Title

A Non-Compensatory Model of Transportation Behavior Based on Sequential Consideration
of Attributes

Permalink

https://escholarship.org/uc/item/8172f94d

Authors

Recker, Will
Golob, Thomas F.

Publication Date

1978

A Non-Compensatory Model of Transportation Behavior Based on Sequential Consideration of Attributes

UCI-ITS-WP-78-2

Will Recker [1]
Thomas F. Golob [2]

[1] School of Engineering, School of Social Sciences and Institute of Transportation Studies, University of California, Irvine. On leave from Department of Civil Engineering, State University of New York at Buffalo

[2] Transportation and Urban Analysis Department, General Motors Research Laboratories

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

by

Wilfred W. Recker
Institute of Transportation Studies
University of California, Irvine*

and

Thomas F. Golob
Transportation and Urban Analysis Department
General Motors Research Laboratories

ABSTRACT

The proposed model of travel choice behavior is based upon an assupmtion 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.

*On leave from Department of Civil Engineering, State University of New York at Buffalo.

TABLE OF CONTENTS

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 purported 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 another one or more attribute. (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 a 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.

1

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 in 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 Krishnan (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 feasible 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. Furthermore, define by A^n_{kj} the evaluation by decision maker n of alternative k with respect to attribute j. Each individual may have a different hierarchical ranking of importances associated with these attributes. This ranking is used to determine the sequence of attributes through which the N alternatives are processed. Denote the rank order of the importance associated with the jth attribute of an alternative in S^n by decision maker n as i^n_j, assumed to be invariant across alternatives in S^n.

Associated with any given attribute j is a critical tolerance $C^n_j(i^n_j)$ between the decision maker n's evaluation of any alternative on an attribute and some acceptance standard. This standard may be a function of the importance level i associated with the particular attribute. It is assumed that this standard can be measured in terms of the percentage difference T^n_{kj} between the individual's evaluation of the alternative that is judged best with respect to attribute j and his or her evaluation of alternative k on attribute j. I.e.,

$$T^n_{kj} = \frac{\underset{\ell \in S^n}{\text{Max}} [A^n_{\ell j}] - A^n_{kj}}{\underset{\ell \in S^n}{\text{Max}} [A^n_{\ell j}]} \tag{1}$$

The criterion for rejection of an alternative k then is simply

$$T^n_{kj} > C^n_j(i^n_j) \tag{2}$$

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.

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 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.

ESTIMATION OF DECISION PARAMETERS

Specification

Consider that for each member n of a sample population of P individuals attitudinal measures $A_{\ell j}^n$ and corresponding importance rankings i_j^n 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 multiattribute models (Wilkie and Pessemier, 1973); survey data collection techniques are well developed. Unknown are the critical tolerance levels $c_j^n(i_j^n)$. Of specific interest to the planner are answers to the following questions: (a) Do clearly defined estimates of critical tolerances $c_j^n(i_j^n)$ exist that are generalizable to groups in the population as a whole? and (b) What are these values?

To provide answers to these questions, two assumptions are made regarding the occurrences of values of critical tolerances, $c_j^n(i_j^n)$, in the sample. Specifically, 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 $\mu_j(i_j^n)$ and standard deviation $\sigma_j(i_j^n)$.

2. Subject to certain random individual differences in preferences in his or her determination of subjective value (see Torgerson, 1958) the individual will employ a value of critical tollerance $c_j^n(i_j^n)$ that is as close as possible to the population mean $\mu_j(i_j^n)$.

The objective is then to determine estimates of the mean values $\mu_j(i_j^n)$ of the critical tolerances which are useful as predictive tools. Consequently these estimates must be sharply defined. The problem thus becomes one of determining $c_j^n(i_j^n)$ $(i,j=1,\ldots, M)$ such that the standard deviations $\sigma_j(i_j^n)$ of the distributions of the normalized tolerances $c_j^n(i_j^n)$ $(i,j = 1,\ldots, M; n=1,\ldots, P)$ 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 $\sigma_j(i_j^n)$ for $i,j = 1,\ldots, M$; i.e.

$$\underset{c_j^n(i_j^n)}{\text{MIN}} \left\{ Q = \frac{1}{M^2} \sum_{i,j=1}^{M} w_j(i_j^n)\, \sigma_j(i_j^n) \right\} \tag{3}$$

where

$$w_j(i_j^n) = \text{weight assigned to the case in which attribute } j \text{ is given}$$
importance level i by individual n.

