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FOREWORD

This RECORD contains various concepts of behavioral analysis in relation to transportation needs and requirements.

Dobson and Kehoe discuss the application of an individual-differences scaling model to a set of perceptual similarity judgments of an automated urban transportation system to find groups of respondents with a homogeneous viewpoint. The significance of the investigation, according to the authors, can be judged by the knowledge it contributes to attitude-behavior relations with regard to urban transport alternatives and the number of new analyses and applications that are generated by it. One major finding is the identification of 3 classes of attributes that influence satisfaction with transportation modes.

Stopher, Spear, and Sucher describe a research task concerned with providing 3 products relating to measures of convenience for urban travel modes: (a) an inventory of previous work concerning comfort and convenience and an assessment of the effectiveness of such efforts in producing a quantifiable convenience variable for inclusion in a travel demand model, (b) a theoretical basis for defining and quantifying convenience, and (c) a prototypical measure of convenience. The authors conclude that the research lent support to the hypothesis that the convenience of travel modes can be quantified for the purposes of travel demand modeling, but that the most effective method to use to carry out this quantification is still uncertain.

Burnett examines the hypothesis that destination choice by a heterogeneous population group may appear to be a random process because of the conflicting and interacting effects of many variables on the choice decision. A formal model of random destination choice was specified, and its predictions were tested by using data for 3 destinations, 8 classes of destinations, and 10 population groups. The model was rejected in 17 out of the 21 tests. The findings support the development of Markov, linear learning, multinominal logit, and multivariate models of destination choice.

Day and Schmidt describe the effect of fare policy and transit service plans on travel mode-choice behavior. San Francisco was the test case city. To aid the process of simulating the effects of various bus and rail service plans and joint fare structures, a disaggregate model of mode-choice behavior was developed. The authors point out that, while the specific questions posed in this study were geographically unique, the underlying technical and policy issues could be applied to other situations that involve the introduction of a new transportation service or facility.

Watson compares the structures and predictive capabilities of disaggregate and aggregate mode-choice models. He concludes that the disaggregate models provide a better statistical explanation of mode-choice behavior and have extremely desirable performance characteristics. He thinks that a serious effort should now be made to incorporate disaggregate models into the transportation planning process.

Haefner and Dickinson describe a case study of route diversion in the Baltimore-Washington corridor developed through disaggregate modeling of individual route choice. The research allowed tentative conclusions to be drawn about study designs of this sort and their place among disaggregate transportation demand models.

Koppelman describes the problem in making aggregate forecasts about travel behavior under conditions in which aggregate behavior is the accumulation of travel-choice decisions by individuals or households. Alternative approaches to the development of unbiased aggregate forecasts based on disaggregate choice models are described.

Costantino, Golob, and Stopher present a series of models concerned with the effect of peoples' attitudes on explaining overall satisfaction with a particular mode, perceived differences between modes, and trip allocation among modes. The hypothesis was that an understanding of the preferences and perceptions of individuals

toward proposed forms of urban transportation is important to successful implementation and operation of those systems. The study examined the respondents' perceptions of 3 proposed automated systems: personal rapid transit, people movers, and dual-mode transit.

DISAGGREGATED BEHAVIORAL VIEWS OF TRANSPORTATION ATTRIBUTES

Ricardo Dobson, General Motors Research Laboratories; and
Jerard F. Kehoe,* University of Southern California

The assessment of attitudes toward various attributes of urban transport alternatives is of interest because of (a) the relation between personal behavior toward transport systems and the perceptions and preferences of individuals toward attributes of the alternatives, (b) the possibility of developing policy-sensitive prediction models, and (c) the compatibility of output from attitude research with ongoing disaggregate behavioral model development. The current investigation applies an individual-differences scaling model to a set of perceptual similarity judgments of an automated urban transportation system to find groups of respondents with a homogeneous viewpoint. The perceptions of 7 distinct groups of respondents were represented by Euclidean distance models. The points of view of the different groups could be identified both by the number of dimensions and the relative position of attributes for their corresponding spaces. Across the axes of the perceptual spaces for the 7 groups, 3 major classes of attributes could be defined: basic transport service, personal luxury service, and general amenities. Satisfactions with modes of a proposed urban transportation system could be predicted from the projections of the attributes on the axes of the spaces, and in addition the particular classes of attributes that differentially contributed to satisfaction with a given mode could be determined. Finally, the potential contribution of the technique for evaluating impact models was demonstrated by the investigation, which indicated those activity pattern and socioeconomic variables that were not uniformly distributed across the 7 homogeneous perceptual groups.

•THE ASSESSMENT of attitudes toward various attributes of urban transport alternatives about which individuals make decisions is becoming more common. The rationale for this application of psychological measurement techniques is based partly on the assumption that personal behavior in the selection of one course of action over another can often be determined in advance by an understanding of the perceptions and preferences that individuals have of the alternatives in question. Another factor that motivates the investigation of points of view that individuals have toward urban transportation is the possibility of developing prediction models that are sensitive to policy variables of concern to administrators (27). Furthermore, the general approach of attitude assessment is highly compatible with disaggregate behavioral models for mode split and other features of the transportation planning process (2, 29).

Several reports describe the application of attitudinal research to urban transportation analysis. Shaffer (24) outlined the need for attitudinal surveys and listed criteria by which to evaluate their effectiveness. In addition, she gave several examples of the insights that may be gained by attitude surveys. Golob (13) reviewed alternative definitions of the concept "attitude" and discussed a variety of specific models that have been proposed for predicting behavior from attitudes. Lovelock (21) addressed specifically the issue of mode split from attitudes toward, perceptions of, and knowledge about the transport modes available to an individual for a trip. Even

*Mr. Kehoe was with the General Motors Research Laboratories when this research was done.

more recently, Golob and Dobson (15) proposed a general schema that was presumed suitable to describe an assortment of transportation-related decisions that are mediated by underlying perceptual attributes of an individual's transportation alternatives.

One aspect of the general schema relates to the disaggregation of a sample of respondents. Golob and Dobson discussed 2 ways to segment a sample of respondents. One method involved separately analyzing the attitudinal judgments of different groups that are selected to be of interest to the researcher and policy-maker. Examples of this method for disaggregating a sample are demonstrated by Golob et al. (14) and Gustafson and Navin (16). The second technique involved splitting the sample into groups that are homogeneous in terms of their perceptual judgments. This latter method ensures that the separate groups will be distinct in terms of their judgments, but it will not necessarily result in respondent groups that are interesting to policy-makers. On the other hand, policy-makers may derive significant insights, which could otherwise be overlooked, from the segmentation of the sample into perceptually homogeneous groups. In practical urban transportation planning contexts, it seems reasonable to use both methods for disaggregating a sample of respondents.

In the interest of facilitating the use of the second method, this report documents the application of a procedure for determining groups of respondents who share a common point of view. Specifically, Cliff's variation (6) of Tucker and Messick's individual-differences scaling model (31) is used to analyze a set of similarity judgments for attributes of an innovative urban transportation concept discussed by Canty (3). The points of view for different respondent segments are compared among themselves and in relation to the satisfactions with the modes for the new hypothetical transportation system. In addition, the composition of the homogeneous respondent segments is examined with respect to traditional socioeconomic and activity patterns variables.

DATA SOURCE

This report is one in a series designed to study the demand for Metro Guideway, an innovative urban transportation concept (3). The investigation is part of the Metro Guideway Attitudinal Demand Study (MADS) by the Transportation and Urban Analysis Department of General Motors Research Laboratories. The total data collection effort, which includes pretests, mail panel surveys, and home-interview and leave-behind questionnaires, is documented by Dobson (11). An analysis of the mail panel data is presented by Golob, Dobson, and Sheth (9), and another analysis of a different segment of the home-interview data is reported by Costantino, Golob, and Stopher (7).

Similarity judgments for a set of 12 attributes were collected by a pick k of n minus 1 task. The general method is discussed by Coombs (8), and an empirical application of the technique is illustrated by Rao and Katz (22). Figure 1 shows a page from a response booklet used to collect data for the current investigation. The respondent's task is to pick those attributes that he or she views as similar to the reference attribute, the one at the top of the page. Each of the 12 attributes was, in turn, a reference attribute for the n minus 1 or 11 remaining attributes.

The advantages of the pick k of n minus 1 task are several. It is a quick and easy way to collect data from respondents. The task requires only yes or no responses that can be made quite rapidly. The simplicity of the task facilitates its administration across a heterogeneous population of respondents. Because the method allows for the rapid collection of data, it is particularly useful when data must be collected on a long list of items or on a short list of items in a limited amount of time. Finally, the method collects data of the sort that can be transformed for analysis by the Tucker-Messick individual-differences scaling technique, the primary data analysis tool used in this report.

In the present application of the pick k of n minus 1 task, each respondent generated a 12 by 12 matrix of entries that are either 1 or 0, according to whether the row attributes were picked as similar to the column attribute, the reference attribute described above. This matrix is not necessarily symmetric, but it can be transformed to a symmetric matrix by computing the Euclidean distance between pairs of columns according to

$$d^{\ell}_{ij} = \left[\sum_{t=1}^{12} (x^{\ell}_{ti} - x^{\ell}_{tj})^2 \right]^{1/2} \tag{1}$$

for i, j = 1, 2, ..., 12 and ℓ = 1, 2, ..., 243 and in which x^{ℓ}_{ti} and x^{ℓ}_{tj} are the 0 and 1 entries of the ith and jth columns respectively of the tth row. The new matrices, with elements d^{ℓ}_{ij} for the ℓth respondent, were transformed further by dividing their elements by the root mean square of elements below their diagonal. These new values are hereafter called dissimilarities. The latter transformation removed the respondents' overall response level differences, which were an unwanted source of variance among them. These matrices, hereafter called attribute dissimilarity matrices, for the 243 respondents who completed the pick k of n minus 1 task are the data to which Cliff's variation of the Tucker-Messick individual-differences scaling model was applied to derive perceptually homogeneous groups.

METHODS OF ANALYSIS

The elements of the attribute dissimilarity matrix for a particular respondent denote the similarity between all possible 66 pairs of 12 attributes. For example, if d^{ℓ}_{ij} equals 0, then attributes i and j have identical response profiles with respect to the remaining 10 attributes and each other. As the response profiles for attributes i and j depart from each other, the magnitude of d^{ℓ}_{ij} will increase for the ℓth respondent. Since d^{ℓ}_{ij} is equal to d^{ℓ}_{ji} from Eq. 1, only dissimilarities below the diagonal will be considered for the remainder of the presentation.

Figure 1. Questionnaire format for collecting similarity judgments about transportation system attributes.

Please read the feature enclosed in the box at the top of this page. Then read each feature listed below it. If you feel the two features are alike "X" the "yes" box. If you feel the two features are not alike "X" the "no" box. Please "X" either "yes" or "no" for every feature listed below.

Is [BEING ABLE TO GET WHERE I WANTED TO GO ON TIME] like:

	WHETHER THIS IS LIKE THE FEATURE ABOVE:	
Having my own private section in the vehicle	yes ☐	no ☐
Having short travel times	yes ☐	no ☐
Having a short waiting for a vehicle	yes ☐	no ☐
Having low fares	yes ☐	no ☐
Having a comfortable ride in a quiet vehicle	yes ☐	no ☐
Having a driver instead of a completely automatic system	yes ☐	no ☐
Being safe from harm by others and from vehicle accidents	yes ☐	no ☐
Having room for strollers or wheel chairs	yes ☐	no ☐
Being able to get to many places in the Detroit area using the guideway	yes ☐	no ☐
Having refreshments and newspapers for sale at stations	yes ☐	no ☐
Having control of temperature in the vehicle	yes ☐	no ☐

The elements of the attribute dissimilarity matrices, d_{ij}^{ℓ}, are suitable for analysis by a set of techniques referred to as multidimensional scaling. Shepard (25) noted 2 general purposes of this class of methods. It finds hidden structure in a data matrix, and it represents that structure in a form that is readily accessible to the human eye. There are numerous multidimensional scaling models, many of which are discussed and applied by Shepard (26) and Green and Rao (12). A comparison of 2 alternative multidimensional scaling models for preference data on transportation attributes of a demand-responsive jitney (14) is illustrated by Dobson et al. (10).

This report applies a 2-stage points-of-view multidimensional scaling model, which was developed originally by Tucker and Messick (31) and more recently modified by Cliff (6) to account for criticism advanced by Ross (23). The first stage identifies respondents with homogeneous perceptual viewpoints, and the second stage analyzes those viewpoints to derive a geometric representation for the relations among the entities being scaled. In the current application, these entities are the attributes shown in Figure 1.

If the dissimilarities below the diagonals of the attribute dissimilarity matrices were strung out to form the rows of a 243 by 66 matrix, X, then the first stage of Cliff's variation of Tucker and Messick's procedure would involve the singular decomposition of X by Eckart and Young's well-known theorem

$$X \cong P \Lambda Q' \tag{2}$$

P is the orthonormal matrix by columns of characteristic vectors of XX', Λ is the diagonal matrix of positive square roots of the characteristic roots of $X'X$, and Q is the orthonormal matrix by columns of characteristic vectors of $X'X$. P, Λ, and Q are of rank r, which is much less than the rank of X, and their product is a least squares approximation of X. The row elements of P are analogous to factor scores; they indicate the weights that must be applied to $(\Lambda Q')$ to recover a close approximation to X, the original attribute dissimilarities. Cliff observes that, when several individuals have similar weights in P, then they can be said to have a similar viewpoint in that their rows in X will be nearly identical to each other. He recommends taking the mean of the weights for respondents with a common point of view and multiplying these values by $(\Lambda Q')$ to recover a set of estimated judgments to represent that viewpoint. Finally, the estimated judgments are submitted to a nonmetric multidimensional scaling program (33, 34) to recover the structure of the perceptions for the viewpoint in the second stage of the analysis. The history of these programs is described briefly by Dobson (11).

There are 2 outputs from a points-of-view analysis. One output is a mutually exclusive segmentation of the sample into a set of groups; each group has a homogeneous point of view, and these outlooks are presumably distinct between groups. The second output is a geometric representation in which the attributes are embedded in a multidimensional space underlying the estimated judgments. It is possible to characterize the viewpoint of each group by the dimensionality and positioning of attributes in its corresponding geometric space.

To facilitate the application of points-of-view analysis to urban transportation planning, travel demand estimation, and impact evaluation analyses requires that the 2 outputs from the analysis be related to satisfactions with modes and to socioeconomic characteristics. Chi-square analyses of contingency tables are performed to determine dependencies between the homogeneous perceptual groups and selected activity patterns and demographic variables. In addition, multiple and simple correlations are computed between attribute coordinates in the group spaces and satisfaction ratings for 3 modes on the same set of 12 attributes. The modes include people-mover, dual-mode transit, and personal rapid transit vehicles of the Metro Guideway system. The verbal and pictorial tableaux of the modes that were presented to the respondents are available in Dobson's documentation of the MADS survey.

FINDINGS

Formation of Homogeneous Perceptual Groups

The attribute dissimilarity matrices for the 243 respondents who completed the pick k of n minus 1 task were decomposed according to Eq. 2. A necessary condition for a valid points-of-view analysis is a good recovery of the initial data matrix. It was possible to account for 90 percent of the trace of that matrix with 3 characteristic vectors. The remaining characteristic vectors failed to significantly augment this percentage, and, in addition, the overwhelming majority of the respondents could be conveniently classified into one or another respondent group with a common viewpoint on the basis of 3 characteristic vectors.

When the rows of the P matrix in Eq. 2 are plotted in the space of characteristic vectors, it is possible sometimes to identify visually respondents with common points of view; each row represents weights for a specific respondent. A visual clustering of the respondents in the characteristic vector space was made difficult for 2 reasons. First, it was extremely difficult to determine when respondents were close to one another in the 3-dimensional space. Even when a physical model of the space was constructed, the task of visually clustering respondents was nontrivial. Second, the heterogeneous nature of the sample made it natural to expect more than a few groups, but the multiple number of groups, in turn, complicated the classification task.

As a consequence of these difficulties and to both simplify and increase the validity of the process of identifying respondents who shared a viewpoint, we divided 3-dimensional respondent space into 48 polyhedrons according to the following rule. Octants with a positive first axis value were assigned the numerals I through IV, and those in the bottom half were assigned the numerals V through VIII. For the top half of the space, the octant with all positive axes was assigned I; II, III, and IV were assigned in a counterclockwise fashion to the remaining octants. Octants in the bottom half of the space were denoted in a similar manner. Each octant could be bisected in any of 3 ways by passing a plane through 1 of its 3 axes. Figure 2 shows an octant with planes passed through all 3 axes; Arabic numerals denote each of the resulting polyhedrons in a counterclockwise manner. With the numbering scheme outlined above, all 48 polyhedrons of the 3-dimensional space may be conveniently designated by a Roman and an Arabic numeral.

A total of 232 respondents occupied 18 polyhedrons. The remaining 11 respondents, who will not be considered further in this analysis, were single or dual members of a polyhedron or they occupied the origin of the 3-dimensional space. A polyhedron that is occupied by only 1 or 2 respondents is not likely to be related to a representative point of view. The clustering of respondents was based on the direction cosines among the mean projections in each of 18 polyhedrons. The procedure for computing the direction cosines is given by Van de Geer (32).

Table 1 gives the direction cosines for the 18 polyhedrons and also the clustering of polyhedrons and their corresponding respondents into 7 homogeneous perceptual groups. The direction cosines for the polyhedrons in a group are enclosed by lines that separate them from the rest of the matrix. Direction cosines can be interpreted like correlation coefficients. The groups were formed so that the direction cosines of the polyhedrons in a group are generally higher than those without membership in the group and so that none of the polyhedrons in a group has a low direction cosine. All further analyses for this investigation are based on the group definitions given in Table 1.

Analyses of Points of View

This report documents the application of a 2-stage points-of-view model to a set of dissimilarity judgments for attributes of a proposed urban automated transportation system. The objective of the second stage of the model is to derive spaces for the attributes that describe the point of view of each of the homogeneous perceptual groups given in Table 1. According to the procedure outlined above, the weights of respondents with a common viewpoint were averaged, and these average weights were multiplied by $(\Lambda Q')$ of Eq. 2 to derive a set of estimated judgments for the second stage of the anal-

Table 1. Direction cosines between pairs of mean vectors of polyhedrons in respondent space.

	Group 1		Group 2		Group 3			Group 4		Group 5			Group 6			Group 7		
Group	I-2	II-1	I-1	III-2	III-1	III-6	III-5	IV-3	IV-4	II-2	IV-2	IV-1	I-6	III-3	III-4	II-3	IV-6	IV-5
I-2	1.00	0.98																
II-1	0.98	1.00																
I-1	0.93	0.83	1.00	0.92														
III-2	0.73	0.62	0.92	1.00														
III-1	0.51	0.44	0.72	0.92	1.00	0.90	0.75											
III-6	0.09	0.02	0.42	0.71	0.90	1.00	0.92											
III-5	-0.08	-0.22	0.60	0.62	0.75	0.92	1.00											
IV-3	0.06	0.09	0.01	0.50	0.79	0.88	0.65	1.00	0.89									
IV-4	-0.27	-0.16	-0.14	0.06	0.42	0.61	0.37	0.89	1.00									
II-2	0.86	0.92	0.76	0.67	0.64	0.30	-0.02	0.46	0.24	1.00	0.87	0.90						
IV-2	0.61	0.63	0.66	0.77	0.89	0.72	0.42	0.83	0.58	0.87	1.00	0.94						
IV-1	0.56	0.66	0.49	0.53	0.68	0.49	0.12	0.76	0.64	0.90	0.94	1.00						
I-6	0.45	0.24	0.71	0.75	0.54	0.42	0.60	-0.03	-0.46	0.10	0.17	-0.15	1.00	0.94	0.87			
III-3	0.39	0.19	0.70	0.85	0.75	0.69	0.81	0.29	-0.15	0.19	0.39	0.06	0.94	1.00	0.92			
III-4	0.01	-0.20	0.38	0.59	0.54	0.63	0.86	0.19	-0.15	-0.20	0.89	-0.25	0.87	0.92	1.00			
II-3	0.32	0.52	0.03	-0.10	0.01	-0.17	-0.53	0.29	0.46	0.65	0.47	0.74	-0.68	-0.60	-0.84	1.00	0.96	0.79
IV-6	0.23	0.42	0.01	-0.02	0.18	0.07	-0.31	0.52	0.67	0.65	0.60	0.83	-0.67	-0.50	-0.72	0.96	1.00	0.92
IV-5	0.03	0.14	-0.14	0.01	0.30	0.34	0.00	0.75	0.90	0.48	0.62	0.79	-0.64	0.39	-0.51	0.79	0.92	1.00

Figure 2. Representation of octant I of the 3-dimensional respondent space with 3 planes bisecting octant along first, second, and third dimensions.

