio expected by chance, using full information concerning aggregate proportions choosing each alternative, is 34.4%.

A more detailed description of the misclassifications that occurred with the hold-out sample of Data Set I is provided in Table 3. The percent of cases for which ratings of the chosen alternatives on the various attributes were within the scale values needed to result in a correct prediction are shown.

The percentage numbers in the table represent the distribution of cases in which a change (measured in units of the seven-point scales) in the ratings on the associated attribute would have resulted in a correct prediction. The "Percent Requiring No Change" column indicates

Table 3. Data Set I: Necessary changes in ratings by holdout sample such that sequential decision model with estimated tolerances holds for all individuals

Attribute	Requiring no change	% of hold-out sample				
		Requiring change in ratings of chosen alternative (7-point scale)				
		+1	+2	+3	+4	+5
Vehicle size	93.0	2.8	4.2	0.0	0.0	0.0
Perceived safety	100.0	0.0	0.0	0.0	0.0	0.0
Flexibility of use	93.7	3.5	2.1	0.7	0.0	0.0
Parking	97.9	1.4	0.7	0.0	0.0	0.0
No. of passengers	97.9	0.0	2.1	0.0	0.0	0.0
Fuel economy	95.1	2.1	2.8	0.0	0.0	0.0
Ability to be seen	97.2	2.1	0.0	0.7	0.0	0.0
Seating comfort	99.3	0.0	0.7	0.0	0.0	0.0
Cargo space	97.2	2.1	0.7	0.0	0.0	0.0

cases in which the estimated value of mean critical tolerances resulted in a "correct" decision at the step in the process where that particular attribute was evaluated. These results offer further evidence that the estimated mean tolerances are generalizable to the total population.

Model goodness-of-fit for Data Set II was similarly tested by applying the critical tolerances shown in Table 2 to a hold-out sample. For this data set the hold-out sample was comprised of 52 individuals. The choices for 59.6% of these individuals were predicted correctly. This compares to an expected 43.5% correct prediction by chance, using random assignments in proportion to aggregate choice frequencies. This sequential elimination model internal validity statistic is not as encouraging as that found for Data Set I. However, a trace of the alternatives through the decision net indicated that in almost every case of the individuals predicted incorrectly the chosen alternative was eliminated at the final step of the decision process (i.e. the actual chosen alternative was the final alternative eliminated).

The misclassifications for the Data Set II hold-out sample are further detailed in Table 4. This table is analogous to Table 3 for Data Set I. These results indicate that in a majority of the cases in which misclassification occurred a one scale-unit shift in the rating of the chosen alternative would result in a corrected decision at the step in the decision process where the particular attribute was evaluated.

Actually, it is not strictly appropriate to evaluate this model by the percentage of correct classifications, since the estimation procedure produces a distribution of individual tolerances (from which the means in Tables 1 and 2 are derived) such that each individual in the sample is classified correctly. χ^2 tests of the distribution of these individual tolerances indicate that these distributions are not significantly different from normal for the two samples considered. This suggests that approximately 68% of the population can be expected to have individual tolerances that are within one standard deviation unit from the means shown in Tables 1 and 2.

Interpretation of results

The Data Set I results of Table 1 can best be interpreted through analogy to utility weights of compensatory models. As the decision maker proceeds through the sequential elimination process, alternatives that were not judged favorably at stages corresponding to higher levels of importance face increasingly stiffer tests to avoid elimination. The utility of passing each successive critical tolerance test has a smaller compensatory effect on judgments made in stages corresponding to higher importance levels.

In the choice context of Data Set I, only the mean critical tolerance associated with the "vehicle size" variable is greater than that associated with a one-point scale difference in rating. This indicates that, considering the aggregate sample results, if an alternative is not judged the "best" in terms of vehicle size (assuming the mean importance ranking of this variable is representative of that of the individual decision maker), then the only way possible for that alternative to be chosen is if it is ranked as high or higher than the remaining alternatives at each successive step in the decision process. The utility of passing all of the remaining stages barely compensates for the disutility of the first stage.

Table 4. Data Set II: Necessary changes in ratings by hold-out sample such that sequential decision model with estimated tolerances holds for all individuals

Attribute	Requiring no change	% of hold-out sample				
		Requiring change in Ratings of chosen alternative (7-point scale)				
		+1	+2	+3	+4	+5
Meat quality	74.0	14.0	8.0	4.0	0.0	0.0
Produce quality	86.0	6.0	4.0	2.0	2.0	0.0
Ease of finding things	86.0	14.0	0.0	0.0	0.0	0.0
Variety of items	90.0	4.0	4.0	2.0	0.0	0.0
Reasonable prices	86.0	4.0	6.0	2.0	0.0	2.0
Ease of returns	98.0	2.0	0.0	0.0	0.0	0.0
Crowding	100.0	0.0	0.0	0.0	0.0	0.0
Convenient hours	94.0	6.0	0.0	0.0	0.0	0.0
Accessibility	100.0	0.0	0.0	0.0	0.0	0.0