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

$$\underset{c_j^n(i_j^n)}{\text{MIN}} \left\{ Q = \frac{1}{M^2} \sum_{i,j=1}^{M} \frac{w_j(i_j^n)}{(p_{ij}-1)^{1/2}} \left[\sum_{n=1}^{p_{ij}} c_j^n(i_j^n) - \frac{1}{p_{ij}} \sum_{q=1}^{p_{ij}} c_j^q(i_j^q)\ ^2 \right]^{1/2} \right\} \tag{4}$$

where p_{ij} = number of individuals assigning importance level i to attribute j. The problem becomes one of satisfying Eq (4) subject to to

$$0 \leq c_j^n(i_j^n) \leq 1,\ n=1,\ldots,p_{ij} \text{ and } i,j=1,\ldots, M \tag{5}$$

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

$$c_j^n(i_j^n) > \frac{\underset{\ell \in \hat{S}_i^n}{\text{Max}} [\Lambda_{ej}^n] - \Lambda_{k^* j}^n}{\underset{\ell \in \hat{S}_i^n}{\text{Max}} [\Lambda_{ej}^n]} \qquad \text{for all i.} \qquad (6)$$

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

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

Introducing a dichotomous variable

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

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

$$\sum_{i=1}^{M} \eta_{ik}^n \geq 1, \qquad (8)$$

$$\eta_{\ell k}^n \geq \eta_{ik}^n \qquad \text{for all } k \neq k^*,$$
$$\ell > i,$$

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 equations (4), (5), (6) and (8). The steps in the algorithm are detailed below:

1. Generate Initial Feasible Solution:
   For each observation, order attributes according to
   the importances stated by the consumer, from most
   important to least important. Ties in importance
   levels are assigned arbitrary orders. Search through
   the ordered attributes. At each level assign the
   minimum value of the normalized tolerance $C_j^n(i_j^n)$
   $(0 \leq C_j^n(i_j^n) \leq 1)$ such that the chosen alternative
   just passes the test for retention. At each level
   remove all other alternatives which do not pass
   the retention test. Continue the process until only
   one alternative remains.

2. If, for any observation, more than one alternative remains
   after the process is completed, remove that observation from
   the analysis, 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.

3. Assign attributes at importance levels below the point at
   which only one alternative remains a value of $C_j^n(i_j^n) = 1$.

4. Compute $\partial Q/\partial C_j^n(i_j^n)$ $(j = 1,\ldots, M; \quad n = 1,\ldots, P)$.

5. Select maximum value of $\partial Q/\partial C_j^n(i_j^n)$, i.e.,

   $$\underset{j,n}{\text{Max}}[\partial Q/\partial C_j^n(i_j^n)] = \partial Q/\partial C_s^t(i_s^t).$$

6. If $\partial Q/\partial C_s^t(i_s^t) < 0$ increase the value of normalized tolerance
   $C_s^t(i_s^t)$ as much as possible toward the current mean estimate μ_s.
   Readjust the values of the tolerances at lower levels of
   importance, if necessary, to remove any previously
   disregarded non-chosen alternatives that may now pass

the retention test at the importance level associated with attributes for observation t. If such adjustments are necessary and cannot be made, return normalized tolerance $c_s^t(i_s^t)$ to its previous value and remove $\partial Q/\partial c_s^t(i_s^t)$ from consideration and repeat step 4. Go to step 4.

7. If $\partial Q/\partial c_s^t(i_s^t) > 0$ decrease the value of the normalized tolerance c_s^t as much as possible toward the current mean μ_s without removing the chosen alternative. Go to step 4.

8. If $\partial Q/\partial c_s^t(i_s^t) \leq \varepsilon$, where ε is a predetermined error tolerance, the process is completed and Min Q can be considered to be achieved. Statements as to whether the above is a local or global minimum cannot be made.

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 minimum achieved with this algorithm and a possibly distinct global minimum 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 in the first step of the algorithm. 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.