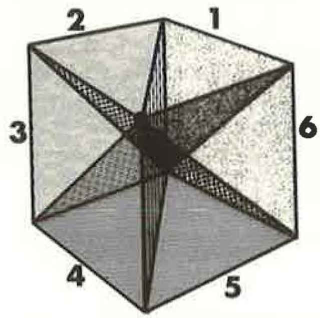
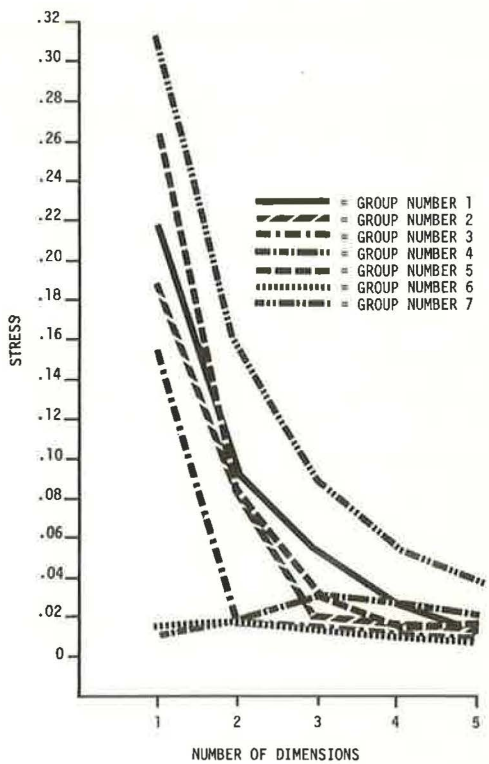


Figure 3. Stress values for 7 homogeneous perceptual groups for 1- through 5-dimensional solutions.



ysis. These estimated judgments are the dissimilarities for each point of view.

Young's nonmetric multidimensional scaling program (33), TORSCA-9, was used to derive Euclidean spaces to represent each point of view. The program accepts data like those described in the preceding paragraph. The details of the computer program are stated by Young (34), and the general principles of nonmetric multidimensional scaling are discussed by Kruskal (19, 20). The objective of nonmetric multidimensional scaling is to find a set of points whose interpoint distances correspond to the order of the dissimilarity judgments for the entities being scaled; in the current application, the entities are the attributes shown in Figure 1. The output from a nonmetric scaling model is a geometric representation of the attributes, in which the distances between them are properly ordered. Thus, the present application of nonmetric scaling provides a picture of each point of view.

The issue of selecting the appropriate number of dimensions for a space is a nontrivial problem for multidimensional scaling, and Kruskal (19) offers 3 criteria to help researchers decide how many dimensions to extract from a set of data. Additional dimensions should be extracted until they fail to appreciably improve the statistical fit of a solution that is already acceptable. The second criterion states that only as many dimensions should be extracted as can be interpreted meaningfully by the analyst. The final criterion is based on the statistical reliability of the data, but it is not used often in practice.

Kruskal (19) proposed a measure of nonmetric goodness of fit, stress, which is widely used. Low values of stress imply a high degree of correspondence between the order of the distances for the geometric representation of the attributes and the attribute dissimilarities for the points of view. A perfect fit to the data would result in 0 stress. A more detailed discussion of stress is beyond the scope of this paper; Kruskal (19) gives a technical presentation of the index.

Figure 3 shows stress as a function of the number of dimensions for 1- through 5-dimensional solutions for each of the 7 homogeneous perceptual respondent groups. The graph for groups 2 and 3 suggest 3- and 2-dimensional solutions respectively because of their "elbow" shape. The stress functions for groups 4 and 6 suggest 1-dimensional solutions since the lowest stress value is obtained at 1 dimension. The stress functions for groups 1, 5, and 7 do not readily suggest a solution in a given number of dimensions, but it was decided on grounds of interpretability to select a 3-dimensional solution for each group. By Kruskal's verbal levels, the goodness of fit was at least fair for all solutions, and groups 2, 3, 4, and 6 had solutions with an excellent goodness-of-fit index. The stress values for all the groups have good metric recovery according to Young's Monte Carlo study (35). Metric recovery measures the degree to which a nonmetric solution corresponds to the underlying distribution when there is error in the dissimilarity judgments.

Groups 1, 3, and 6 will have a detailed analysis of their points of view presented through a discussion of their respective geometric representations. These groups illustrate 1-, 2-, and 3-dimensional solutions. Table 2 gives a summary of the number of dimensions, the labels of the dimensions for each homogeneous perceptual group, and the sample size of each group.

Figure 4 shows the geometric representation of the attributes for group 1; part a shows dimension 1 versus dimension 2, and part b shows dimension 2 versus dimension 3. Dimension 1 contrasts basic transport service with general amenities. Basic transport service includes 4 attributes for group 1: short travel time, arrive on time, many available destinations, and short wait time. General amenities include temperature control and room for strollers. Dimension 2 also appears to contrast 2 sets of attributes. In this case, low fares is at one end of the axis, while attributes that describe personal luxury service are at the other extreme of the axis. The latter class of attributes is defined by private section, comfort and quiet, and temperature control. Dimension 3 differentiates 2 attributes from the remaining ones: safety and automatic vehicle control.

Figure 5 shows the 2-dimensional geometric representation for group 3. Aside from the different number of attributes necessary to typify this group, its multidimensional space is also radically different from group 1 in terms of the arrangement of the attri-

Table 2. Dimension descriptions for perceptual groups.

Group	Sample Size	Dimension Number	Dimension Description
1	114	1	Basic transport service versus general amenities and personal luxury service
		2	Low fares versus personal luxury service
		3	Automatic vehicle control and safety versus other attributes
2	26	1	Basic transport service versus general amenities
		2	Low fares versus personal luxury service
		3	Safety versus refreshments and newspapers
3	26	1	Refreshments and newspapers versus other attributes
		2	Room for strollers and private section versus other attributes
4	16	1	Refreshments and newspapers versus other attributes
5	27	1	Basic transport service versus general amenities
		2	Basic transport service versus personal luxury service
		3	Automatic vehicle control versus other attributes
6	10	1	Room for strollers versus other attributes
7	13	1	Refreshments and newspapers versus other attributes
		2	Automatic vehicle control versus temperature control
		3	Basic transport service versus personal luxury service

Figure 4. Perceptual space for group 1 in 3 dimensions, where stress = 0.54 (dimensions 1 and 2 are respectively horizontal and vertical axes of part a, and dimensions 2 and 3 are respectively horizontal and vertical axes of part b).

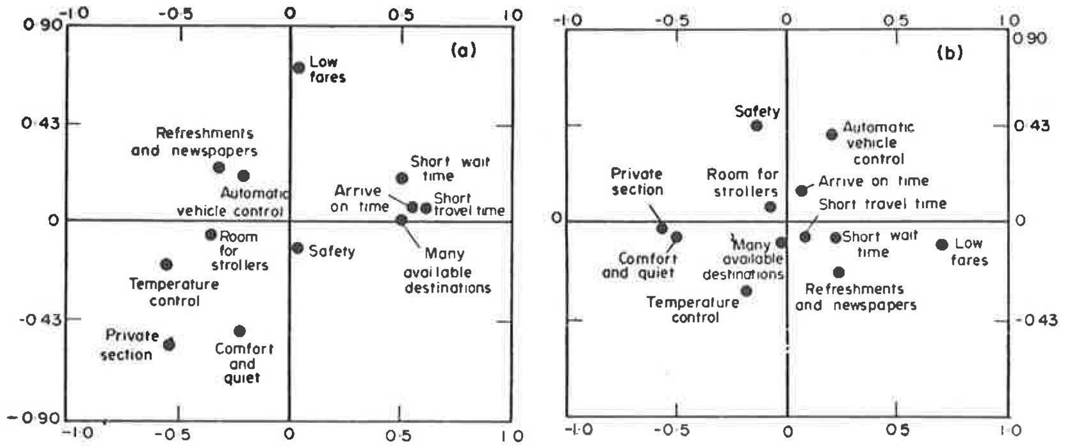
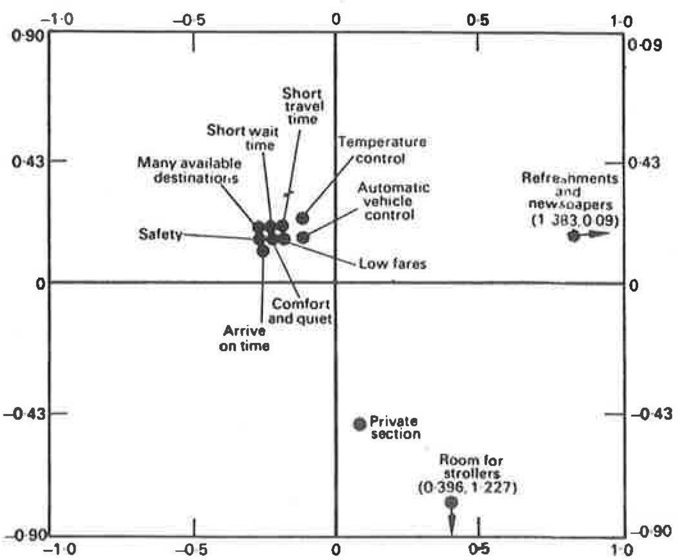


Figure 5. Perceptual space for group 3 in 2 dimensions, where stress = 0.015 (dimensions 1 and 2 are respectively horizontal and vertical axes).



butes. Nine attributes are clustered together tightly near the origin, and the remaining 3 attributes are separated along the 2 axes of the solution. The cluster of attributes contains such a variety that it does not readily suggest a label. The first dimension distinguishes refreshments and newspapers from the other attributes, while the second dimension discriminates room for strollers and private section from all other attributes. This group appears to be quite sensitive to 3 amenities, but it fails to differentiate between basic transport and personal luxury service.

The 1-dimensional representation for group 6 is shown in Figure 6. This group exhibits the lowest degree of differentiation among the attributes. Room for strollers is contrasted with the remaining attributes. There are no other significant distinctions among the attributes. The uniqueness of the viewpoint of group 6 is clearly identifiable from this points-of-view analysis.

The other 4 groups were distinguished from each other in ways similar to groups 1, 3, and 6. For example, group 4, like group 6, also exhibited a 1-dimensional solution. However, its sole axis discriminated refreshments and newspapers from all other attributes. On the other hand, the dimension descriptions for groups 1, 2, and 5 are similar (Table 2), and data given in Table 1 corroborate the similarity of the 3 groups from the first stage of the points-of-view analysis.

Across the axes of the perceptual spaces for the 7 groups, 3 major classes of attributes can be defined: basic transport service, personal luxury service, and general amenities. Particular attributes were contrasted occasionally with all other attributes or a more select set of attributes. This latter set of particular attributes included automatic vehicle control, safety, low fares, and room for strollers. When the axes of a space contrasted attributes, as was frequently the case, meaningful pairs were often placed opposite each other. For example, personal luxury service was contrasted with basic transport service and low fares. Finally, when attributes or sets of attributes were paired with each other, they formed generally meaningful liaisons. Instances of the latter type of pairs include general amenities and personal luxury service for group 1 and room for strollers and private section for group 3.

Relation of Viewpoints to Mode Satisfactions

Respondents in the MADS survey also rated 3 transportation modes for their anticipated satisfaction with respect to the 12 attributes shown in Figure 1. The details of the procedure are described by Dobson (11). To facilitate an understanding of the analysis that follows, brief descriptions of the 3 modes are given. Dual-mode transit vehicles are small, bus-like, and demand-responsive vehicles that drive along regular streets to an automated guideway where they go under remote control. People-mover vehicles are larger, bus-like vehicles that operate on a regular schedule, travel only on an automated guideway, and must be boarded at a station. Personal rapid transit vehicles travel on an automated guideway, must be boarded at a transit station, and provide point-to-point service to all stations on the guideway network for a party of no more than 4 passengers.

Two kinds of correlational analyses were performed to determine the relations between the satisfaction ratings of the homogeneous perceptual groups and their corresponding viewpoints. Both analyses required the averaging of satisfaction ratings with a mode for the members of a group. This preliminary processing resulted in 21 vectors of satisfaction ratings; each of the 7 groups had 3 vectors for the 3 modes in the investigation. The first analysis was the multiple linear regression of the 3 vectors for each group against the coordinates of the attributes in the groups' perceptual space. The output selected for interpretation from this analysis was the multiple correlation coefficient. In the case of groups 4 and 6, both 1-dimensional groups, the output was a simple correlation coefficient. The second analysis was the simple correlation of the satisfaction vectors for a group with the projection of the attributes along each dimension of the corresponding group's perceptual space. The simple correlation coefficients from this analysis as well as the multiple correlation coefficients from the other analysis are given in Table 3.

Table 3. Correlations of perceptual spaces for groups with satisfaction ratings for transportation modes.

Group	Number of Dimensions	Vehicle	Simple Correlations: First Dimension	Second Dimension	Third Dimension	Multiple Correlation
1	3	Dual-mode transit	0.847	0.081	0.313	0.906[a]
		People-mover	0.874	0.180	0.339	0.916[a]
		Personal rapid transit	0.631	-0.321	0.234	0.884[a]
2	3	Dual-mode transit	-0.747	-0.127	-0.641	0.926[a]
		People-mover	-0.752	0.020	0.526	0.851[b]
		Personal rapid transit	-0.476	-0.647	0.536	0.952[c]
3	2	Dual-mode transit	-0.823	0.498		0.859[a]
		People-mover	-0.890	0.357		0.892[c]
		Personal rapid transit	-0.661	0.493		0.725[b]
4	1	Dual-mode transit	-0.541			0.541
		People-mover	-0.635			0.635[b]
		Personal rapid transit	-0.699			0.699[b]
5	3	Dual-mode transit	-0.686	0.307	-0.466	0.794[b]
		People-mover	-0.496	0.670	-0.321	0.807[b]
		Personal rapid transit	-0.546	0.116	-0.609	0.764
6	1	Dual-mode transit	-0.677			0.677[b]
		People-mover	-0.459			0.459
		Personal rapid transit	-0.796			0.796[a]
7	3	Dual-mode transit	-0.445	-0.271	-0.130	0.532
		People-mover	-0.357	-0.224	-0.753	0.832[b]
		Personal rapid transit	-0.397	0.142	-0.372	0.557

[a] $p < 0.01$. [b] $p < 0.05$. [c] $p < 0.001$.

Figure 6. Perceptual space for group 6 in 1 dimension, where stress = 0.015.

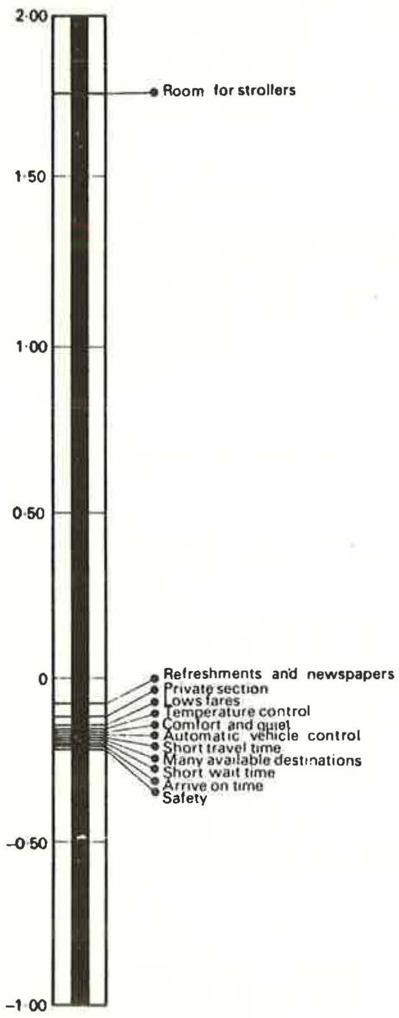


Table 4. Variables ordered by chi-square values for independence among perceptual groups.

Variable	χ^2/d.f.	Probability	Proportion of Cells Less Than 5
Trip type	2.443	<0.05	0.07
Sex	2.114	<0.05	0.14
Income	2.017	<0.05	0.57
Age	1.679	<0.10 >0.05	0.64
Education	1.630	>0.10	0.21
Race	1.228	>0.10	0.21
Number in household	1.227	>0.10	0.14
License possession	0.982	>0.10	0.21
Number of cars	0.586	>0.10	0.14
Type of housing	0.310	>0.10	0.36
Marital status	0.276	>0.10	0.14
Use of transit	0.263	>0.10	0.21

The multiple linear correlation coefficients indicate the degree to which the perceptual spaces for the homogeneous groups relate to their corresponding satisfaction ratings. Most of the multiple correlation coefficients are significant by traditional criteria, and others approach statistical significance. Satisfactions with different modes are nearly equal in their relation to the perceptual spaces. The root mean square of the multiple correlation coefficients across the 7 groups for dual-mode transit vehicles, people-mover vehicles, and personal rapid transit vehicles are respectively 0.764, 0.785, and 0.777.

The differences are more pronounced between the homogeneous perceptual groups than between the modes. The root mean squares of the multiple correlation coefficients across the 3 modes are the following for the first through the seventh group: 0.902, 0.911, 0.828, 0.628, 0.788, 0.659, and 0.654. The 4 groups with the largest root mean squares all had 2- or 3-dimensional perceptual spaces, while 2 of the lowest 3 root mean squares were obtained for groups 4 and 6, both of which had 1-dimensional perceptual spaces. The only group to have a relatively low root mean square and a 3-dimensional perceptual space was group 7, which also had an abnormally large stress value (Fig. 3).

The simple correlations between attribute projections on particular dimensions of the perceptual spaces and the satisfaction ratings for the modes reveal which sets of attributes are especially important in accounting for satisfaction with the modes. Groups 1 and 2 have their largest correlations between their satisfaction ratings for dual-mode and people-mover vehicles with the first dimension, which contrasts basic transport service with general amenities. Both of the latter vehicles are viewed as providing a more basic sort of transport service than that provided by the personal rapid transit mode. The largest correlations for group 3 are not readily interpretable. Group 4 has strong correlations between a dimension that distinguishes refreshments and newspapers and the 2 modes that may only be accessed from a transit station, where these items can be purchased. Group 6 shows a similarly significant relation between a dimension that discriminates room for strollers from the other attributes and the 2 modes that are more likely than is a people-mover vehicle to have the space.

There are a number of other correlations that are generally somewhat smaller in magnitude, but they are nevertheless subject to interesting interpretations. For example, the correlation between the second dimension of the perceptual space for group 2, which contrasts low fares and personal luxury service, is much higher for personal rapid transit vehicles than for the other 2 modes. The same type of linkage is shown also for the second dimension of group 1.

Relations of Perceptual Groups to Socioeconomic and Activity Pattern Variables

Although it is not necessary for groups formed on the basis of similarity judgments concerning the transportation attributes to map perfectly into arbitrary segmentations of the sample for socioeconomic and activity pattern variables, it is natural to expect some correspondence among the alternative means of dividing the sample. In fact, when there is a correspondence between a perceptual and a socioeconomic segmentation of a sample, the agreement between the 2 ways of partitioning the sample signals the greater substantive significance of both segmentations.

To help identify segmentations of greater substantive significance, we divided the sample into 2 or 3 groups on the basis of 12 socioeconomic and activity pattern variables. These groupings were cross-tabulated in turn with the 7 homogeneous perceptual groups, and a chi-square value was computed for each of the 12 contingency tables. Table 4 gives the socioeconomic and activity pattern variables in the order of magnitude of their corresponding chi-square values divided by the appropriate degrees of freedom. Since some of the sample sizes for the perceptual groups were rather small, the proportion of expected cell frequencies less than 5 exceeded 0.20 for 7 variables. Although the latter condition makes it impossible to test statistical significance for these variables, the $\chi^2/d.f.$ value can be interpreted as a descriptive statistic that reveals, to some degree, the dependence between the grouping on perceptual similarity judgments and the grouping on the socioeconomic or activity variable being cross-tabulated with it.