A second effect evidenced by the results is that of increased pressure to operationalize a decision as the options for making that decision decrease. Since a constraint of the model is that each individual in the sample used for estimation be assigned his/her stated choice, there is a general bias in the model structure toward assigning the "correct" choice as soon as possible in the postulated decision process. The closer the decision maker gets to the "deadline" (i.e. running out of attributes), the greater the pressure to eliminate alternatives. Absence of a feedback process in the model structure both amplifies this pressure and also allows for the possibility of choosing an alternative that has less total utility than another. In this choice situation, for example, an alternative judged second best on the most important attribute may be chosen over that judged best on that attribute if those two alternatives are the only ones to survive the first stage and the former alternative is judged best at the second stage. In cases such as this, the model structure indicates that the "phantom utility" associated with effecting a simple decision process (i.e. uncomplicating the life of the decision-maker) is greater than the marginal utility of complicating the decision.

A similar interpretation is possible for Data Set II.

Potential planning usefulness

As one example of the potential usefulness of model results, suppose the parameter estimates for Data Set II (Table 2) are provided to the management of a particular store. The effect of the various policy options available to the management can be assessed with the information contained in this table. For example, if ratings of "Meat Quality" of the store's competitors generally are high and fairly uniformly distributed, a marginal increase in this perceived aspect of the store would probably not result in diverting a significant portion of shoppers from the stores they currently frequent, since the tolerance of this attribute is also relatively high. On the other hand, (again assuming relatively high ratings) setting new standards in store layout which would significantly increase "ease of finding things" would be expected to cause significant diversion since it is associated with an attribute with a very small tolerance. However, such a move would be successful only if the two quality aspects of the store were maintained at a sufficiently high level not to cause rejection of the store at importance levels higher than that of "ease of finding things".

Another alternative to consider might be to increase the business hours of the store. While diversion is sensitive to this attribute, it only occurs among choices which have not been eliminated at any of the seven preceding stages. The probability that a choice has not been made prior to a given stage decreases with each subsequent importance level. Hence, the number of decisions affected by changing the business hours would be significantly less than that at a higher importance level. In addition, for such a change to have an effect, all attributes at the seven higher levels must be maintained at a standard that would insure that the store not be eliminated on any of the higher levels. These factors indicate that increasing business hours would not be an effective policy change.

CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

The model replicated well the choices of consumers in two transportation contexts: choice of hypothetical concepts of small urban vehicles and choice of destination for shopping trips within an urban area. The algorithm employed to estimate the parameters of the sequential elimination model performed well on the two data sets, where performed is measured in terms of convergence properties and correspondence among the resulting estimates and those of other types of choice models. Furthermore, policy interpretations of the results were shown to be plausible. Thus, the authors are confident in concluding that the principles of (1) sequential consideration of attributes and (2) thresholds of critical tolerance have passed initial tests of relevance to transportation decision-making behavior.

These two principles potentially could provide foundations for incorporating many of the decision considerations which are largely ignored in current compensatory models. For example, the concept of choice constraints fits nearly into the sequential elimination model in its present form. Constraining attributes simply are assigned the highest importance ranks, and

nonlinear programming constraint equations can be introduced to insure adherence of the critical tolerances to observed behavior.

As a second example, it appears possible to incorporate a number of dynamic elements within the postulated decision process. The critical tolerances could be specified as dynamic functions of experience. The next step would be then to link the evaluation ratings to the tolerances as a feedback mechanism in the estimation procedure. This represents an approach to modeling the cognitive dissonance phenomena recently uncovered (Horowitz, 1978; and Golob *et al.* 1977).

Further examination of the present model is clearly called for before any such extensions should be attempted. The implications of the functional form assumed for the critical tolerances must be thoroughly explored and positioned in the context of economic theory. Questions of whether a totally non-compensatory approach is any more realistic than a totally compensatory construct must be addressed. The authors are inclined to believe that most decision processes contain elements of both, with, perhaps, a non-compensatory process used in the initial phases of the decision process to obtain a "short list" and compensatory thereafter. The crude algorithm designed for this initial test of the model must be refined and questions regarding the properties of the constrained solution space answered. Also, questions regarding potential application of model results must be addressed. Whereas compensatory models typically assign a specific utility to each alternative from which a probability of choice may be inferred with a certain degree of accuracy, the proposed model assigns confidence intervals to ranges of attribute levels that dictate choice. The implications of this in a planning context are not clear.

Extended research on a near-term basis is perceived to lie in three directions. First, the sequential elimination model could be compared rigorously to competing choice models in a variety of decision contexts. Second, an algorithm possibly could be developed to estimate the importance ranks for each individual simultaneously to the estimation of tolerances. This would avoid the necessity of relying upon individuals stated importances. Third, mathematical probability properties of the model and its potential variants could be derived. Such properties encompass issues of scalability and stochastic transitivity.

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