Questions regarding which constraints are binding on the final solution also depend upon the data and cannot be answered analytically. However, for the particular results described herein, a trace of the final solution indicated a high degree of diversity in terms of which, if any, constraints were binding upon individual decision makers.

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

$$C_j^n(i_j^n) = C_j^n .$$ (9)

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

In addition, the weights $w(i)_j$ in Eq. (4) were assumed equal to
unity. The objective function then reduces to the special case

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

or,

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

Support for this assumption is provided in arguments originally
proposed by Thurstone (1959). Briefly, if the σ_j (j = 1,..., 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 Eq (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 1 565 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 1 500 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 or 6.5%. The standard deviations

DATA SET I: ESTIMATED ATTRIBUTE TOLERANCES IN SEQUENTIAL DECISION MODEL (ATTRIBUTES IN ORDER OF DECREASING MEDIAN IMPORTANCE RANK)		
ATTRIBUTE	CRITICAL TOLERANCE	
	MEAN	STD. DEVIATION
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 1.

of the distributions of the critical tolerances are all small, with a mean standard deviation of 0.023. The assumption $\sigma_j = \sigma (j = 1,\ldots, M)$ is supported by the small standard deviation about this mean of standard deviations, 0.011.

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 assymptotic t-statistics, are precisely the three attributes with the highest mean critical tolerance and median importance rank: "vehicle size," "perceived safety" and "flexibility of use." This result calls for further investigations.

The results from estimation of model parameters for Data Set II are shown in Table 2. A random subsample of 80 decision makers was used, leaving a hold-out sample of 52 for goodness-of-fit tests. Convergence was achieved, and the results indicate smaller tolerances associated with

DATA SET II: ESTIMATED ATTRIBUTE TOLERANCES IN SEQUENTIAL DECISION MODEL (ATTRIBUTES IN ORDER OF DECREASING MEDIAN IMPORTANCE RANK)		
ATTRIBUTE	CRITICAL TOLERANCE	
	MEAN	STD. DEVIATION
QUALITY I	0.165	0.113
QUALITY II	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

TABLE 2.

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 $\sigma_j = \sigma$ $(j = 1,\ldots, M)$ as in the case of Data Set I.

Results for Data Set II are consistent with those for Data Set I with respect to correspondence 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: "Quality I," "Quality II," "Variety of Items" and "Reasonable Prices." This result further emphasizes the need for further research.

<u>Goodness-of-Fit</u>

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%. This is judged to be an encouraging overall internal validity statistic. Unfortunately, the sequential elimination model predictive power cannot be directly compared to that of the multinomial logit model since sample-size consideration in the application of the logit model did not allow creation of a hold-out sample to test logit predictions. Further research is again called for.

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.

DATA SET I: NECESSARY CHANGES IN RATINGS BY HOLD-OUT SAMPLE SUCH THAT SEQUENTIAL DECISION MODEL WITH ESTIMATED TOLERANCES HOLDS FOR ALL INDIVIDUALS						
ATTRIBUTE	% OF HOLD-OUT SAMPLE					
	REQUIRING NO CHANGE	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
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

TABLE 3.

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 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 corectly. 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.

Interpretation of Results

The Data Set I results of Table 1 can best be interpreted through analogy to utility weights of compensatory models. The estimated mean critical tolerances are rank ordered approximately according to the attributes' median importance rankings. This result reflects both the notion of decreasing utilities associated with less important attributes as well as the pressure of decision making under "deadline conditions." As the

16

DATA SET II: NECESSARY CHANGES IN RATINGS BY HOLD-OUT SAMPLE SUCH THAT SEQUENTIAL DECISION MODEL WITH ESTIMATED TOLERANCES HOLDS FOR ALL INDIVIDUALS						
	% OF HOLD-OUT SAMPLE					
ATTRIBUTE	REQUIRING NO CHANGE	**REQUIRING CHANGE IN RATINGS OF CHOSEN ALTERNATIVE(7-POINT SCALE)**				
		+1	+2	+3	+4	+5
QUALITY I	74.0	14.0	8.0	4.0	0.0	0.0
QUALITY II	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
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

TABLE 4.

decision maker proceeds through the sequential elimination process, alter-natives 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, 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.