By the above reasoning, the first 2 variables given in Table 4 are strongly related to the perceptual grouping of the respondents; the relations are also statistically significant by conventional criteria. Trip type, the variable with the largest χ^2/d.f. value, refers to whether the respondent makes at least 1 work trip per week. This variable is significantly related to the sex of the respondent ($\chi^2 = 44.90$, d.f. = 1, $p < 0.01$), and the 2 variables therefore identify a common factor for socioeconomic and activity pattern variables. Other variables that are related to the perceptual grouping include income, age, and education. An analysis of importance ratings by a mail panel to a similar but larger set of public transit attributes also found sex, income, and age to be related in a significant way to the attitude of the respondents (9). The variable that showed the weakest relation to the perceptual grouping was use of transit. Current use of public transit does not exert a great influence on the point of view that individuals have toward public transportation attributes.

The distribution of the socioeconomic and activity pattern variables reinforces interpretations of group viewpoints. For example, the sixth group made the smallest percentage of work trips; 90 percent of its members did not make at least 1 work trip per week. This group separated room for strollers from the other attributes to form its unidimensional perceptual scale, which emphasized an attribute not at all important for work trips. The fourth group, which emphasized a general amenity to form its unidimensional perceptual scale, had the largest percentage of females. Two previous investigations (9, 10) have noted that females show a preference for general amenities in public transit systems. These correspondences support the validity and significance of the perceptual groupings reported above.

DISCUSSION OF FINDINGS

The major objective of the reported investigation was to demonstrate the usefulness of disaggregating a sample of respondents according to the viewpoints of individuals in the sample. The merits of the technique have been established with respect to 3 criteria. It has been possible to identify 7 distinct points of view. These viewpoints were shown to have a statistically significant relation to satisfaction ratings with new modes of a proposed automated urban transportation system. Finally, membership in the homogeneous perceptual groups uncovered by the analysis was found to covary with socioeconomic variables known to be related to preferences for public transit attributes from previous empirical investigations.

A new result, for the transportation research literature, is the success of nonmetric multidimensional scaling for analyzing subjective evaluations of attributes. A previous application of 1 nonmetric scaling model was considerably less successful (10). Several factors distinguish the 2 studies and deserve further empirical research. The earlier application scaled preference judgments with an unfolding model, which attempts to embed respondents and attributes in a common perceptual space, but the current application used a nonmetric distance model to embed only attributes within a space. The previous investigation was based on an aggregate analysis of a sample; in the current study, the sample was disaggregated before an attempt was made to uncover the relations among the attributes. Furthermore, in the current analysis, the data base was designed to be suitable for multidimensional scaling models, while the previous analysis attempted to transform the data to make them suitable for the unfolding model.

The success of Cliff's variation of the Tucker-Messick individual-differences scaling model in forming homogeneous perceptual groups and then subsequently identifying their point of view prompts a concern for, among other interesting research issues, the new insights that might be gained by alternative individual-differences scaling models. One class of these alternative models has been discussed by Bloxom (1), Carroll and Chang (4, 5), Horan (18), and Tucker (30). These authors all describe individual-differences scaling models that assume a group space that is transformed to represent specific viewpoints by different kinds of linear transformations. Although the latter class of models is superior to the Tucker-Messick approach in that the commonality between different points of view is explicitly indicated, the authors of these models fail to address specifically the means by which to identify which respondents share a viewpoint prior to determining the dimensions of that point of view. After the resolution of this clustering issue, the alternative models appear to offer an attractively different way for investigating similar research topics. In fact, the authors are currently preparing a companion paper to this one that compares Carroll and Chang's INDSCAL model (5) to the Tucker-Messick model.

The ultimate goal of research designed to assess attitudes toward urban transport alternatives is the development of prediction equations that relate perceptual and evaluative judgments, such as those studied in the current investigation, to behavior patterns resulting from modifications of the urban transport alternatives available to an individual. The current investigation has been centered primarily around the linkage between perceptual similarity judgments and satisfaction ratings for innovative urban transport modes. Nevertheless, membership in the homogeneous perceptual groups was found to be sensitive to at least 1 activity pattern variable that undoubtedly influences travel behavior. This connection between whether an individual makes a work trip and the point of view for attributes of transport modes interfaces the current investigation with the goal stated above.

The methodological and substantive outcomes that are reported have several immediate implications for the urban transportation planning process. Since individual-differences scaling models specify points of view for different segments of the population, they provide the transportation planner a means for identifying the potential impact of modifications to the urban transportation system for groups of particular interest to the policy-maker. Perhaps as important, these models provide a means for testing whether groups selected as interesting on a priori grounds are really unique in their viewpoints toward the system. With respect to the issue of travel demand estimation, the demand for travel to various destinations by specific modes is likely to vary in a manner that is related to the interface between system design features and an individual's point of view about those features. Therefore, a points-of-view analysis allows the transportation planner to identify which system design modifications will alter the travel demand of specific segments of a heterogeneous urban community.

The significance of the investigation reported here can be judged by the new knowledge that it contributes to attitude-behavior relations with regard to urban transport alternatives and by the number of new analyses and applications that are generated by it. One major finding is the identification of 3 classes of attributes that influence satisfaction with transportation modes. Also, the current investigation has determined a variety of different points of view toward attributes of urban transport alternatives. An incipient link is reported here between individual viewpoints and actual urban travel behavior. Additional quantitative relations between attitudes and behavior for urban travel patterns need to be uncovered so that attitude-behavior relations can play a meaningful role in the urban transportation planning process.

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TOWARD THE DEVELOPMENT OF MEASURES OF CONVENIENCE FOR TRAVEL MODES

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This paper describes a research project aimed at investigating the effect on disaggregate, behavioral, modal-choice models of the inclusion of 2 alternative measures of convenience. The 2 measures investigated compare a proxy variable for convenience, which could be included in many existing models without further data collection, and a scale index that was developed from the use of psychological scaling techniques, which will require longer term development and additional data collection. Both measures correlated highly with travel mode choices, although data limitations prevented any actual model building with the scale index. The proxy variable for convenience was found to add significantly to the explanatory power of a modal-choice model and to improve substantially the specification of the model. This paper describes the data sets used to generate these results and discusses the analytical processes used to derive scale information from preference and attitude data. A survey of previous work in the topic area, which is also included, shows that this paper reports on one of the first successful attempts to incorporate a measure of convenience in an urban modal-choice model.

•THIS PAPER describes a research task concerned with providing 3 products relating to measures of convenience for urban travel modes. The first product is an inventory of previous work concerning both comfort and convenience and an assessment of the effectiveness of such efforts in producing a quantifiable convenience variable for inclusion in a travel demand model. Second, the research is intended to provide a theoretical basis for defining and quantifying convenience. Third, the research is to produce prototypical measures of convenience. One of these measures would be of immediate practical use, and another would require a longer time to develop but might provide a more conceptually satisfying and more accurately measured convenience variable. During the research, some data collection was carried out and detailed analysis was performed on some preexisting data sets.

A search of the literature revealed that previous attempts to postulate comfort and convenience variables can be grouped into 3 general categories. The first category does not lead directly to the definition of a variable per se, but is rather a mechanism for determining whether comfort and convenience are important variables. This is done by asking open-ended questions designed to elicit information on the level-of-service characteristics that individual travelers consider to be important. Such questions, however, lead to unstructured responses and a tendency to produce superficial attitudes and opinions rather than stable preferences. Nevertheless, a number of the early studies used this approach. Stopher (23) provided an open-ended question in his survey of faculty and staff of University College, London. From this, using a simple counting procedure (order of reporting of attributes was considered to be irrelevant), he defined time, convenience, cost, and comfort as being the most important

*When this research was performed, Mr. Stopher was at Cornell University.

modal attributes affecting choices of travel modes for the work trip. Because there were no techniques at that time to handle convenience and comfort in a quantitative model, this study developed models in terms of costs and times of travel only. Similarly, Bock (1) established, by this mechanism, that both comfort and convenience were among the most important modal attributes affecting choices between travel modes, but was unable to include quantities relating to these attributes in a travel demand model. Sommers (20, 21) also used the same technique, but then went on to use the second category approach.

This second approach is a simple ranking procedure in which a number of travel mode attributes are presented to the survey respondent, who is asked to rank order those attributes in the context of a specific mode use. This technique is better structured and provides less encouragement to a superficial response than the open-ended question. However, it depends for its worth on the analyst's listing of qualities or attributes and the nonambiguity of the description of those terms. There is also a tendency to lead the respondent to a bias because of the inclusion or omission of specific attributes and because of the order in which the attributes are presented to the respondent. The technique, similar to the first category approach, was used only to estimate the order of importance of various attributes. For example, Sommers (22) found the rank order of attributes to be time, convenience, comfort, safety, weather reliability, cost, noise, and mechanical reliability. It is interesting to note the similarity between this ordering, which was obtained for the author's workplace in the northeast United States, and the ordering from Stopher's survey at a university in central London. Neither study, however, leads to a quantification base for comfort or convenience.

The third category of approaches to working with modal attributes stems from the nonquantification from the first 2 categories already described. This category may be summarized as the application of psychological scaling techniques to modal attributes. A large number of approaches and techniques are available within this general category, and many of these are in their infancy both in general and in specific applications to transportation. The most extensively used data collection technique for scaling models in transportation applications is the semantic differential. This technique involves questioning respondents about a quality and requesting an answer on a numerical scale representing the range between 2 extreme adjectival phrases. In general, the scale is divided into 5 or 7 intervals; the central interval denotes impartiality, lack of preference, or indifference. The following might be a response scale for a typical question, How do you rate the level of service offered by your local bus service?

1	2	3	4	5	6	7
very satisfactory				very unsatisfactory		

This technique has been used extensively in attempts to quantify travel attributes or at least to rank order them. The earliest application appears to have been by Sommers (20) in an attempt to determine the market for a short-haul air service based on V/STOL. However, no quantification of hitherto intangible mode attributes was reported from this study; rather, the technique was used to produce rankings of attributes only. At the same time, a national survey was conducted for the Highway Research Board (8) of attitudes about modes of travel. Again, the semantic differential was used both for degree of satisfaction with each of the automobile and public transportation modes for 15 transportation attributes and for ranking these same attributes in order of importance. Convenience, per se, was not included in the list of attributes. The 7 most important attributes were found to be safety, reliability, independence, transfers, protection from weather, crowding, and comfort. In all of these attributes, the automobile scored more satisfactorily than public transportation.

A further use of the semantic differential technique was at the University of Maryland (16) in a survey that was designed originally to determine the most important modal attributes. To this end, attributes were ranked and factor analysis was performed on the attribute rankings. This led to the definition of major factors relating to reliability, travel time, weather exposure, cost, convenience, unfamiliarity, and state of the vehicle. This same data set was subsequently used by Hartgen and Tanner (7) to quantify attitudes and incorporate them in a modal-choice model. They hypothesized that modal choice is determined by a traveler's degree of satisfaction with a modal attribute, weighted by his order perception of the importance of that attribute for the specific trip. Because of limitations in the data base, the model was not conspicuously successful. However, the results obtained were sufficiently good as to suggest that further investigations along this approach would be worthwhile and also that work should be done to relate engineering and attitudinal measures.

If the semantic differential is used to provide the type of indexes postulated by Hartgen and Tanner, the following assumptions must be made: The respondent has knowledge of the absolute position of an attribute on the psychological continuum, the questions on attitude and the adjectival phrases used on the scale are unambiguous to all respondents, and the same scale extremes are used for all attributes since different adjectival phrases cannot be equated. The first of these assumptions is not theoretically acceptable, and the second and third present operational problems.

A second data collection technique—paired comparisons—has also been applied to transportation modeling. Like the semantic differential, this technique has been used primarily for unidimensional scaling models. (The difference between unidimensional and multidimensional scaling is discussed later in this paper.) With this technique, a respondent is asked to make a series of trade-offs between pairs of specific qualities of some entity, such as a trip or a travel mode. The technique has had little use, so far, in transportation work; the primary instance, which is discussed later in this section, was by Golob et al (6). There are several variations on this technique, but all have a similar analytical interpretation. In the simplest case, a respondent may be asked,

> In respect to this bus ride, which would you rather have (assuming you could have only one):
>
> | | | |
> |---|---|---|
> | A faster trip | or | a more frequent service? |
> | A quieter ride | or | a wider seat? |

Some researchers, as noted by David (4), have claimed that bias may arise because of the ordering of the elements of a pair and of the set of pairs. Therefore, the ideal questioning procedure would provide every permutation of the attributes, taken 2 at a time and in random order, where the random order may be different for each respondent. Whether or not this avoidance of bias is elected, all combinations of the attributes should be included in the overall design. [A note on paired-comparison designs is included in this paper. Torgerson (29) presents several methods of treating incomplete data matrices by Thurstone's law of comparative judgment.] A rank ordering can then be obtained by determining how many times one attribute is preferred over others and how many times it is rejected. Using all permutations permits consistency checks and bias checks to be made for each respondent. Rank orderings are best obtained for aggregate groups rather than for individuals.

Questioning may also be carried out by generalizing for an attribute and questioning on mode preference, e.g.,

> In terms of quietness of ride, which do you prefer:
>
> | | | |
> |---|---|---|
> | Automobile | or | bus? |
> | Subway | or | elevated? |

The same remarks apply as before concerning the structuring of the pairs and the initial analysis. Fuller details of the analytical procedures used for obtaining scale intervals are discussed later in the paper.

Golob et al. (6) used semantic differences and paired comparisons to assess the importance of the attributes of a new service (or mode)—the jitney taxi—to a specific community. No attempt was made in this research to quantify comfort or convenience parameters or to build forecasting models. Its major impact on the present research into convenience is the innovative use of unidimensional scaling in a transportation choice problem.

A number of other scaling techniques are available, particularly in multidimensional scaling. Since none of these techniques has been used thus far in transportation applications, they will not be discussed in this section. However, some note was taken of them in following the research reported here, and some discussion of them is given in a later section on the methodology adopted in this study.

Apart from the studies already mentioned, a number of researchers have noted an intuitive expectation that comfort and convenience are likely to be important factors in transportation demand analysis, and some have put forward suggested procedures for quantifying these attributes. Claffey (3) hypothesized that both attributes would be important in mode choice and suggested that serious consideration be given to research in this. More recently, Lave (11) and Hoel and Demetsky (9) reiterated this sentiment and put forward suggestions for how to do it. The suggestions of Lave are particularly pertinent and comprise a prescription for simultaneous measurement of traveler attitudes and corresponding physical and engineering attributes in an attempt to develop variables of comfort and convenience that may be computed from the physical specifications of a travel mode. Lansing, Mueller, and Barth (10) implicitly recognized the importance of comfort and convenience by including questions relating to them in their journey-to-work survey. They did not carry out any analytical work on these attributes, however.

Some further attempts at quantifying comfort and convenience should be noted. Bock (1) used integer values as dummy variables to describe the comfort and convenience of modes of travel. The values used were based partly on attitudinal survey results and partly on intuition; they are 1 for automobile, 2 for railroad, 3 for subway, and 4 or 6 for bus. The effectiveness of these values in the modal-split models was minimal. Lave (11) and Parker and Clark (17) attempted to add comfort and convenience through an implicit value of travel time by permitting (or forcing) this implied value to be different for different modes of travel. The disadvantages of these 2 approaches are the arbitrariness of the values used and the lack of responsiveness to service quality changes or new travel modes. Finally, Watson (31) proposed a convenience measure, comprising the number of journey units in a trip. A journey unit is defined as being each separate modal usage, walk, or wait involved in a trip (where each occasion of mode use, walking, or waiting is counted with a value of unity). In his intercity study, Watson found the journey-unit difference to be one of the most significant variables for explaining mode choice, more significant than cost difference and generally equal to time difference.

DEFINITIONAL PROBLEMS

There are at least 2 reasons for the general lack of success, so far, in quantifying comfort and convenience attributes of travel modes. First, the techniques used to date have been somewhat inappropriate or unresponsive to the requirements of quantification. Second, a comprehensive definition of either convenience or comfort has been lacking. It is most probable that each individual respondent to a transportation survey defines comfort and convenience in an individual fashion. Consequently, those studies that used the terms "comfort" and "convenience" without prior definition have, in fact, gathered data on ambiguous qualities of transportation. Therefore, the apparent failure of past efforts to quantify comfort and convenience and to include these quantities in travel demand models are very likely due to this lack of definition of the attributes.

Claffey (3) defines convenience as being "greatest when users least have to adjust their personal plans and living habits to use transit, and when the difficulties of getting to transit stations and aboard transit vehicles are minimized." Sommers (20, 21, 22) does not explicitly define convenience in any of his papers. However, he implies quite strongly that he defines convenience as the number of origin and destination connections, i.e., a function of the number of transfers. Bock (1) cites convenience as being made up of "convenience; inconvenience; flexibility; mobility; independence; no schedule; easy, simple, practical; lack of flexibility; lack of mobility; and lack of independence." Most of these terms, however, are still broad and ambiguous and provide little help in defining convenience.

Solomon et al. (19) summarize numerous studies that are concerned with determining factors that affect travel choices. By averaging overall studies, these authors determine the most important factors to be safety, reliability, time savings, and convenience respectively. They define convenience as comprising waiting, transferring, parking, and fare collection. Hartgen and Tanner (7) noted that the University of Maryland data, which they used, defined convenience as "avoiding walking more than a block." Golob et al. (6) define convenience as being made up of "having a seat, calling without delay, shelters at pickup, choose pickup time, easy fare paying, more phones in public places, ability to ask questions of a system representative, and coffee, newspapers, and the like on board." These authors also define a level-of-service variable that comprises "arriving when planned, no transfer trip, less wait time, longer service hours, less walk to pickup, direct route, and dependable travel times." Finally, Watson (31) defines convenience as the number of journey units in a trip, i.e., as a function of the number of transfers.

Clearly convenience has not been defined in unambiguous terms and with adequate breadth to cover all situations. An attempt to provide such a definition was made in this study. Modal attributes are defined in the following manner. A trip may be considered to possess 4 principal attributes: safety, cost, comfort, and convenience. Safety relates to the likelihood of harm from accidents while the traveler uses the system; cost is the monetary outlay by the traveler; comfort refers to the environment in which the trip is made, the extent to which a trip may be enjoyed or not; and convenience refers to the efficiency and effectiveness with which a person can be transported from origin to destination.

Thus, convenience includes all time attributes of a trip (access, egress, line-haul, walking, waiting), reliability (the variance associated with travel time), and level of service (number of transfers required, availability and proximity of parking or boarding points). Since conventional travel models have included travel times as explicit quantified variables, the primary concern of this research was to provide a means of assessing the remainder of this definition of convenience and to attempt quantification of reliability and level of service as defined here.

RESEARCH APPROACH

The task of determining a convenience measure may proceed on at least 2 levels. The first level is to propose a simple proxy measure of convenience, which may be readily determined in new data collection or from existing travel data and which may be incorporated immediately in travel-choice models. Because of the breadth of the convenience definition already put forward, such an approach must be suboptimal with respect to the content of the variable. However, it may be optimal in terms of both cost and ease of use. The second level is to use psychometric scaling methods with survey responses to define an index of convenience and then incorporate such a measure in future model building. Both of these approaches have been adopted in this research task.

In the first-level definition of convenience, the journey-unit measure proposed by Watson (31) was adopted. As mentioned before, this measure comprises simply a count of the number of journey units in one complete trip, where a journey unit is defined as each part of a trip that involves a change of mode or travel activity. Thus, a trip that comprises a walk to the suburban station, a commuter train ride, a downtown bus ride, and a walk to the office has the following journey elements: walk, wait, rail ride, walk, wait, bus ride, walk. The total number of elements is 7, and this would be the value of the journey-unit variable for this trip. Compared with this, an automobile trip might comprise walk, car ride, park, walk. Thus, the automobile trip has a journey-unit variable value of 4.

The convenience rating is one that increases with decreasing convenience, and might more appropriately be labeled an inconvenience factor. In the intercity study conducted by Watson, the journey-unit difference was found to enter the modal-choice models significantly and provided a high degree of "explanation" of the variance of actual travel choices. This research is the first test of this variable in an intracity context. The journey-unit difference, however, may produce a variable that, rather than measuring just inconvenience, measures discomfort, additional time taken, and inconvenience of transfers.

The second approach is based on the use of psychometric scaling techniques to provide the data needed to derive an index of convenience. The precise way in which scaling techniques are used to do this is described in the next section.

It is hypothesized that the traveler's decision process regarding choices, particularly of travel modes for a particular trip, is based primarily on his or her perception of the differences between alternative modes with respect to specific attributes, weighted by his or her perception of the relative importance of each attribute for the particular trip. It is further postulated that the relative ranking of modes on the basis of some modal attribute is a function of a real difference that exists between the modes. In other words, it is assumed that perceived differences are a function of real differences. It is also assumed that the perceived importance of the attributes themselves will be a function of personal characteristics of the traveler and his or her trip purpose.

On the basis of these assumptions, an index can be defined for measuring the relative importance of 2 or more modes, or other choices, with respect to a generalized attribute of convenience. Such an index could be expressed mathematically as

$$I_m^i = \sum_j w_j^i x_{jm}$$

where

x_{jm} = scale value of mode m along the continuum of rankings of all the modes for the jth attribute and is a function of x_{jm}^*, where x_{jm}^* is some measurable system attribute that affects the perception of the relative ranking of the modes (11);

w_j^i = weight that individual i attaches to attribute j relative to other attributes of the travel modes; and

j = attribute number, taken from a limited set of attributes.

Thus, the convenience index is defined for each individual i as being the sum over all attributes of the products of the attribute weight and the attribute rank for each mode. Within the modal-choice model, or other travel-choice model, the indexes for 2 modes could be entered as ratios, as differences, or in any other relative mathematical form desired by the analyst.

The task of the research is to determine the values of w and x in the above formulation. The formulation implies that the weight assigned to an attribute, w_j^i, is independent of the mode, m, and the ranking of the attribute, x_{jm}, is independent of the individual, i. These are somewhat important fundamental assumptions that are necessary in order to be able to proceed further.

SCALING METHODOLOGY

Two primary scaling approaches could be considered for this research: unidimensional and multidimensional. In simple terms, unidimensional scaling is based on the assumption that the stimulus (convenience in this case) may be represented as point values on a line, where each mode or submode has one value. In other words, convenience is represented as a 1-dimensioned attribute like cost or time. In contrast, multidimensional scaling assumes that the stimulus (convenience) is represented as a point in a space of several dimensions. Thus, it is assumed that the stimulus may vary simultaneously in several dimensions. Regardless of which method is used, the index product will be formulated identically. In fact, it is possible to generalize and say that multidimensional scaling is an extension of unidimensional scaling, which provides more information about the stimulus by relaxing dimensionality constraints. Dobson et al. (5) demonstrated that, in at least one practical application, the unidimensional solution was consistent with a multidimensional solution, thus demonstrating that the methods are complements rather than competitors.

Nevertheless, the multidimensional scaling approach involves a more extensive data analysis phase. Therefore, the simpler and more efficient (from the analysis viewpoint) method of unidimensional scaling was used for this research task. Unidimensional scaling generally requires the use of semantic differences and paired-comparison questions to provide the attitudinal data from which scale values will be derived. Multidimensional scaling is used generally for similarity (or dissimilarity) questions, such as,

> In terms of quietness of ride, which of these 2 pairs of travel modes are more alike:
>
> Automobile and bus or subway and railroad?

Thus, it is clear that further research into multidimensional approaches to quantifying convenience can be conducted and still use the results of this present work.

Although the questioning procedures for paired comparisons have already been described, the derivation of scale values from the results of the questions has not been discussed. Before that discussion, however, some further points concerning survey designs using paired comparisons should be considered.

Modal rankings and scale values are required for the unidimensional approach used in this research. Although rankings can be derived easily from paired comparisons, it is advisable to obtain rankings also with a technique such as semantic differences. This provides an important consistency check on the results. There are then several versions of the paired-comparison method, whose applicability depends on the subject of the survey. Two basic designs are possible—complete and incomplete. A complete design is one in which all possible permutations of attributes, or objects, taken 2 at a time, are judged. An incomplete design is one in which some subset of permutations is not included. In this application, each order of each pair represents a separate permutation. The case in which all combinations of attributes taken in pairs are judged is a special instance of an incomplete design. In addition to the design, response sampling may also be single judgment or multiple judgment. In single-judgment sampling, each judge (or respondent) is asked to compare a single ordered pair of attributes; in multiple-judgment sampling, each judge is asked to compare a set of pairs, as specified by the design. In the use of paired comparisons for the type of work involved in this research, only multiple-judgment sampling is practical.

In a multiple-judgment sample, the problem of respondent fatigue becomes important. Bock and Jones (2) suggest that an upper limit of 50 judgments should be anticipated, even for highly motivated respondents. Beyond this limit, although responses may still be obtained, irrationality of decision will become evident and the responses will be worthless. This maximum number of comparisons implies a maximum of between 9 and 10 attributes for a complete design. Therefore, one of the major uses of incomplete designs is to provide a means by which a population of judges can be asked to provide comparisons on a larger set of attributes than this limit implies for complete designs. Specification of the appropriate design for a particular study is, however, highly dependent on the application and the number of attributes to be considered. David (4) gives an excellent discussion of incomplete designs.

The results of a paired-comparison survey can be converted into a linear scale by a number of techniques, based on Thurstone's law of comparative judgment (28, 29). A number of cases have been developed from this law. They make various assumptions about the homogeneity of the population and the distributions of expected responses to paired-comparison questions. The most well-known cases are documented by David (4) and Bock and Jones (2). However, without additional information on choice responses, the only feasible case that can be applied is case V.

The application of case V to paired-comparison data requires that 2 basic assumptions be made about the individuals who are surveyed.

1. The sample population is homogeneous with respect to its familiarity with the stimulus, and
2. The discrepancy in preference among individuals in the placement of the stimulus along the continuum is due to fluctuation in the discriminal process of the group (this

fluctuation is assumed to be normally distributed with a mean value located at the scale value of the stimulus along the continuum).

It is, therefore, clear that the scale values derived are aggregate values for a population or subgroup of a population and cannot readily be derived for single individuals, unless they are asked to repeat judgments on several discrete occasions.

To use the method of paired comparisons requires that, to fulfill the assumptions of Thurstone's case V, a survey population be selected that is relatively homogeneous with respect to both perception of the relative importances of the attributes and perception of the mode ranking for each attribute. Since it is also assumed that mode ranking for each attribute is a function of some real difference in the modes themselves, one may argue that individuals who have used the same modes are homogeneous in their knowledge of the characteristics of these modes. Therefore, the sample must first be grouped on the basis of a commonality of knowledge about a particular mode before a paired-comparison survey is undertaken.

The assumption was also made that attribute ranking is based on the characteristics of the individual making the comparisons. This poses somewhat greater problems for adequate measurement. However, selection of a common trip purpose and socioeconomic grouping of the individuals should effectively provide homogeneous groups for the analysis of attribute weightings. In the full-scale application of this methodology, the analysis may have to be refined at some point by investigating in more detail the extent of homogeneity of responses among different socioeconomic groups within a single trip-purpose category, and the disparities between trip purposes may also have to be determined.

"WATSON" METHOD

The intention of the task reported in this section was to determine the feasibility of "reconstructing" journey-unit data for existing data sets and to determine the usefulness of a journey-unit difference in a modal-choice model for existing data sets. Two data sets were chosen for this work: the Greater London Council journey-to-work data, collected by Stopher (26) in 1966, and the Skokie journey-to-work data, collected by Lisco (12) in 1964. The London data set comprised 1,315 usable observations, and the Skokie data yielded 211 usable observations.

For each observation of each data set, the reported and alternative trip details were analyzed and journey units were assigned on the basis of one for each of the separate elements, as defined earlier. Original survey information was available for the Skokie data so that journey units could be determined in an accurate manner. For the London data, however, it was necessary to infer from transportation maps the most probable trip structure that conformed with the reported trips. Thus, the journey units assigned to that data set are likely to be somewhat inaccurate for some respondents. Furthermore, the home addresses of those respondents (i.e., the trip origins) were coded to London traffic districts, containing an average population of 40,000. Thus, some considerable aggregation error is likely to have been incurred in calculating journey units for those data.

For each data set, several models were constructed by using the logit form [Stopher and Lavender (27) give a description of the logit method and a justification for its selection]. These models were based on variable sets with the same data sets as used previously in earlier research followed by the same sets with the journey-unit difference variable added. The standard statistical goodness-of-fit measures produced directly from logit analysis were used, and the correlation ratio and F-statistic were also computed for each model. The results for the Skokie data are given in Tables 1 and 2 and those for the London data in Tables 3 and 4. For the Skokie models, the table value of t is 1.652 for 95 percent confidence and 2.344 for 99 percent confidence. The 95 and 99 percent confidence values for F are 1.93 and 2.52 respectively; the chi-square values vary with the different degrees of freedom. However, all computed chi-square values are much larger than the 99.9 percent table values. Thus, all the Skokie models are highly significant, and the journey-unit difference is statistically significant in each model. The inclusion of the journey-unit difference consistently reduces the significance of the constant.

Table 1. Results of analysis of Skokie data with and without journey-unit difference.

Model	Constant	Time Difference	Cost Difference	Journey-Unit Difference	Income	Age	Stage in Family l.c.
Variable Coefficients							
I	-2.629	-0.062	-1.97	—	2.295	0.236	2.54
II	-1.687	-0.072	-2.03	-0.21	2.07	0.240	2.53
III	-2.42	-0.048	-2.01	—	1.91	0.215	—
IV	-1.534	-0.058	-2.08	-0.204	1.73	0.216	—
V	-1.42	-0.044	-1.81	—	—	—	—
VI	-0.32	-0.058	-1.911	-0.267	—	—	—
t-Scores							
I	3.51	2.89	3.42	—	3.28	3.14	3.49
II	1.82	3.16	3.45	1.70	2.90	3.15	3.49
III	3.38	2.38	3.62	—	2.86	2.96	—
IV	1.75	2.69	3.66	1.72	2.54	2.93	—
V	2.29	2.38	3.54	—	—	—	—
VI	0.41	2.90	3.61	2.35	—	—	—

Table 2. Statistical analysis of Skokie data.

	χ^2			F	
Model	Value	d.f.	η^2	Value	d.f.
I	68.32	5	0.306	9.851	9,201
II	71.31	6	0.315	10.273	9,201
III	50.46	4	0.223	6.39	9,201
IV	53.49	5	0.253	7.584	9,201
V	24.72	2	0.124	3.186	9,201
VI	30.49	3	0.148	3.871	9,201

Table 3. Results of analysis of London data with and without journey-unit difference.

Model	Constant	Time Difference	Cost Difference	Journey-Unit Difference	Income 1	Income 2	Income 3	Income 4	Income 5	Income 6
Variable Coefficients										
I	1.096	0.0491	0.033	—	-0.11	0.002	0.253	0.095	0.753	-0.153
II	0.966	0.0489	0.033	-0.094	-0.13	-0.035	0.197	0.050	0.71	-0.18
III	1.128	0.0484	0.033	—	—	—	—	—	—	—
IV	0.953	0.0483	0.033	-0.0998	—	—	—	—	—	—
t-Scores										
I	2.51	10.36	7.55	—	0.24	0.005	0.54	0.20	1.24	0.19
II	2.19	10.29	7.52	2.73	0.29	0.077	0.42	0.103	1.18	0.22
III	14.99	10.40	7.58	—	—	—	—	—	—	—
IV	10.125	10.32	7.55	2.904	—	—	—	—	—	—

Table 4. Statistical analysis of London data.

	χ^2			
Model	Value	d.f.	η^2	F
I	287.4	8	0.279	56.08
II	294.9	9	0.291	59.46
III	279.3	2	0.280	56.41
IV	287.9	3	0.285	57.81

For the London models, the table value of t for 99.5 percent confidence is 2.583. The 95 and 99 percent confidence values for F are 1.90 and 2.43 respectively, and all chi-square values obtained for the models are far larger than any table values. Again, all the models are highly significant, and the journey-unit difference is statistically significant in each model in which it was entered. The effect of entering the journey-unit difference is to reduce the statistical significance of the constant, though less markedly than in the Skokie data. The inclusion of the journey-unit difference in both data sets improves the statistics of the total models while having little effect on the coefficients and t-scores of the cost and time differences. In all cases, the journey-unit difference enters with the correct sign (each model having been constructed such that an increasing positive journey-unit difference should lead to a decreasing probability of choice).

The significance of the reduction in the value and statistical significance of the constant lies in the properties of the logit model formulation. If 2 modes are identical in all respects, then a potential traveler should be indifferent in his or her choice; i.e., the traveler should have a choice probability of 0.5. This can only arise if the linear function (detailed in Tables 1, 2, 3, and 4) becomes 0 when modal attribute differences are 0. When the model contains system attributes only, this implies a 0 constant. When the models contain socioeconomic variables, it implies that the constant must equal the negative of the contribution to the function of all the socioeconomic variables. This latter instance is more difficult to determine, but is also the result of a less behavioral formulation of the models (27). The results from the Skokie models V and VI and the London models III and IV show a significant reduction in the size and significance of the constant term when the journey-unit difference is introduced. This suggests that the addition of this variable improves substantially the specification of modal attributes since a large, significant constant term in models of the form of Skokie V and London III implies serious lack of specification of modal attributes. Also, the fact that the significance of the coefficient of travel time does not change suggests that the time taken to transfer is not being confounded with the inconvenience of transferring.

PSYCHOMETRIC METHOD

The second approach explored in this research is the use of psychometric scaling techniques to define convenience and to permit the evaluation of a convenience index, as described earlier in this paper. To investigate the feasibility of this approach, it was necessary first to hypothesize a set of unidimensional attributes to be considered as convenience attributes. Based on earlier research and intuitive reasoning, the following attributes were put forward as constituent elements of convenience:

1. Ride in a safe vehicle,
2. Arrive at the intended time,
3. Avoid stopping for repairs,
4. Arrive in the shortest time,
5. Avoid changing vehicles,
6. Avoid a long wait for the vehicle,
7. Avoid a long walk,
8. Ride in a vehicle that is unaffected by weather,
9. Pay as little as possible for the trip,
10. Avoid having to leave early to be on time for work,
11. Have the station easily accessible to home,
12. Avoid traveling in undesirable areas,
13. Avoid paying daily for the trip,
14. Have easy-to-understand schedules and routes, and
15. Have a choice of departure times.

It was then necessary to design a survey form and select a sample for the purposes of testing the usefulness of the scaling approach. Some small samples were selected from the Chicago area; the commute trip was used, and a captive audience of respondents was obtained by surveying at the place of work. The questionnaire was designed in 4 parts. The first part requested details of the journey to work on the day on which the respondent received the questionnaire. Detailed questions were included on the elements of the trip so that the findings of this exploratory research could be refined in subsequent work. Information was also requested about alternative modes that the respondent considered he or she could have used. Questions were also included to determine mode captivity.

Part 2 comprised 42 paired-comparison questions on the convenience attributes. On the basis of pretest results, the safety attribute (1 on the list above) was omitted from the set of attributes. An incomplete design was used so that all 14 attributes could be examined without seriously overtaxing a respondent. Ten attributes were presented in part 3, and the respondent was asked to select the mode of travel that was most accurately described by the stated attribute. Respondents were given a choice only among automobile, public transport, and no difference. In addition, respondents were asked to list the 3 most important characteristics of a transportation system, without restriction on the attributes to be considered. Finally, part 4 contained questions on the demographic characteristics of the respondent, including age, sex, marital status, income, and education.

A total of 150 questionnaires were sent to employees in 2 Chicago CBD locations, and 97 usable replies were obtained. For the purposes of this research, the primary analysis was the use of the Case V program to produce scales of convenience. The respondents were grouped by age and then by sex, and scales were derived for each grouping. Unfortunately these groups become very small so that results become statistically less reliable.

Figure 1 shows the scale values for the entire sample. The 4 attributes clustered at the top of the scale all relate to travel time and traveler effort. These are conformal with the prior hypotheses of convenience put forward at the beginning of this research. Figures 2 and 3 show the scales for females and males respectively. The same 4 attributes appear at the top of the scale, although the ordering is somewhat changed. Having understandable schedules remains as the 0 point of the scale in both cases. Grouping by age shows greater variability in response (Figs. 4 through 7), but some of the group sizes are now quite small. Avoiding a long wait and arriving in the shortest time continue to appear among the top 4 attributes on all the scales, and having understandable schedules remains close to the bottom of the scale. However, the group aged 25 and under has paying as little as possible among the top 4 attributes, while all the previous scales showed this to be near the halfway point or below. For the group aged 35 to 45, the avoidance of transfers moves to fourth place and an easily accessible station drops to seventh place. The scale for the group aged 45 and over shows a cluster of 5 attributes some distance below the overriding attribute, arrive at the intended time, this latter being an attribute with a much lower scale value in all other groups.

Based on the scales, the responses on the importance of attributes, and the ratings of automobile and public transit on selected convenience attributes, convenience indexes were computed for survey respondents. In this case, the x_{jm} were the scale values of the attributes used, and the w_j^i were assumed to be either unity or 0 according to whether the respondent did or did not consider the mode best with respect to attribute j. After captive riders and those who gave insufficient cost or time data on usual and alternative modes were excluded, a sample of 49 respondents was left for analysis. This sample contained 17 automobile preferrers and 32 transit preferrers. The sample was judged insufficient for modeling purposes, so an analysis was made of the extent to which each of the convenience index difference, time difference, and cost difference conformed in sign with the preference of mode. The cost difference conformed in sign for 37 of the respondents, the time difference for 16 of the respondents, and the convenience index difference for 32 respondents. In only 8 cases did all 3 variables simultaneously conform with the preference. The index was computed from 5 attributes, ranging down the full length of the scale:

1. Arrive at the intended time,

Figure 1. Case V scale values for all respondents (97 in sample).

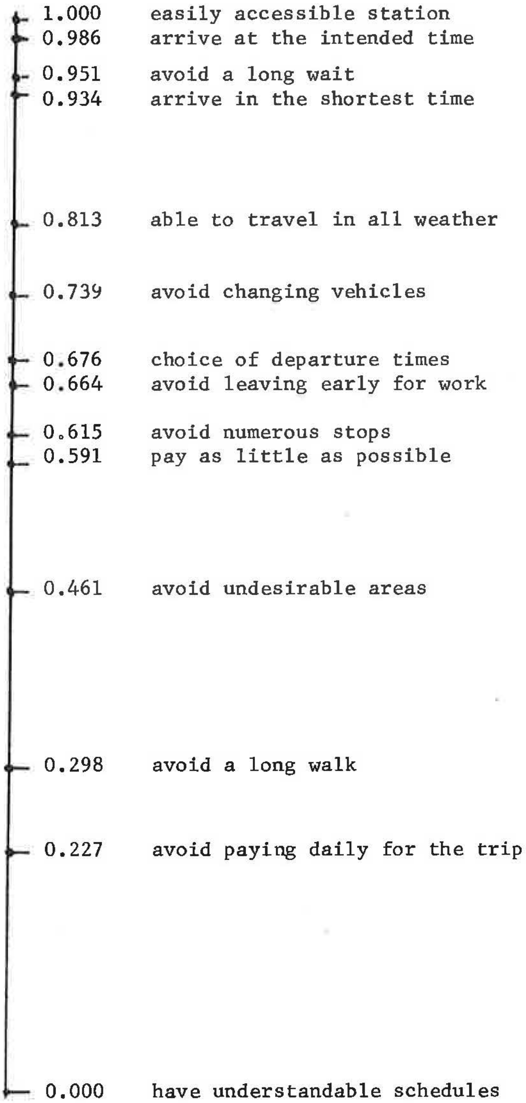


Figure 2. Case V scale values for female respondents (22 in sample).