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 "Quality I" of the store's competitors are 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 relatively high. On the other hand, 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."

18

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 preceeding 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 performance 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 neatly into the sequential elimination model in its present form. Constraining attributes simply are assigned the highest importance ranks, and nonlinear programing 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 fruitful 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.

ACKNOWLEDGMENTS

REFERENCES

Alexis, M., G. H. Haines and L. Simon (1968). Consumer Information Processing: The Case of Women's Clothing. In R. L. King, ed., Marketing and the New Science of Planning. Chicago: American Marketing Association.

Bettman, J. R. (1970). Information Processing Models of Consumer Behavior. Journal of Marketing Research, 7: 370-376.

Bettman, J. R. (1971). Analyzing Consumer Information Models: A Graph Theoretic Approach. Management Science, 18: 114-128.

Clarkson, G. P. E. (1963). A Model of the Trust Investment Process. In E. A. Feigenbaum and J. Feldman, ed., Computers and Thought. New York: McGraw-Hill.

Cramer, H. (1957). Mathematical Methods of Statistics. Princeton: Princeton University Press.

Golob, T. F., A. D. Horowitz and M. Wachs (1977). Attitude-Behaviour Relation-ships in Travel Demand Modelling. Presented at Third International Conference on Behavioural Travel Modelling, Tanunda, South Australia, April 4, 1977. Available as General Motors Research Laboratories Publication GMR-2398.

Guilford, J. P. (1954). Psychometric Methods. New York: McGraw-Hill.

Horowitz, A. D. (1978). A Cognitive Dissonance Approach to Attitudinal Modelling in Travel Behavior Research. Presented at Annual Meeting of Transportation Research Board, Washington, D. C., January 18, 1978.

Kostyniuk, L. P. (1975). A Behavioral Choice Model for the Urban Shopping Activity. Unpublished Ph.D. Dissertation, University of New York at Buffalo.

Krishnan, K. S. (1977). Incorporating Thresholds of Indifference in Probabilistic Choice Models. Management Science, 23: 1224-1233.

Krishman, K. S. and T. F. Golob (1977). Using Focus Group Interviews and Workshops to Develop Transportation Concepts. Presented at Joint National Meeting, Institute of Management Sciences/Operations Research Society of America, San Francisco, May 10, 1977. Available as General Motors Research Publication GMR-2428.

Newell, A. and H. A. Simon (1972). Human Problem Solving. Englewood Cliffs, New Jersey: Prentice-Hall.

Recker, W. W. and L. P. Kostyniuk (1978). Factors Influencing Destination Choice for the Urban Grocery Shopping Trip. Transportation, in press.

Russ, F. A. (1977). Consumer Evaluation of Alternative Product Models. Unpublished Ph.D. Dissertation, Carnegie-Mellon University.

Schroder, H. M., M. J. Driver and S. Streufert (1967). Human Information Processing. New York: Holt, Rinehart and Winston.

Simon, H. A. (1955). A Behavioral Model of Rational Choice. Quarterly Journal of Economics, 69: 99-118.

Simon, H. A. (1956). Rational Choice and the structure of the Environment. Psychological Review, 63: 129.

Simon, H. A. (1959). Theories of Decision-Making in Economics and Behavioral Science. The American Economic Review, 49: 253

Stevens, S. S. (1962). The Surprising Simplicity of Sensory Metrics. American Psychologist, 17: 29-39.

Thurston, L. L. (1959). The Measurement of Values. Chicago: University of Chicago Press.

Torgerson, W. S. (1958). Theory and Methods of Scaling, 7th Printing. New York: Wiley.

Tversky, A. (1969). Intransitivity of Preferences. Psychological Review, 76: 31-48.

Tversky, A. (1972a). Choice by Elimination. Journal of Mathematical Psychology, 9: 341-367.

Tversky, A. (1972b). Elimination by Aspects: A Theory of Choice. Psychological Review, 79: 281-299.

Wilkie, W. L. and E. A. Pessemier (1973). Issues in Marketing's Use of Multi-Attribute Attitude Models. Journal of Marketing Research, 10: 428-441.