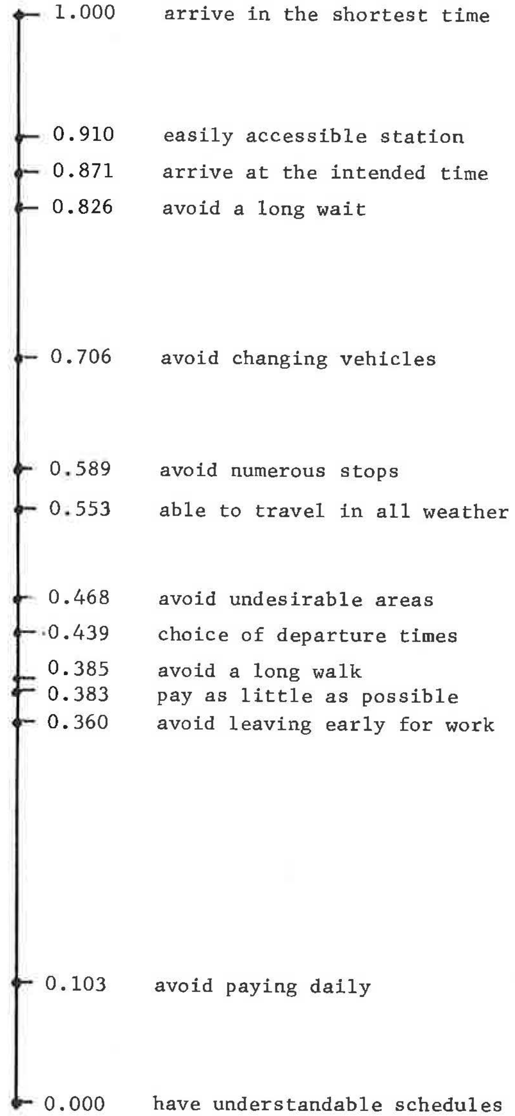


Figure 3. Case V scale values for male respondents (75 in sample).

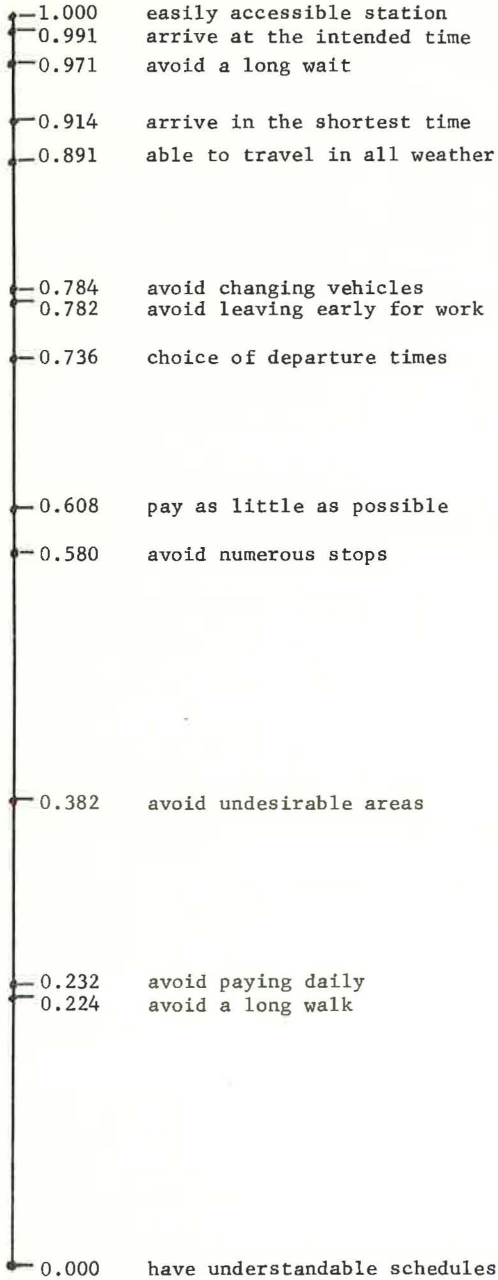


Figure 4. Case V scale values for respondents aged 25 and under (16 in sample).

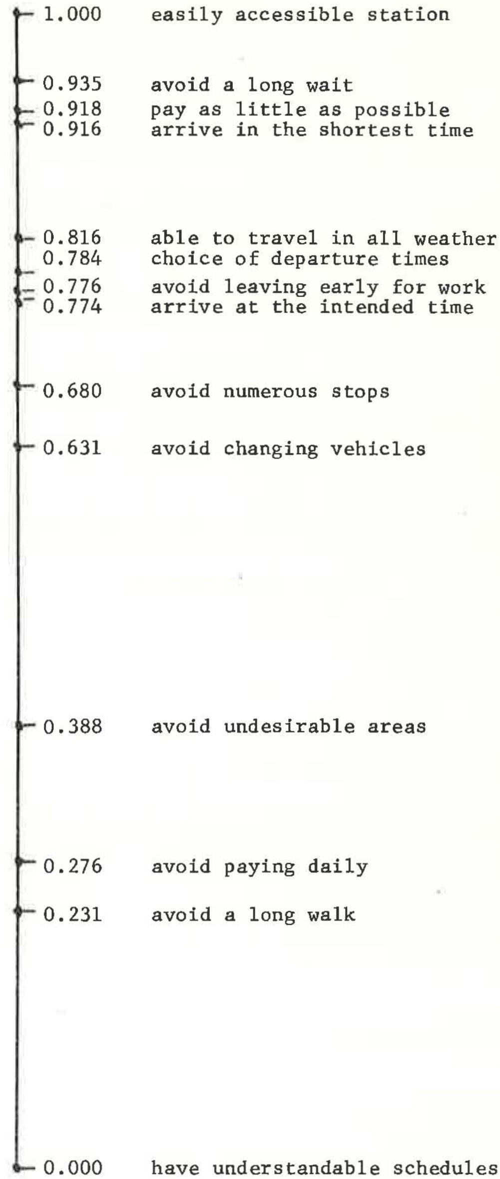


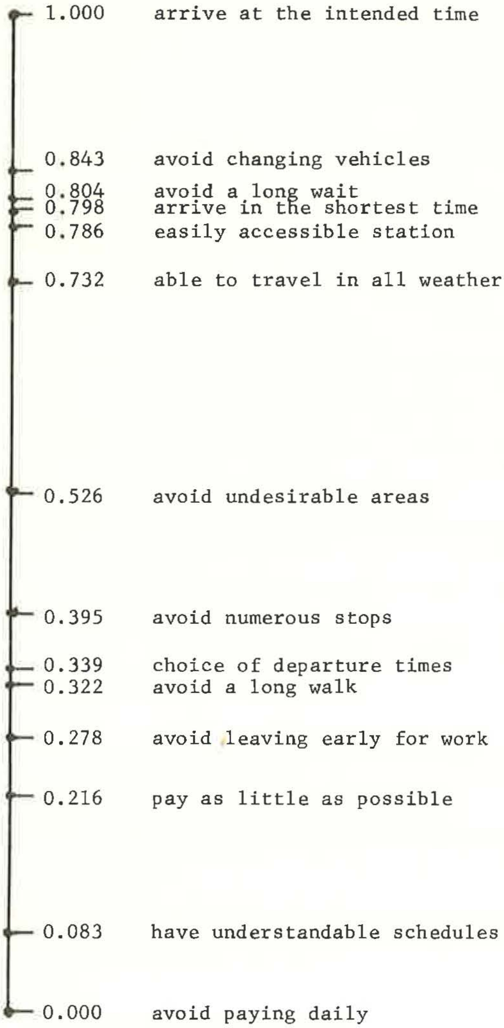
Figure 5. Case V scale values for respondents aged 25 to 35 (45 in sample).

1.00	easily accessible station
0.874	avoid a long wait
0.844	arrive at the intended time
0.817	arrive in the shortest time
0.716	able to travel in all weather
0.659	avoid leaving early for work
0.650	choice of departure times
0.649	avoid numerous stops
0.641	avoid changing vehicles
0.549	pay as little as possible
0.472	avoid undesirable areas
0.275	avoid paying daily
0.261	avoid a long walk
0.00	have understandable schedules

Figure 6. Case V scale values for respondents aged 35 to 45 (15 in sample).

1.000	arrive at the intended time
0.906	arrive in the shortest time
0.894	avoid a long wait
0.815	avoid changing vehicles
0.768	able to travel in all weather
0.747	choice of departure times
0.744	easily accessible station
0.663	avoid leaving early for work
0.589	pay as little as possible
0.456	avoid numerous stops
0.416	avoid a long walk
0.320	avoid paying daily
0.222	avoid undesirable areas
0.000	have understandable schedules

Figure 7. Case V scale values for respondents aged 45 and over (21 in sample).



2. Able to travel in all weather,
3. Avoid numerous stops,
4. Avoid a long walk, and
5. Avoid undesirable areas.

Separate indexes were computed based on the different population groupings, but no significant differences in conformance of signs was detected. Since no models were built, and the size of the differences was not computed, definitive statements cannot be made about the effectiveness of the convenience index in modal-choice modeling. However, the extent of the apparent correlation between the convenience index and the modal preference suggests that it is likely to be of significance in modeling mode choice.

CONCLUSIONS

Both approaches used in this research produce useful results toward the inclusion of a measure of convenience in travel demand models. From a policy standpoint, however, the journey-unit difference appears to be less useful, for it provides the decision-maker with one additional policy variable only—the number of transfers—and may also be confounded with some aspects of trip time. In contrast, the psychometric scaling approach requires the collection of some fairly extensive new data on preferences and attitudes of travelers and requires much more detailed and involved analysis before a measure is produced. The convenience scales produced for the small sample used in this exploratory study also suggest that convenience could possibly be quantified by defining additional time variables in a model. Over the total sample, an easily accessible station (i.e., access time), arrival at the intended time (i.e., travel time variance), avoidance of a long wait (i.e., waiting time), and arriving in the shortest time (i.e., overall travel time difference) appear to be the most important measures of convenience. Thus, a comparative analysis on the same data sets in which the journey-unit difference, the psychometric convenience index difference, and the specification of the 4 travel time parameters listed above are used appears to be worthwhile.

In conclusion, this research has lent support to the hypothesis that the convenience of travel modes can be quantified for the purposes of travel demand modeling. However, it is not possible to state, on the basis of this research, which is the most effective method to use to carry out this quantification. The results obtained in this research provide indications that the pursuit of further research in this area is worthwhile and is likely to lead to more accurate travel demand models and to the adding of important policy variables to the models.

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A BERNOULLI MODEL OF DESTINATION CHOICE

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Many attempts have been made to identify the variables that condition the destination choices of individuals and groups. Diverse models of spatial choice now incorporate many descriptors of the socioeconomic characteristics of decision-makers, of their cognitive and evaluative processes, and of the objective features of destination alternatives. No single model is generally acceptable. This seems to reflect both the complexity of the destination choice decision and the difficulty of developing a single model to predict the choices of a heterogeneous population group. This paper explores an alternative approach. We assume that the individual's destination choices over time, for a given purpose, may appear to be a random process because of the conflicting or interacting effects of many variables. A simple Bernoulli model is developed to describe this process for a heterogeneous population group. A preliminary test of the model is carried out by using data on successive grocery store choices of a sample of 90 households in Uppsala, Sweden. The model fails to fit sections of the data describing the use of particular stores, the use of different classes of store, and the behavior of different population groups. The population groups were differentiated by their degree of store familiarity, by their distance from both the stores they used and from all stores, and by their life-cycle stage. The consistent rejection of the model lends some support to new efforts to isolate variables conditioning destination choice, for example, through the application of learning models and perhaps even the multinomial logit models currently used to study mode choice.

•A VARIETY of models of destination choice have been developed and tested during the past decade (7). They are relevant for the trip distribution phase of urban transportation planning, for they attempt to isolate variables that condition the spatial choices of individuals and groups.

Destination choice involves the selection of a facility at which to conduct a short-duration, recurrent activity (work, shopping, recreation, social visits); it also involves choice of locations or facilities, such as business, industrial, or residential sites, to investigate for future long-duration activities (44).

It is somewhat discouraging, but perhaps not surprising, that no single, generally acceptable model has been found. As Huff suggested in 1960 (30), many variables appear to impinge on destination selection. Thus, models of this kind of spatial behavior now include

1. Gravity, entropy, and central place hypotheses of the effects of distance and benefits of travel to destination alternatives (2, 5, 26, 50);
2. Learning theory, space preference, and subjective utility models of how destinations are cognized and evaluated (1, 3, 8, 17, 19, 20, 21, 22, 24, 30, 38, 41);
3. Hypotheses about the effects of socioeconomic, demographic, personality, and attitudinal variables (6, 28, 33, 36); and
4. Trip linkage studies relating the time sequencing of activities and the individual's successive destination choices (16, 32, 37, 42).

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In addition, recent work on the perception of places, locations, distances, and directions in the city obviously bears on modeling destination decisions (13, 27, 41, 49).

To determine which of the many variables may best be incorporated in models of destination choice is not easy. Moreover, to specify mathematically the ways in which most factors shape this kind of travel decision is difficult. Therefore, continued attempts to develop models to explain or predict destination selections must be justified in terms of variables conditioning the individual's choices. Since, at the moment, there is little indication that any simple set will be influential and measurable for many decision-makers in many destination choice situations, general multivariate models are difficult to derive. Accordingly, we need some evidence as to whether to accept or reject the following hypothesis: Successive destination selections by heterogeneous individuals may better be modeled as the outcome of a random process. (Definitions of heterogeneous and random process are given in later sections.)

Acceptance of this hypothesis would permit at least 2 possible conclusions. First, so many variables might impinge on destination decisions (including variables that would describe alterations in origins and activity combinations over time) that their conflicting and interacting effects make choices appear as if they were random. This kind of argument has been advanced to explain the success of random choice models in predicting complex brand choice behavior (35, p. 121). Second, it is possible that individuals choose destinations at random from a given choice set in some instances. This is likely in cases where destinations are not strongly differentiated, as, for example, supermarkets for convenience food shopping (21, p. 8). Alternatively, rejection of the hypothesis would support the contention that only a few variables may condition destination choice and that these have not yet been successfully identified. This would justify continued work to isolate relevant variables. The rejection of the hypothesis should also hearten policy-makers who urgently require the identification of a few manipulatable factors controlling trip distribution to assist with urban land use and transportation planning.

The first part of this paper accordingly presents a Bernoulli model of a random destination choice process for a heterogeneous population. Because of limitations of space, a knowledge of probability theory and elementary stochastic process theory has to be assumed (14). However, the present model closely follows Massey, Montgomery, and Morrison's application of Bernoulli process theory to brand selection (34, chap. 3), and a simplified description of the theory and its testing may be found in their work.

The present model's predictions are tested by using 1971 travel diary information on the successive store choices of a random sample of 90 households in Uppsala, Sweden. An analysis was made of data showing all stores used for grocery purchases by each household during 39 days. These kinds of data were chosen for 2 reasons. First, most work has been done on shopping trips, which conform clearly with the general characteristics of the individual's destination choice problem for an activity [formally specified by the author in another paper (7) and in a later section in this paper]. Second, longitudinal data for the most frequently purchased convenience goods are obviously the least expensive to collect. These data also provide the greatest number of observations of destination choices during any given period.

The results of the tests support the rejection of the hypothesis of random destination choices by individuals and groups. This paper, therefore, provides impetus for further work to isolate the socioeconomic, attitudinal, learning, or other variables that condition individual and group destination choice.

SPECIFICATION OF THE BERNOULLI MODEL

Destination Choice as a Stochastic Process

Formally, stochastic process models of destination choice deal with the following problem. An alternative characterization of the destination choice problem, which is shown to apply to current work, is given in another paper (7).

If the following are given

1. A constant set of k destinations that represent alternatives for the conduct of an activity (for example, a set of shopping places for the purchase of a good),

$$D = \{D_1, \ldots, D_i, \ldots, D_k\}$$

2. A group of m individuals in given locations (for example, their place of residence), every one of whom is aware of and accessible to each destination,

$$I = \{I_1, \ldots, I_j, \ldots, I_m\}$$

3. That the set of destinations D constitutes the "state space" for each of the individuals, that is, each decision-maker can choose one of the destinations on any selection (be in one of k mutually exclusive and exhaustive states);

4. That the m individuals differ in their probability of selecting any destination on any choice, but have identical decision-making criteria (for example, all individuals may decide to select destinations at random or according to what they subjectively decide is best); and

5. That the m individuals have made n past destination selections for the conduct of the activity,

then derive a probability for each of the k destination alternatives that it will be selected by the group of m decision-makers on their next (n + 1) th choice; that is, derive

$$P_{D,n+1} = \{P_{1,n+1}, \ldots, P_{i,n+1}, \ldots, P_{k,n+1}\}$$

A mathematical solution to this kind of problem has been demonstrated to exist and to yield testable results only for the simplified case in which the number of states is reduced from k to 2 by some prior classification procedure (34). In other words, D, the destination set, must be reduced to $D^* = \{D_0^*, D_1^*\}$, where D_0^* and D_1^* are mutually exclusive and exhaustive subsets of D, neither of which is empty. The problems that arise from classifying or aggregating states (here, destinations) in this way are discussed in Bush and Mosteller (9, sect. 1.8): Aggregation remains a recommended, though dubious, procedure for constructing operational stochastic models. Moreover, the purpose of this paper is not to produce a new model of destination choice but to test a hypothesis of random destination selection and, ideally, to reject it and further the development of multivariate models. In this context, a high degree of simplification of real-world choice states may be acceptable, although admittedly undesirable.

Bernoulli Hypothesis

The Bernoulli hypothesis involves the following definitions and assumptions:

1. Define X as a variable whose values represent the outcome of an individual's random selections between a 0 (destination class 0) and a 1 (destination class 1) on each of n successive choices. For example, let n = 3, so that 001 is a possible trip history or sequence of values for X on the individual's third last choice, second last choice, and last choice (for X_{t-2}, X_{t-1}, X_t).

2. Assume that each individual has a constant probability over time, p, of a destination class 1 choice on any occasion and, consequently, a constant probability 1 - p of a destination class 0 on any occasion (the implications of this will be discussed later).

Then these assumptions and definitions constitute a hypothesis of destination choice as a Bernoulli process. This is formally denoted as a process such that

$$\{X_t, t \in T\}, X_t \in R$$

$$P[X_t = 1 | X_{t-1}, X_{t-2}, \ldots, X_{t-n}] = p$$

for all $(X_{t-1}, \ldots, X_{t-n}) \in R^n$. $n = 1, 2, 3, \ldots$. Here $R = \{0, 1\}$, and $T = \{1, 2, \ldots\}$.

To allow for differences among individuals, we may make the further assumption that any individual is a random sample from a heterogeneous population who choose destinations according to H_B, but who have different p values. Thus, any individual's p may be regarded as a random sample from the distribution of p values over the population, described by the density function f(p).

The assumption of a constant p value for all individuals over time may seem questionable. However, it considerably simplifies the derivation of predictions to test H_B. The assumption also has a well-documented behavioral interpretation. It implies that most individuals have stable patterns of behavior with respect to each destination class; that is, that a decision-maker will generate the same relative frequency of trips to any class in each time period over the long run. This seems to be the case in reality, except in newly established neighborhoods or where facilities are rapidly changing. For example, Cunningham (10, 11) early identified "store loyal" segments with stable shopping behaviors, while Golledge (20, p. 418) and Stone (45) also discuss store choice behavior of this kind. In addition, the assumption of a constant yet different p value for different individuals implies that, although each individual may have a stable pattern of behavior, the pattern of any 2 individuals need not necessarily be the same. This also seems realistic.

Predictions of the Bernoulli Model

x_1 is a trip history for a randomly sampled decision-maker who has n past trips to either destination 1 or destination 0.

$\ell(x_1 | p)$ is the likelihood of this history, given that the individual's behavior can be described by a Bernoulli process with probability p of a destination 1 choice next after any single past choice.

f(p) is the prior distribution of p for the randomly sampled decision-maker, that is, the distribution of the probability that the individual will choose destination 1.

$b(p|x_1)$ is the posterior distribution of p for the randomly sampled decision-maker, that is, the distribution of the probability that the individual will choose destination 1 next after the particular sequence of past choices given by x_1.

$P(1|x_1)$ is the probability under H_B that the individual who has history x_1 will visit destination 1 next.

N_{x_1} is the number of decision-makers in a hypothetical random sample who have history x_1.

R_{x_1} is the number of decision-makers in N_{x_1} who visit destination 1 next, under H_B.

$\overline{p}_{x_1} = R_{x_1}/N_{x_1}$ is the probability (relative frequency) under H_B of a destination 1 choice next by a randomly selected group of individuals who have the same history x_1 but different p values.

By the use of the rules of conditional probability for the individual

$$b(p|x_1) \propto \ell(x_1|p) \cdot f(p) \tag{1}$$

(Bayes Theorem) and

$$P(1|x_1) = \int_0^1 p \cdot b(p|x_1) \cdot dp = \text{mean of } b(p|x_1) \tag{2}$$

(34, p. 63, Eq. 3.1, and pp. 64-66). It can now be shown that

$$\lim_{N_{x_1} \to \infty} \frac{R_{x_1}}{N_{x_1}} = \lim_{N_{x_1} \to \infty} \overline{p}_{x_1} = P(1|x_1) \tag{3}$$

This means that, in the limit, as the size of the group of individuals who have history x_1 and different p values becomes large, the relative frequency with which the decision-makers choose destination 1 next, $\overline{p}_{x_1}$, is equal to the posterior expectation of p. This is the expected probability that any individual with history x_i will travel to destination 1 next, $P[1|x_i]$. [One proof of this Bernoulli law of large numbers is given by Massey, Montgomery, and Morrison (34, pp. 66-67).]

Equations 1 and 3 may now be used to derive the testable model prediction: that groups of decision-makers will have equal probabilities of a destination 1 choice next (that is, the same $\bar{p}_{x_1}$) if they have histories with proportional likelihoods of occurrence. Consider any 2 past histories of length n, labeled x_1 and x_2, such that $\ell(x_1|p)$ = constant $\ell(x_2|p)$. Then, from Eq. 1,

$$b(p|x_1) \propto \ell(x_1|p) \cdot f(p) = \frac{\ell(x_1|p) \cdot f(p)}{\int_0^1 \ell(x_1|p) \cdot f(p) \cdot dp}$$

$$= \frac{\cancel{c}\, \ell(x_2|p) \cdot f(p)}{\int_0^1 \cancel{c}\, \ell(x_2|p) \cdot f(p) \cdot dp}$$

$$= b(p|x_2) \qquad (4)$$

and from Eqs. 2 and 3

$$\lim_{N_{x_1} \to \infty} \frac{R_{x_1}}{N_{x_1}} = \lim_{N_{x_2} \to \infty} \frac{R_{x_2}}{N_{x_2}}, \text{ i.e., } \bar{p}_{x_1} = \bar{p}_{x_2} \qquad (5)$$

The converse should also hold. Groups will have unequal probabilities of a destination 1 choice next (e.g., $\bar{p}_{x_3} \neq \bar{p}_{x_4}$) where their last trip histories are such that their likelihoods of occurrence are not proportional [i.e., $\ell(x_3|p) \neq$ constant $\ell(x_4|p)$].

Which histories of length n should have proportional likelihoods of occurrence under H_B and which should not remain to be found. We may then use data to see whether randomly sampled groups of individuals with each of these past histories display the expected similarities and differences in the proportions of decision-makers choosing destination 1 next.

First, consider the group of histories of length n with r visits to destination 1, where each history is generated by a Bernoulli process. Then the likelihood of any past sequence of length n with r ones is equal to the binomial probability $\binom{n}{r} p^r (1 - p)^{n-r}$, and the likelihood of each past sequence of length n with r ones is equal to $p^r(1 - p)^{n-r}$. That is, under H_B, all past histories of the same length and with the same number of ones will have not only proportional but equal likelihoods of occurrence. Similarly, it may be shown that all histories of the same length, but a different number of ones, have different and disproportionate likelihoods of occurrence. Accordingly, under H_B, groups with past histories of the same length and number of ones should have the same proportions making a destination 1 choice next. Also, groups with past histories of the same length but different numbers of ones should have different proportions choosing destination 1 next.

It is only necessary now to choose an appropriate value of n to test H_B. If n is not small, then large, costly samples of individuals and their travel diary data will be necessary, since there must be a reasonable number of persons in each of 2^n possible past destination choice histories. On the other hand, if n is relatively small, then any individual's observed destination sequence may be broken into nonoverlapping subsequences of the given length, and this will increase the number of observed histories of the correct length without increasing the sample of decision-makers. (Where subsequences are used, observations will not be independent. This will introduce unknown biases into any standard statistical test of the model; they may be counteracted by selecting a 0.01 instead of 0.05 confidence interval for the rejection of a hypothesis.) Accordingly, a small value for n is preferred here for practical reasons.

To yield sufficient observations from a data base for initial tests of the model, we let n = 3. Table 1 then gives the model's predictions for each of the 8 possible histories of 3 successive destination choices. From the information given in column 3 of Table 1, H_B and the Bernoulli model can be rendered unacceptable by the rejection of any one of the following hypotheses; conversely, at least all three of the hypotheses have to be upheld before H_B can be accepted.

Table 1. Predictions of Bernoulli model.

History x_i (sequence of last 3 destination choices)[a]	Likelihood of x_i for the Individual[b]	Proportion of Individuals Choosing Destination 1 Next, Given History $(x_i)_{\bar{p}_{x_i}}$
000 (n = 3, r = 0)	$(1 - p)^3$	Different from all other histories
100 (n = 3, r = 1)	$p(1 - p)^2$	Same within this group;
010	$p(1 - p)^2$	different from $\bar{p}_{x_i}$ for
110	$p(1 - p)^2$	histories not in group
110 (n = 3, r = 2)	$p^2(1 - p)$	Same within this group;
101	$p^2(1 - p)$	different from $\bar{p}_{x_i}$ for
011	$p^2(1 - p)$	histories not in group
111 (n = 3, r = 3)	p^3	Different from all other histories

[a]n is the trip history length, or number of past destination choices; r is the number of destination 1 choices.
[b]Under the Bernoulli model, the likelihood of an individual making a destination 1 choice on any trip is p and a destination 0 choice is (1 - p).

$$H_1: \bar{p}_{100} = \bar{p}_{010} = \bar{p}_{001}$$

$$H_2: \bar{p}_{110} = \bar{p}_{101} = \bar{p}_{011}$$

$$H_3: \{\bar{p}_{100}, \bar{p}_{010}, \bar{p}_{001}\} \neq \{\bar{p}_{100}, \bar{p}_{101}, \bar{p}_{011}\} \qquad (6)$$

In these hypotheses, the subscripts of $\bar{p}_{x_i}$, that is, the relevant trip histories x_i of length 3, have been written out in full. (For example, H_1 states that the probabilities of a destination 1 choice next should be the same for groups of individuals with past histories 100, 010, and 001. In other words, the relative frequencies with which individuals go on to make a destination 1 choice next should all be the same for each history.) The 3 hypotheses are each verifiable by the chi-square test of homogeneity (12, pp. 224-226). The approach differs only from the well-known chi-square test of the independence of classifications in that "the totals for columns are given in advance... [and] we are actually testing that the various columns have the same (or different) proportions of individuals in various categories" (12, p. 225). The results of tests of hypotheses H_1, H_2, and H_3 constitute the substance of Tables 3 and 4 and of the concluding section of this paper.

TESTS OF THE BERNOULLI MODEL

Data Base

The data that were used were the grocery shopping records of 90 households randomly sampled from 6 life-cycle groups. [A detailed description of the field survey design and questionnaires that supplied these data is given in other reports (51, 52).] The record for each household consisted of every store in which a grocery purchase was made during a 39-day period and each store's location, land use activity, size (square meters of gross floor area), and chain affiliation. The stores were listed in each household's record in the sequence in which they were visited. The data were analyzed to see whether there was any evidence of

1. Random use of a given destination;
2. Random use of destinations classed by activity, scale, and organizational affiliation; and
3. Random destination choice by different population groups.

Random Use of a Given Destination

The patronage of each of 3 stores was examined in turn; only those stores generated during the 39-day period a large enough sample of trip histories for analysis. All those households using a given store were first isolated. The successive destinations in each household's trip record were then coded so that a destination scored 1 if the designated store were visited and 0 otherwise. This produced a binary matrix of the type given in Table 2. Each row represents a household's sequence of visits to either the designated store or to any other.

Each household's binary destination choice sequence was broken into subsequences of length 3, as indicated by the columns of Table 2; incomplete subsequences of 2 choices or fewer at the ends of records were ignored. The length 3 subsequences constitute the histories of each kind, x_i, which are given in Table 1, and which are required to test the Bernoulli model. For a given store, the number of histories of each kind was totaled for all households, and then the proportions of each kind that were followed by a destination 1 choice were added. These observed proportions were then compared to see whether they were as expected according to the model's 3 hypotheses (Eq. 6 and Table 1). Chi-square tests of the hypotheses and of the Bernoulli model were performed for each store.

In every case for the 3 stores, H_1 and H_2 were accepted, but H_3 was not (Table 3); thus, these limited tests offered no support for the hypothesis that the selection of particular destinations is a random process of the kind specified by the Bernoulli model. Individuals may switch destinations for a given activity in a simple purposive fashion, as described, for example, in learning theory explanations of consumer use of a given store (19). Alternatively, some simple set of variables, as yet unidentified, may determine the sequence of destination choices over time by a heterogeneous population group.

Random Use of Classes of Destination

A similar procedure was followed to ascertain whether different classes of destination are used at random. Stores were classified by product range (large grocery store, specialist food stores, grocery sections in department stores), size (above or below the median gross floor area), and chain affiliation (KONSUM, ICA, VIVO, and others).

The Bernoulli model was tested for each class of store; data matrices with a similar format to that given in Table 2 were used. In a matrix for a class of store, the rows comprised the trip records for every household using that class of store during the 39-day observation period; a 1 represented a visit to a designated store class, and a 0 represented a visit elsewhere. The Bernoulli model fit the destination choice behavior of households using 3 classes of store, but did not fit the data for 5 classes (Table 3).

Random Destination Choice by Population Groups

The question was also addressed as to whether the destination choices of some population groups might be modeled as a random process. The Uppsala households were classified in turn by store familiarity (3 groups), by mean distance from all grocery stores (2 groups), and by stage in life cycle (3 groups). Ten arbitrarily defined groups were thus examined altogether (Table 4).

It seemed likely that the groups with least information might switch destinations in an apparently random manner as they learned about alternatives, and that the more experienced groups might fluctuate randomly among "destination states" while in an effort-minimizing equilibrium choice pattern (19, 20, 22, 44). Moreover, it seemed plausible that groups at greater distances from shopping place alternatives, on trade-area margins, might select destinations in an apparently random fashion, and closer groups might develop simple stable trade-off functions between distance to store and other costs and benefits of travel (21, pp. 12-13). Finally, groups with different demographic characteristics seemed likely to have distinctive destination selection behaviors. Households with the least time and money constraints (the well-endowed, older Swedish households without children) especially might appear random in destination selection (33).

The Bernoulli model was tested for each group in turn; again data matrices similar in format to that given in Table 2 were used. Each data matrix comprised the trip records for all the households belonging to a group. The household's successive

Table 2. Example of binary data matrix for test of Bernoulli model.

Household Using Store Y at Least Once During 39 Days	Destination for Grocery Purchase[a]							
	1st	2nd	3rd	4th	5th	6th	...	q th
1	1	0	1	0	0	1	...	1
2	0	1	0	1	1	0	...	0
3	1	1	1	0	1	1	...	1
4	1	0	0	0	0	0	...	0
5	1	0	1	0	0	1	...	1
.	.	.	.	.	.	.	...	.
.	.	.	.	.	.	.	...	.
.	.	.	.	.	.	.	...	.
y	0	1	1	0	1	0	...	0

[a]1 = store Y visited; 0 = another store visited.

Table 3. Results of tests of Bernoulli model: random use of selected destinations.

Destination Store	Sample Size[a]	Accept or Reject at 0.01 level			Acceptance of Bernoulli Model
		H_1	H_2	H_3	
Store 1	93	A	A	R	Reject
Store 2	40	A[b]	A[b]	R[b]	Reject
Store 3	57	A[b]	A[b]	R[b]	Reject
Product range					
Large	200	A	A	A	Accept
Small	53	A[b]	A[b]	R[b]	Reject
Groceries in department stores	162	A	A	A	Accept
Gross floor area					
<200 m^2	113	A	A	R	Reject
>200 m^2	158	A	A	R	Reject
Affiliation					
KONSUM	137	A	A	A	Accept
ICA	99	A[b]	A[b]	R	Reject
VIVO and others	56	A[b]	—[c]	R[b]	

[a]Total number of length 3 histories over all households.
[b]A fourth to a half of expected frequencies in chi-square tests were less than 5. In these instances, Yates' correction for continuity was used. This correction is described for the case of a 2 x 2 contingency table by Dixon and Massey (12, pp. 225-226).
[c]Not estimated (small sample).

Table 4. Results of tests of Bernoulli model: random destination selection by population groups.

Population Group	Sample Size	Accept or Reject at 0.01 Level			Bernoulli Model
		H_1	H_2	H_3	
Familiarity: visits to favorite store					
<15	69	A[c]	A[c]	R[c]	Reject
<25	138	A	A	R	Reject
>25	96	A	A	R	Reject
Distance[a]: avg kilometers from stores used					
<1.07	144	A	A	R	Reject
>1.07	159	R	A	A	Reject
<2.24	132	A	A	R	Reject
>2.24	171	A	A	R	Reject
Stage in life cycle[b]: age of main income source					
<50, no children	134	A	A	A	Accept
18 to 49, no children	67	A	A	R	Reject
18 to 49, children	102	A	A	R	Reject

[a]For each household, the average distance from the grocery stores the household used and all grocery stores was calculated. The median household value for each distance measure was used to separate households into the 4-distance groups.
[b]Life-cycle groups as defined for the purposes of the Uppsala field survey (52, 53).
[c]A fourth to a half of expected frequencies for chi-square tests were less than 5; Yates' correction for continuity was used.

destination choices across a matrix row were now coded 1 if the store used were that household's most frequently visited (most preferred) store and 0 if otherwise. Thus, the data matrix for a group described the switching behavior of component households between the nearest store in their psychological space and other stores. The Bernoulli model holds that switching behavior should appear to be random for all population groups.

The test results given in Table 4 show that the Bernoulli model holds in only one case: that of older households with no children. In other instances, H_1 and H_2 are accepted, but H_3 is rejected. The consistency of this pattern of rejection suggests that the lack of verification of the model is more than the artificial product of arbitrary group definitions. Some underlying, simple, purposive destination selection process may be common. Since the same conclusion was indicated by the tests for random selection of particular destinations and of classes of destination, we tentatively explore the results of the data analysis for indications of an appropriate general model of destination choice.

Conclusions

From Eq. 6, the acceptance of H_1 and H_2 and the rejection of H_3 implies that households with trip histories 001, 100, and 010 have the same probability of a destination 1 choice next as households with trip histories 110, 101, and 011. This in turn means that households with the relatively larger number of destination 1 choices are generating a relatively higher proportion of destination 1 choices in their records than households with fewer destination 1 choices. Since in each set of tests a 1 choice designated a particular destination, or a particular destination class, or a most preferred store, the data seem to indicate 2 possibilities:

1. Households tend to converge toward "loyalty" to a single shopping place or set of shopping places, or
2. Households tend to be "loyal" to the most frequently used place in an immediate past period.

Either possibility points to some kind of adaptive learning behavior on the part of households in which experience with destinations as the outcome of trip-making influences next destination choice. The results support the specification and application of Markov or linear learning models to destination choice behavior, as has, of course, often been suggested by Brown (4), Golledge (20), and Ginsberg (18). The results are also consistent with findings from studies of choice between complex objects (stores, brands) in marketing, where Markov and linear learning models for both heterogeneous and homogeneous population groups have met with some success (1, 15, 29, 31, 39, 40, 43).

An alternative approach to destination choice modeling also seems both plausible and operational. If destination choice is adaptive, the process may be conditioned by the individual's socioeconomic characteristics and attitudes. Huff (30) provides a theoretical rationalization for this point of view. Hence, methodologies now employed to probe the effects of attitudinal and demographic variables on mode and route choice (23, 25, 28, 48) may be extended to destination choice. The extension of multinomial logit models to destination selection and the development of multivariate models of "destination demand" that incorporate attitudinal variables seem especially promising.

SUMMARY

This paper examines the hypothesis that destination choice by a heterogeneous population group may appear to be a random process because of the conflicting and interacting effects of many variables on the choice decision. A formal model of random destination choice was specified, and its predictions were tested by using data for 3 particular destinations, 8 classes of destinations, and 10 population groups. The model was rejected in 17 out of the 21 tests. The findings support the development of Markov, linear learning, multinomial logit and other multivariate models of destination choice.

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TRAVELER PREFERENCE FOR FARE ALTERNATIVES AS A TRANSPORTATION PLANNING INPUT

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This paper deals with the effect of fare policy and transit service plans on mode-choice behavior. These issues were studied in the context of coordinating a new rail rapid transit service in San Francisco with the existing surface bus system in order to maximize the overall service level. To aid the process of simulating the effects of various bus and rail service plans and joint fare structures under study, a disaggregate model of sub-modal-choice behavior was developed. The model was calibrated with data collected in a field survey of bus patrons. These data were used to estimate the relative influence of fare level and time savings on sub-modal-choice behavior and to forecast the probable extent of rail rapid transit usage by current bus riders. Although the specific questions posed in this study were geographically unique, the underlying technical and policy issues could be applied to other similar situations involving the introduction of a new transportation service or facility.

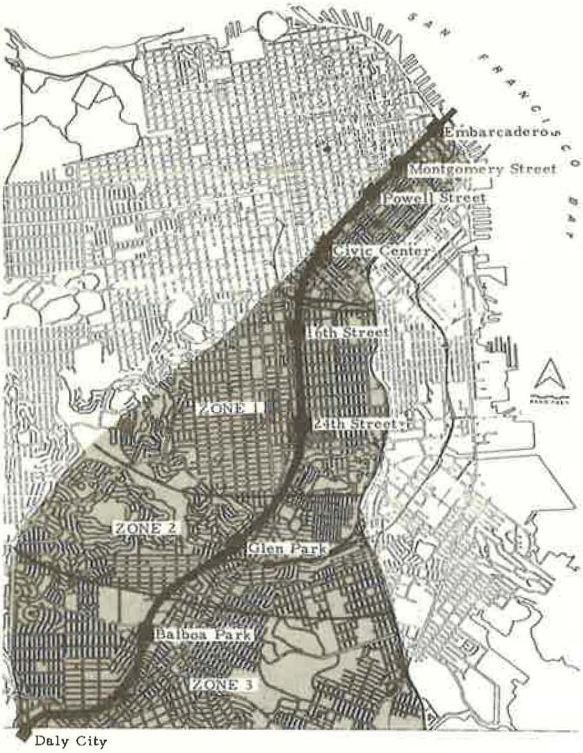
•PRIOR to the introduction of rail rapid transit service by the Bay Area Rapid Transit (BART) District in the San Francisco Mission corridor, an extensive analysis of service options was conducted. The analysis focused on a comparison of alternative service and fare plans for coordinating the bus lines and BART service. An integral part of the evaluation procedure was the development and calibration of a disaggregate model of sub-modal-choice behavior. That model is described in this paper. The survey research design that was used to estimate the relative influence of fare level and time savings on the sub-modal-choice process is reviewed in detail. Although the specific questions stemming from the introduction of BART service are geographically unique, the underlying technical and policy issues discussed here may be generalized to a wide variety of situations.

THE STUDY AREA

Figure 1 shows the 7-mile-long BART system within San Francisco, the 4 downtown stations, the 4 stations within the Mission corridor proper, and the terminal station in Daly City. The study area encompassed roughly one-third of the land area of the city of San Francisco and contained more than 200,000 persons in 1970. The inner area in particular included a high proportion of ethnic minorities, predominantly of Mexican-American descent; population density was moderate to high, and much of the housing was multiple-unit structures. Almost 40 percent of the residents owned no automobile in 1970.

At the time of the study (November 1972) the buses, streetcars, and trolley coaches of the San Francisco Municipal Railway (MUNI) carried almost 24 million annual passengers in the area to be affected by BART service. During peak hours, MUNI provided on the order of 6,000 coach seats through the Mission corridor. Operation of BART was to commence in September 1973 on the San Francisco line. Thus, with an additional 21,000 seats available in each direction during the peak hour, a substantial impact on MUNI was expected.

Figure 1. Study area.



FARE POLICY ISSUES

The MUNI fare was 25 cents anywhere within the city limits; transfers were free. Limited peak-period express bus service was provided for a premium fare of 35 cents. BART adopted a graduated fare based on distance; the minimum fare was 30 cents. A BART patron could ride between any of the stations in San Francisco for the minimum fare.

Depending on the degree of joint-fare discounting between MUNI and BART, a combined MUNI-BART round trip to downtown San Francisco from the Mission corridor might cost from 60 cents to $1.10. The 60-cent fare represented the possibility of a free MUNI feeder bus, and the $1.10 fare was the full fare for both MUNI and BART. A passenger using only MUNI to get downtown would have a corresponding round-trip fare of only 50 cents. The wide array of potential fares in combination with the relatively high proportion of low-income groups in the Mission corridor suggested that price sensitivity could be highly significant in influencing choices between BART and MUNI. In turn, traveler mode-choice decisions have an important bearing on the requirements for feeder bus and other surface transit routing and service levels, operating requirements, and fiscal positions of MUNI and BART. Thus, a major element of this study design focused on estimating price sensitivity in traveler decision-making.

STUDY DESIGN

The study design entailed specification of a series of models and an evaluation framework for judging the relative performance of alternative transit route, service level, and fare plans. Five major steps were followed.

1. An estimate was made (in which data from previous studies were used) of travel demand in the study area and the modal split between automobile and transit.

2. A transit sub-modal-split model was specified to estimate the number of transit trips that would use BART and the number that would continue to use MUNI.

3. A field survey was conducted to obtain data for calibrating the time and price variables in the sub-modal-split model.

4. Operating cost and service evaluation models were developed to determine performance measures for each alternative. Both direct traveler benefits and estimates of community benefits were considered.

5. Specific transit networks, service levels, and fare plans were delineated, and the models were applied to evaluate each of the alternatives.

Since the primary purpose of the project was to develop service coordination plans, primary attention focused on the submodal split of travel between bus and rail modes rather than on the absolute transit patronage level. Field studies of traveler preferences were limited, therefore, to current MUNI riders.

Specification of the sub-modal-split model form and structure was developed after a literature review was made of traveler mode-choice behavior research. The model chosen included variables reflecting relative service quality attributes of the available mode alternatives and socioeconomic characteristics of the traveler. Because of the large number of variables included in the model specification, a combination of a priori selection of coefficients from empirical data and field survey research was used to calibrate the relations. Elaboration of the model specification and design is presented in the next section of this paper.

An assumption was made that the number of people who would use transit had been determined. The process involved splitting those people among the transit modes, e.g., best BART-only route, BART-MUNI combination route, and MUNI-only route. The interzonal cost impedance for each of the modes was estimated so that the probability of a traveler choosing each alternative could be calculated. The sub-modal-split model was defined algebraically as

$$P_{ij}^{M} = \frac{1}{1 + \left(\frac{C_{ij}^{M}}{C_{ij}^{B}}\right)^{n}} \tag{1}$$

where

P_{ij}^{M} = probability of choosing MUNI between origin i and destination j,
C_{ij}^{M} = generalized cost impedance via MUNI between i and j,
C_{ij}^{B} = generalized cost impedance via BART or BART-MUNI between i and j, and
n = constant of calibration.

Recent travel behavior research has revealed significant information about many of the factors influencing choice of travel mode. From this research has evolved the concept of "generalized cost" impedance, which represents the relevant transportation system attributes travelers perceive in making travel decisions. Each traveler is presumed to behave according to a unique set of circumstances (e.g., travel time, fares, walking and waiting, socioeconomic attributes), which implies an individual weighing of the various attributes. In the development of a travel model, we seek to determine the aggregate behavior of travelers and use a concept of individual travel behavior to guide the specification of the model. The generalized cost concept provides a framework for inclusion of transportation system variables that people apparently take into account when making travel decisions and that can be used to analyze alternative plans and policies (1).

The generalized cost impedance, C_{ij}^{k}, was defined as

$$C_{ij}^{k} = a_1 + a_2 + a_3 + a_4 + \gamma_k \tag{2}$$

where

C_{ij}^{k} = generalized travel cost between origin i and destination j by mode k,

γ_k = residual mode bias factor for mode k,
a_1 = weighing coefficient for in-vehicle time,
a_2 = weighing coefficient for access time,
a_3 = weighing coefficient for waiting and transfering time, and
a_4 = weighing coefficient for travel cost.

a_2/a_1 is the perceived weighing of access time relative to in-vehicle time. The residual mode bias factor, γ_k, is incorporated to reflect the influence of other unquantified factors such as comfort, reliability, and privacy on mode-choice behavior. These coefficients and the mode bias factor may be expected to vary for different trip purposes and model specifications.

DESIGN OF SURVEY RESEARCH

The objectives of the survey research phase of the study were

1. To develop a data base suitable for the calibration of the sub-modal-split model,
2. To test the hypothesis that the sub-modal-choice process is sensitive to fare level,
3. To provide insights into the relative importance of nonprice determinants of demand for BART and the differences in demand between socioeconomic and demographic groups, and
4. To forecast the extent of usage of BART prior to the beginning of service.

The specific research objective was to estimate the impact of 3 fare structures on the relative preference of downtown-bound MUNI bus riders for either the existing bus alternative or a BART plus a MUNI feeder bus to the same destination. The fare alternatives examined were 30, 40, and 55 cents for a 1-way trip by BART plus MUNI. The fare for MUNI alone remained at 25 cents.

Methodology

The general method adopted for the survey involved exposing randomly assigned groups of MUNI bus riders to the 3 fare alternatives. Similar procedures have long been used to estimate the price elasticity of demand for new durable goods (2). The major limitation of this method is that the choice decision is artificial since no explicit trade-offs are required. In this situation the traveler must trade off higher fares against a possible reduction in travel time and improvement in equipment. So that they would have no problems in comparing a familiar with an untried mode, bus riders were given full information on the relative merits of the 2 alternatives. This was achieved by tailoring the information in the questionnaire to the conditions at the rider's originating bus stop.

An interviewer stationed at a bus stop gave each respondent a questionnaire (Fig. 2). If the respondent was unable to complete the questionnaire before the arrival of the bus, the interviewer would accompany him or her until the questionnaire was completed. Refusals were fewer than 3 percent. Information on wait and downtown travel times from the bus stop via the 2 modes was provided on the questionnaire. The estimates were based on route structures and service levels that the rider would encounter when BART went into service. Only one BART price alternative was presented (randomly) to each respondent.

Comparison of the 2 modes was made by using a 5-point scale reading from "strongly prefer BART plus MUNI" to "strongly prefer MUNI." Additional questions on bus usage, distance from residence to bus stop, trip purpose and final destination, automobile availability, age, sex, and income were asked. Questions that required an evaluation of the alternative modes in terms of attributes such as reliability of service, safety, comfort, and convenience were not included. Although these attributes have been found to influence modal-choice behavior (3), exclusion of these questions was necessary to facilitate completion of the questionnaire by riders while awaiting arrival of their buses. If further information had been requested, this procedure would have been impractical and a more costly interview method would have been required.

Figure 2. Sample questionnaire.

YOU MAY TAKE THIS ON BOARD THE BUS WITH YOU
YOUR SIGNATURE IS NOT REQUIRED

Dpt Dte No. Stp 1 3

How many minutes does it take you to get to the bus stop from your residence?
- 0 - 3
- 4 - 6
- 7 - 9
- 10 - 12
- 13 and over

How many round trips during an average week do you usually travel by Muni bus? (Check one)
- One or less
- Two
- Three
- Four
- Five
- Six
- Seven
- Eight or more

Are you going downtown on this trip?
- Yes
- No

What is the purpose of this trip?
- To Work
- To Shop
- To School
- To Home
- Other

. . . .
Specify

When BART is in operation, which way would you prefer to get downtown at this time of day? Please read A and B then mark the one box ☒ which says how you feel.

A: Connecting bus every minutes to the nearest BART station for 30¢ (Your total time to get downtown minutes)

B: Muni bus to downtown every minutes for 25¢ (Your total time to get downtown minutes)

- Strongly Prefer A
- Somewhat Prefer A
- ?
- Somewhat Prefer B
- Strongly Prefer B

Are you a licensed driver?
- Yes
- No

Is an auto usually available to you to get downtown?
- Yes
- No

What is your age?
- Under 18
- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 54
- 55 - 64
- 65 and over

What is your sex?
- Male
- Female

What was your total family income from all sources last year?
- Under $5,000
- $5,000 - $7,999
- $8,000 - $11,999
- $12,000 and over

Will you transfer before the end of this trip?
- Yes
- No

Where will this trip end? (Final destination - not Muni Stop)

Nearest intersection:

. . . .
and
. . . .

MA4728 PLEASE RETURN QUESTIONNAIRE BEFORE LEAVING THE BUS

The validity of the survey procedure was dependent on the degree to which the bus riders (a) received similar information about travel time and wait time differences between the 2 modes (as was presented to the survey respondents) and (b) maintained their attitudes toward the attributes of BART between the time of the survey and the opening of BART in San Francisco.

Sample

The sample was limited to those Mission corridor bus stops attracting 30 or more boarders on inbound buses during the morning peak period (7 to 9 a.m.). Stops with less activity would not economically support an interviewer. Predetermination of boarding activity at each bus stop proved difficult because of substantial errors in the available boarding count data and uncertainties in the estimation procedure. The problem was accentuated by the exclusion of students and elderly persons from the sample because of their eligibility for fare discounts.

A stratified sample in which the interval was inversely related to the number of inbound boarders was drawn from suitable bus stops. The resultant sample contained

11 of the top 30 stops (100 or more boarders),
9 of the next 56 stops (50 to 99 boarders),
5 of the next 57 stops (30 to 49 boarders), and
0 of the remaining 289 stops.

The 289 excluded stops comprised 66 percent of the stops, but contributed only 21 percent of the total MUNI riders. The total response sample consisted of 1,433 interviews of which 1,085 were usable and 348 were unusable. These latter responses were distributed as follows:

Response	Number
Not going downtown	199
No answer; do not know preference answer	67
Age 65 and over after 9 a.m.	34
Miscellaneous other nonusable interviews	48

One drawback of the stratified sampling procedure was an overrepresentation of bus patrons from the densely populated areas closest to downtown. This overremphasis can be seen in the following:

Zone	Total Boarders (7 to 9 a.m.) Number	Percent	Sample (all hours) Number	Percent
1	5,118	38	618	57
2	3,366	25	174	16
3	4,982	37	293	27
Total	13,466	100	1,085	100

Zone 1 represents the area closest to downtown; Zone 3 is the area farthest away from downtown.

Timing

Fieldwork for the survey was completed between November 2 and 10, 1972. At that time BART had been in operation (weekday schedule, 6 a.m. to 8 p.m.) on the Fremont to Oakland segment of the system since September. Several events that occurred close to the time of the survey and that might have colored respondents' attitude toward the BART or MUNI systems should be noted.

1. The interviewing took place 1 month after a BART train derailed at the Fremont station;
2. Fieldwork was completed prior to the publication of findings by the state legislative analyst regarding alleged safety defects in the BART train control system;
3. During the period of the field survey, no significant media attention was devoted to BART or MUNI;
4. The project team did not publicize information on fares or service levels preceding the interviews; and
5. Throughout the interview period, the weather was good.

Each weekday was equally represented in the sample. The distribution of the questionnaires by time of day corresponded roughly to the pattern of boarding during the hours in which the study was in progress.

DESCRIPTION OF THE DATA

Because of the survey design, each BART fare alternative received equal representation in the sample. In the results, each alternative was presented as the difference, ΔP, between the fare for BART plus a MUNI feeder bus and the MUNI fare. On the average, BART plus a feeder bus provided a modest time savings, ΔT, of 4.4 min. This average varied considerably: 26 percent of the sample saw no time saving, and 20 percent saved 10 min or more. The difference among geographic zones was especially noticeable.

ΔT (min)	Zone 1 Number	Zone 1 Percent	Zone 2 Number	Zone 2 Percent	Zone 3 Number	Zone 3 Percent	Total Number	Total Percent
-7 to 0	279	44.8	0	0	3	1.3	282	25.9
1 to 4	111	18.3	38	21.4	59	27.1	228	21.3
5 to 9	179	29.1	46	26.4	129	43.8	358	32.8
10 to 22	50	7.8	90	52.2	62	27.8	217	20.0
Total	619	100	174	100	293	100	1,085	100

The average time saving was somewhat misleading because (a) the statistics were dominated by the larger sample base from zone 1 bus stops where BART was frequently at a competitive disadvantage and (b) the headways for feeder buses to BART were generally longer than for MUNI downtown buses by an average of 1.4 min. To the extent that respondents perceived these factors as meaning they would have a longer wait for BART service, they would be less likely to choose BART.

Service levels for both transit modes were significantly reduced after the 9 a.m. departure time, thus reducing the average time savings.

(ΔT)	7 to 9 a.m.		9 to 12 Noon		12 to 4 p.m.		Total	
(min)	Number	Percent	Number	Percent	Number	Percent	Number	Percent
-7 to 0	108	20.0	111	32.3	61	30.8	282	25.9
1 to 4	135	24.8	59	16.7	40	19.7	228	21.3
5 to 9	150	27.7	97	28.0	68	33.4	358	32.8
10 to 22	150	27.5	80	23.0	29	13.1	217	20.0
Total	543	100	347	100	198	100	1,085	100

Selected Rider Characteristics

The sample data revealed the following rider characteristics.

1. Of the total number of respondents, 69 percent were going to work and 15 percent were going shopping.
2. The majority of the riders made at least 5 round trips a week.
3. The majority of the riders lived near a bus stop: 42 percent had a 3-min walk, 31 percent had a 4- to 6-min walk, and 12 percent had a walk of 13 min or more.
4. Thirty-nine percent of the respondents transferred during their trips.
5. The majority of the riders (64 percent) did not have automobiles available for their use, although 54 percent of them were licensed drivers.
6. There were almost equal numbers of males (48 percent) and females (52 percent) in the survey sample. The average age was 32 years, and average incomes were low. Approximately 88 percent were below the average 1972 California household income of $11,400, and 27 percent were under $5,000.

PREFERENCE ANALYSIS

An indication of the preference for BART plus a feeder bus was obtained from the marginal distribution of responses to the choice question. Since the least preference for BART was found in zone 1 (which was overrepresented in the sample relative to the population), it was necessary to adjust the marginals by weighing responses in zones 2 and 3 more heavily.

Service	Preference	Sample (percent)	Population After Adjustment (percent)
BART plus feeder bus	Strongly prefer	12.1	13.5
	Somewhat prefer	14.9	16.6
	Not sure	9.1	10.0
MUNI bus	Somewhat prefer	28.1	27.4
	Strongly prefer	35.8	32.5
Total		100	100

A plausible, overall estimate of the population proportion that would switch from the MUNI to BART plus a MUNI feeder bus is the 30 percent who fall into the combined "strongly prefer" plus "somewhat prefer" categories. Excluding the "not sure" category from the estimate allows for the probability that some of those riders who "somewhat prefer" BART would not switch. These combined categories correspond directly to $P^{B}_{IJ} = (1 - P^{M}_{IJ})$ in the sub-modal-split model.

The overall estimate of the proportion of population preferring BART, P^B, masks the effect of fare differences. These differences are given in Table 1. The range of unadjusted entries from 0.43 to 0.17 suggests that the respondents were able to discriminate between the alternatives and that the survey design was sufficiently sensitive to capture the difference.

A further conclusion from Table 1 is that the aggregate results of the sub-modal-choice process are sensitive to fare differences. For example, the degree of preference for BART plus a feeder bus is 44 percent higher at a 30-cent differential. It would seem that when significant time savings are possible (as in zones 2 and 3) riders are not especially sensitive to fare differences increasing from 5 to 15 cents. However, in zone 1 where BART is generally at a time disadvantage, a fare difference is very meaningful.

ESTIMATION OF FARE SENSITIVITY

The analysis discussed in this section is of holding constant other determinants of modal preference, such as time savings, to precisely estimate the effect of fare differences. In addition this analysis will reveal the relative influence of the various determinants of preferences. A 3-step procedure was followed. First, the patterns of interactions among various explanatory variables were identified. This served as the basis in the second step for specifying a multiple regression equation to directly estimate the effect of different fare levels on modal preference; other explanatory variables were held constant. Finally, the data were aggregated across bus stops and fare alternatives in the form used to calibrate the sub-modal-split model. A regression analysis, using the aggregate data set, estimated the strength of the relation of preference and fare level when the unexplained variance due to individual differences was eliminated. The criterion variable in the above analyses, P^B, was in the form of a dummy or dichotomous variable that took the value of 1 when the respondent strongly or somewhat preferred BART plus a feeder bus and 0 otherwise. Similar results were obtained by using the 5-point preference scale. The advantage of the dummy variable formulation was that it required no interval scale assumption and could be used directly in the sub-modal-split model. The drawback was that the distribution of the error term cannot be assumed to be homoscedastic as required by the linear regression model used here. This raised several difficult interpretation problems (4).

The following were used as possible explanatory variables for P^B:

ΔP = difference in fares (5, 15, or 30 cents);
ΔT = difference in elapsed time to get downtown (MUNI minus BART), in min;
ΔH = difference in headways (MUNI minus BART), in min;
TRIPS = number of round trips per week by MUNI bus;
WORK = 1 if purpose of trip was to get to work and 0 otherwise;
TRANS = 1 if transfer was necessary and 0 otherwise;
DEPART = 1 if departure was before 9 a.m. and 0 otherwise; and
INCOME = total family income, in thousands of dollars.

Identification of Interactions

The analysis of the preliminary results in Table 1 suggested there were possible

Table 1. Proportion preferring BART plus feeder bus by zone and fare condition.

Zone	Proportion by ΔP: 5 cents (n = 343)	15 cents (n = 355)	30 cents (n = 387)	Total (n = 1,085)
1 (n = 619)	0.26	0.18	0.17	0.20
2 (n = 174)	0.41	0.40	0.31	0.37
3 (n = 292)	0.43	0.38	0.26	0.35
Total (n = 1,085)	0.33	0.27	0.22	0.27
Population estimate after adjustment[a]	0.36	0.30	0.25	0.30

[a] Results for zones 1, 2, and 3 were weighted 0.38, 0.25, and 0.27 respectively to adjust for sampling rate bias.

interactions between ΔP and ΔT; that is, ΔP would have a different relation with P^B depending on ΔT. An exploratory data analysis program (5), automatic interaction detector (AID), was used prior to the regression analysis to isolate the ΔT groups in which different relations occurred.

AID is a sequential procedure. At each step it searches all the explanatory variables and finds that variable which, when split into 2 groups, reduces the unexplained sum of square deviations the most. (This is the same as finding the 2 nonintersecting groups that have the smallest within-group variation.) The procedure starts with the total sample and splits it into 2 groups. Further splits are attempted on the resulting groups until either the groups become too small or the groups become homogenous.

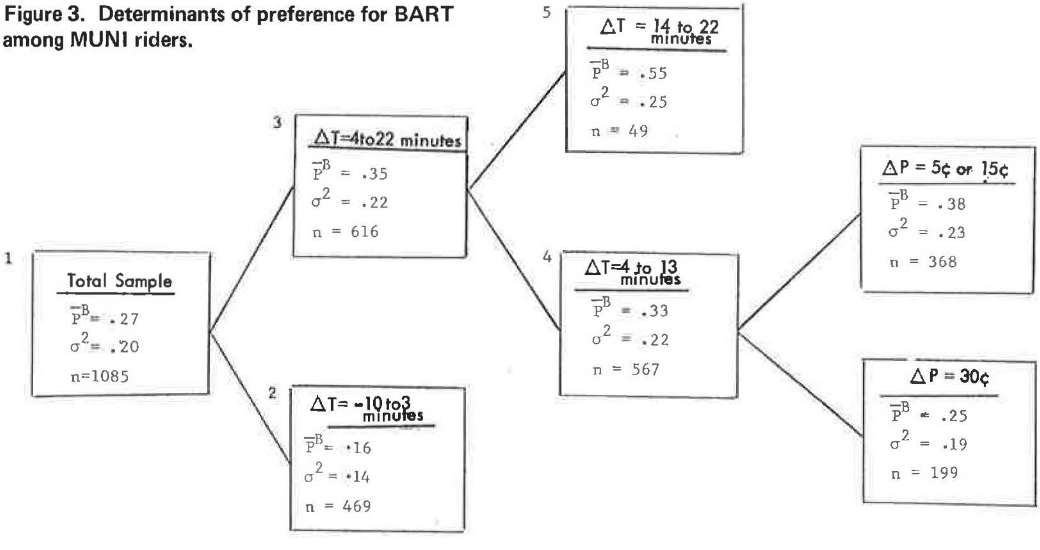
The results of the AID procedure applied to this data set are shown in Figure 3. Each box shows the categories of the explanatory variables used to split the data, the size of the group, the group mean value, and variance of the preference for BART, $\overline{P}^B$ and σ^2.

The results of the AID analysis highlighted the interaction that was only suggested in Table 1. That is, ΔP only had a relation with preference when the time saving a rider expected was between 4 and 13 min. When there was little or no time saving, a hard core group of 16 percent (mostly living in zone 1) still preferred BART regardless of the fare level. MUNI riders may have placed high premium on comfort, which could put MUNI at a disadvantage, or realized that the downtown BART stop was much more convenient to them or that transfers may be easier via BART. Obviously this survey design was unable to shed any direct light on these hypotheses. Analogously, when the time savings via BART were more than 13 min, the fare level also did not matter. Even when time savings were significant, a large proportion (45 percent) still did not choose BART, perhaps because they refused to pay even 5 cents more, had uncertainties about BART, or knew that the downtown BART stop was less convenient than their present MUNI stop.

Regression Analysis

The above AID analysis was used to specify a regression equation that would reveal (a) the relative influence of the various explanatory variables and (b) the ability of the explanatory variables to account for variability in preferences. The interactions isolated above were incorporated in Eq. 3. Logarithmic transformations of the ΔP and income variables did not produce appreciably better results.

Figure 3. Determinants of preference for BART among MUNI riders.



$$P^B = a + b_1\Delta P + b_2\Delta T + b_3\Delta P(\Delta T_d) + b_4\Delta H + \ldots + b_9 \text{ INCOME} \qquad (3)$$

where T_d = 1 when ΔT was between 4 and 13 min and 0 otherwise.

The first observation from the regression results in Table 2 is that, with an R^2 of 0.067, the variance in preference is predominantly unexplained. Some of the factors contributing to this situation have already been discussed (primarily that conditions at the end of the trip were not considered). Other reasons for the lack of explained variance in preference include (a) measurements and coding errors, (b) lack of consideration of attitudinal variables (toward the safety, comfort, and convenience of BART relative to MUNI, for example), (c) differences in the perception of the control variables (especially in the believability of the time savings), and (d) the inevitable stochastic element in choice behavior and preferences, which may be especially pronounced here because of lack of information about BART. Results of this magnitude are frequently encountered in studies of individual consumer behavior for these same reasons.

A low R^2 is a problem if there is a possibility of bias in the estimate of the conditional mean preference, given the explanatory variables (6). Such bias would also reduce the value of the data set for the calibration of the sub-modal-split model. The key question is whether there were systematic individual differences favoring either BART plus a feeder bus or MUNI alone in the downtown destination. To test this possibility, a second regression analysis was conducted on a new data set obtained by aggregating the individual responses to the level of the bus stop and fare combinations. Since there were 25 bus stops in the sample and 3 fare alternatives, the new data set contained 75 observations. The dependent variable was the proportion of the sample in each observation group who strongly or somewhat preferred BART. The extent of systematic bias due to the omission of information on the exact destination was revealed by differences in the coefficients of the 2 regression equations for the 2 data sets. These coefficients are compared in Table 2.

The immediate effect of aggregation was to increase the R^2 (adjusted for loss of degrees of freedom) from 0.067 to 0.513. In view of the potential for measurement error and the fact that the upper bound on R^2 (the overall measure of variance explained) is less than 1.0 when a binary dependent variable such as P^B is used (7), the large increase in R^2 was encouraging for it suggested that the explanatory variable set was reasonably complete. More important was the fact that the coefficients for ΔT and ΔP were virtually identical in the 2 data sets (despite the difference in formulation of the dependent variable), and the interaction of these 2 variables was not significant. Thus, we had a clear indication of the relative importance of these 2 explanatory variables: For every 10 min of time saving via BART, the proportion preferring BART (that is P^B) increased between 0.14 and 0.15. Conversely, a fare difference of 10 cents between BART plus a feeder bus and MUNI alone reduced this proportion by approxi-

Table 2. Multiple regression analyses of determinants of preference for BART plus feeder bus.

	Individuals[a]		Aggregation of Individuals for Bus Stop and Fare Combinations[b]	
Variable	Regression Coefficient	t Value	Regression Coefficient	t Value
ΔP, cents	-0.0041	2.6[c]	-0.0040	2.3[c]
ΔT, min	0.015	5.0[c]	0.014	4.5[c]
Δ headway, min	0.001	0.0	0.016	2.0[d]
$\Delta P \cdot (T_d)$	-0.0002	0.1	-0.0023	1.3
Trips per week	-0.002	0.3	-0.030	1.4
Trip purpose	-0.028	0.8	0.004	0.6
Transfer	0.047	1.6	-0.31	0.5
Departure time	-0.001	0.1	-0.002	1.9[d]
Income	0.005	1.2	0.001	1.3
Intercept	0.181		0.240	
R^2 (adjusted)	0.067		0.513	

[a] P^B = 1 if strongly or somewhat preferred BART and 0 otherwise.
[b] P^B = proportion who strongly or somewhat preferred BART.
[c] Coefficient significant at < 0.01 level.
[d] Coefficient significant at < 0.05 level.

mately 0.04. Thus, the real leverage was in time savings. A second conclusion from these results was that no significant source of bias in the data due to omitted variables existed that would affect the use of the data in the calibration of the sub-modal-split model.

SUB-MODAL-SPLIT MODEL CALIBRATION

The sub-modal-split model specified earlier required calibration of 3 coefficients for travel time components, the coefficient for traveler perception of fare relative to family total income, and the exponent for the ratio of generalized cost impedance. Initially, several model calibration formulations were specified and investigated. A nonlinear least squares method was attempted in which survey data aggregated to bus stops were used. This procedure proved unworkable because of the extreme variances encountered and the implied weak statistical relation. A second calibration procedure used each survey observation and assigned a specific probability of using MUNI based on the respondent's answer to the mode and fare preference question. However this method also yielded poor statistical results.

A decision was then made to make a priori estimates for the travel time coefficients on the basis of other empirical research and to calibrate the remaining variables by using the survey data for MUNI riders. Subsequent to the work reported in this paper, the application of maximum likelihood techniques for calibrating a logit model formulation had been initiated. However the results of that work are not yet available.

A Priori Estimate of Travel Time Coefficients

In-Vehicle Time Coefficient, a_1—A value of unity was selected for the weighing factor, a_1, for travel time aboard a transit vehicle, consistent with the interpretation that the aboard-vehicle time is the base time component. All other time components are viewed relative to the unit weight assigned to riding time.

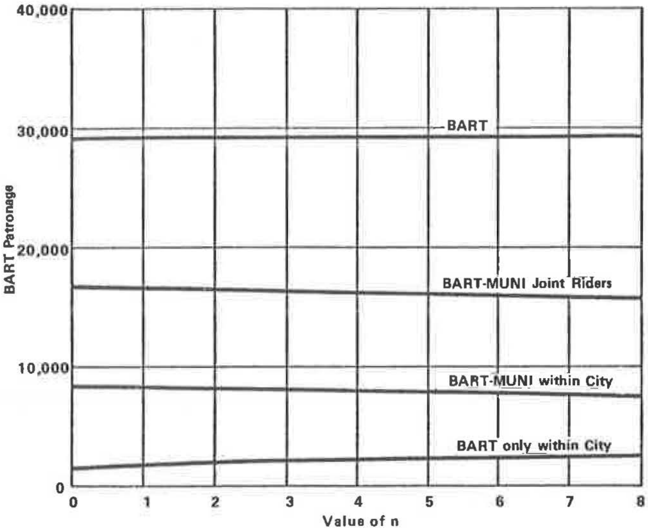
Access Time Coefficient, a_2—Studies of mode-choice behavior indicate that people weigh time for walking more highly than time for riding. Quarmby deduced a value for walking of 2 to 3 times the value for riding in Leeds, England (8). Lisco found a similar pattern in Chicago, where commuters would pay a rate of 12 cents per minute to avoid walking, or 2.8 times the average value of riding time (9). The Regional Plan Association in New York deduced a weight for walking of 3.2 times the value for riding time (10). In work done in New York with respect to the Port Authority Terminal, a walking time weight of twice the riding time seemed to reflect people's behavior most accurately (11). Based on this empirical evidence, a time weight of 2 times the riding time weight was selected.

Waiting and Transferring Time Coefficient, a_3—Waiting for a bus or transferring between transit vehicles has a degree of uncertainty and inconvenience that make such time more onerous than either walking or riding time. Therefore, it is postulated that most travelers attach a higher weight (e.g., disutility) to time spent in waiting or transferring. Although significant empirical research is sparse, one survey in Paris concluded that a weight of 3 times the riding time weight was appropriate (11). This value was adopted as the wait time coefficient.

Time and Cost Equivalents

The generalized cost impedance equation included money costs (fares) and travel time terms. An equivalency to place the money and time impedance elements into common units may be perceived as the value that a traveler places on travel time savings (e.g., the amount that a traveler is willing to pay to achieve unit time savings). A number of studies have investigated the value that commuters place on travel time savings for journeys to work. It appears that commuters value their travel time for work journeys at between 20 and 40 percent of their wage rate. Less is known about the value of time savings for nonwork travel (12, 13, 14). The travel cost reflected in Eq. 2 corresponds to the fare charged for the various mode alternatives (e.g., BART-only, BART and feeder bus, or MUNI-only). For computational ease, the travel time

Figure 4. Sub-modal-split sensitivity to value of n.



components were translated into equivalent cost units by multiplying each of them by a value of time equivalency, V_i, where $V_i = cY_i$, Y_i = median household income of residents in origin i, and c = fraction of income assumed to reflect value of time.

Model Calibration

The model calibration process sought to determine the income fraction c to be used in translating value of time savings and the exponent n for the generalized cost impedance ratio. The calibration used the survey data from 25 MUNI stops as to preference of riders. For each stop, the percentage of all respondents preferring MUNI ("strongly prefer" and "somewhat prefer") and the ratio of impedance were calculated for each fare difference subset.

Experimentation with the value of the exponent n disclosed relatively modest sensitivity (Fig. 4). Therefore, it was reasoned that n could be estimated by using a preliminary value for the income coefficient, c; accordingly, c was set at 0.25 to find an initial solution for n. A value of n = 3 seemed to best replicate respondent preferences. Next, for stops with a large number of samples, the c coefficient was relaxed and successively incremented to solve for the value that best reflected the survey responses to alternative fares. From these analyses, a value for c of 0.17 was determined.

The a priori coefficients and derived values for n and c were incorporated within the model and used to simulate the distribution of travel between BART and MUNI for several different transit service alternatives and fare policies.

Sensitivity Analysis

Each of the a priori-determined coefficients was perturbed individually and in combination so that the effect on the distribution of trips by mode could be examined. Varying the riding and waiting coefficients led to only nominal impact (less than 10 percent) on the distribution of trips by mode. However the access coefficient proved more critical resulting in changes up to 25 percent in the resulting trip allocation by mode as a_2 varied from a value of 0 to 3.2.

No significant compounding effect was observed when the coefficients were varied in combination; the resulting mode allocation reflected additive combinations of the individual sensitivities. By far the greatest sensitivity was evident with respect to c, the fraction of income reflecting value of time. Above a value for c of 0.25, the mode-choice sensitivity was not so pronounced, changing only about 10 percent as c varied up to 0.80. However, for c values between 0.10 and 0.25, the modal split was more sensitive, changing by nearly 25 percent in that interval.

CONCLUSIONS

The research reported in this paper focused on traveler behavior under different mode, service level, and pricing combinations. Two issues were addressed: (a) survey research design and methodology to provide a data base for developing a model of traveler behavior and (b) formulation and calibration of a sub-modal-choice model that reflects traveler behavior and is responsive to policy variables.

The survey research design was reasonably time and cost efficient, although it proved very difficult to establish a reliable sample universe and distribution because of problems of incompleteness and reliability in the available transit boarding count data. The survey effort was restricted to existing bus riders because of budgeting reasons and because it was hypothesized that present bus riders would constitute a very high proportion of travelers affected by the BART and MUNI coordination plans. It would have been desirable to include nontransit users in the survey design, but cost considerations precluded doing so.

The sub-modal-split model calibration results proved less than ideal. Several calibration methods were attempted, but yielded little in the way of useful results toward determining coefficients for the various generalized cost impedance components. Recourse was made to a priori estimates of travel time impedance coefficients on the basis of other empirical research, and survey data were used to determine the remaining model parameters—an income fraction, c, representing value of time relative to median household income and n, the exponent applied to the impedance ratio. Sensitivity tests were executed to examine the effects of varying the coefficients assumed a priori as well as those determined empirically. The sensitivity tests considered the coefficients individually as well as in various combinations. The coefficient for access time and fraction of income equated to value of time, c, proved most sensitive. Compounding effects of changing more than one time variable coefficient were not significant.

Further work toward the objectives of this research is clearly needed. Investigation of different model formulations is in progress, and post-BART data on traveler behavior will permit further assessment and refinement of model relations.

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COMPARISON OF THE MODEL STRUCTURE AND PREDICTIVE POWER OF AGGREGATE AND DISAGGREGATE MODELS OF INTERCITY MODE CHOICE

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This paper reports the construction of both disaggregate and aggregate models of intercity mode choice; data from the Edinburgh-Glasgow Area Modal-Split Study were used. The models are then compared in terms of their structure (i.e., the variables included) and their ability to predict modal split. The disaggregate models provide a better statistical explanation of mode-choice behavior. Moreover, the failure of the variable representing relative travel time to reach a satisfactory level of statistical significance in the aggregate models indicates that the alleged behavioral nature of aggregate models is not supported by the empirical evidence. In addition, the predictions of modal split derived from the aggregate models are inferior to those obtained from the disaggregate models. Several tests show that the errors associated with the aggregate models are several times as large as those associated with the disaggregate models. Disaggregate models have extremely desirable performance characteristics. It is, therefore, time to make serious effort to incorporate them into the transportation planning process.

THE RECENT developments in the use of disaggregate, behavioral, stochastic models in the area of transport mode choice have been most encouraging in terms of both the explanatory and the predictive powers of the models. From a transport planning point of view, however, the more important feature is the ability of the models to predict the behavior of travelers. It has been shown that the disaggregate models of mode choice can be used to predict aggregate mode-choice behavior with a high degree of accuracy (7) and also that models calibrated in one situation may be transferred spatially to yield accurate predictions of behavior in other situations (10). These results, however, suffer from one serious drawback: Although they demonstrate the predictive efficiency of disaggregate models, comparisons with the predictive abilities of the aggregate or zonal mode-choice models commonly used by urban transportation planners are difficult. This difficulty is the result of 2 main factors. First, evidence on the errors associated with predictions from zonal mode-choice models is not readily available. Although it has been claimed that the errors may run as high as 300 percent, no evidence has been produced to support such claims. Second, because zonal models use the aggregate data, the aggregate data sets cannot be used to construct disaggregate models for the purposes of comparison. Thus, the controversy over which type of model is better has continued in the absence of either a means (in terms of data) or a method (in terms of error results for zonal models) of making a comparison and, hence, of reaching a conclusion. The analysis reported in this paper offers a way out of this impasse by way of a single data set that is sufficiently versatile to allow the construction of both an aggregate and a disaggregate model. These models are used to produce predictions of modal split, and the errors associated with these predictions may then be compared. Thus, the relative merits of disaggregate and aggregate models of mode choice may be assessed.

This research attempts to compare current practice, as embodied in the urban transportation planning package of models, with practice as recommended by the developers of the disaggregate models. Thus, each type of model is presented in such a way as to represent its use in a planning context.

STUDY BACKGROUND AND DATA

The data used to perform these tests are derived from the Edinburgh-Glasgow Area Modal-Split (EGAMS) Study (8). The data collected in this study (which represent all journey purposes) were originally used to build disaggregate models of mode choice for medium-range, intercity journeys in the Forth-Clyde corridor of the Central Lowlands of Scotland. This model development effort represents the basis for the predictions of modal split used to represent disaggregate models in the comparison reported below.

Each individual observation in the EGAMS Study has its origin and destination coded to the traffic zones developed for use in the Land Use and Transportation Study for South-East Scotland and the Greater Glasgow Transportation Study. The result of this method of coding is that all observations may be allocated to pairs of zones, which are the same zones used in actual zonal analysis of this area. Thus, the zones used in the development of the aggregate models in this paper are not an academic construct; rather they are the zones used in 2 actual transportation studies.

In fact, the number of zones used in this analysis is smaller than the number of zones included in the EGAMS study area. A number of zones were eliminated because no trips either originated or terminated in them. Then the zonal boundaries were redrawn to combine existing zones into larger zones while maintaining regional characteristics and contiguity. Since most of the "empty" zones were in areas that were peripheral to the cities themselves, the reconstruction of the zones emphasizes the intercity nature of the choice being analyzed. Each city was divided into 10 zones; an identifiable central area was surrounded by a group of zones divided approximately by geographical quadrants. Identifying the zone-to-zone pairs that represented an intercity trip yielded a 200-cell trip matrix. Since 42 of those interzonal pairs were empty (i.e., no trips were observed between that pair of zones), 158 zone-to-zone pairs remained for analysis.

The number of observations in each zonal pair ranged from 1 to 101. Although the sample sizes are somewhat smaller than would be encountered in a transportation study (as a result of the fact that the total disaggregate data set is limited), the range of observations and the existence of cells that are either empty or that contain a small number of observations are a realistic representation of the data available to a transportation study.

The mean value for each variable was calculated for each zonal pair, and these means were used as the independent variables in the analysis. The dependent variable was the proportion of travelers in each zonal pair who chose to travel by train. The aggregate models were calibrated by multiple regression analysis; given the fact that the dependent variable in the aggregate case is the proportion of travelers choosing the train, the problems associated with a binary (coded 0 or 1) dependent variable do not arise, i.e., heteroscedasticity and invalid tests of significance. The problems of out-of-range predictions are not eliminated. However, the results presented by Watson (9) indicate that this is not a serious problem. Thus, to use logit analysis for the aggregate model was not considered necessary. [Tests where logistic transformations were made are discussed by Watson and Westin (10).] By contrast, the disaggregate models were calibrated by logit analysis; the data for each individual traveler made up the inputs to the model.

MODEL STRUCTURE

The first stage of the comparison between the disaggregate and the aggregate models takes the form of an examination of the structure of the models. The term "structure" may be interpreted in a number of ways; for example, the use of either multiple regression or logistic analysis intrinsically imposes a structure on the models. In this sense, the structural difference between the disaggregate and aggregate models is self-evident. For comparative purposes, the structure of the models in terms of the variables that they contain is more interesting.

Disaggregate Model

The model calibrated by logistic analysis on the disaggregate data set took the following form:

$$P(T) = F(\text{TD REL, CD REL, JU DIF, WW TIM})$$

where the relative time difference, TD REL, or relative cost difference, CD REL, is the difference in time or cost between the 2 modes relative to the average time or cost of the journey; walking-waiting time, WW TIM, is the time spent walking and waiting during the train journey; and the journey unit difference, JU DIF, is the difference in the number of segments (walking, waiting, and riding) associated with the journey by each mode. The estimated coefficients are as follows:

Variable	Coefficient	t-Value
TD REL	-1.050	-6.84
CD REL	-0.666	-8.95
WW TIM	-0.002	-9.45
JU DIF	-0.132	-5.95

The likelihood ratio value (χ^2, 4 d.f.) = 527.28. All the variables, and the equation as a whole, were statistically significant at the 0.01 level of significance; and all the variables had the hypothesized sign. The structure of this model parallels the models of intracity commuter mode choice (3, 5, 6). The original type of model has been modified by the inclusion of a proxy variable for convenience and by transforming the time and cost variables into a relative form that reflects the nature of the intercity journey.

Aggregate Models

Since the aggregate model is to be used to produce predictions that are comparable with the predictions from the disaggregate model, the first aggregate model tested was made up of the same 4 variables that had yielded the best disaggregate model. The coefficients, t-values, and related statistics are as follows:

Constant and Variables	Coefficient	t-Value
Constant	1.0107	9.89
JU DIF	-0.08607	-4.17
WW TIM	-0.41454	-1.45
TD REL	-0.14862	-1.04
CD REL	-0.32668	-5.19

$R^2 = 0.419$, and $F = 27.59$. Although the R^2 and F statistics for the significance of the equation as a whole are satisfactory, this model cannot be considered adequate as the coefficients of 2 of the independent variables are insignificant. Nevertheless, although this model is not the model that best represents the aggregate data, it will be used to provide predictions for comparative purposes since it corresponds directly with the disaggregate model.

Clearly, to use an inferior model is to do less than justice to the aggregate modeling technique; thus, the aggregate data were analyzed in order to find a better model. Trials with numerous variable combinations and choice hypotheses revealed that it was not possible to use variables representing both time and cost differences in the same equation without the coefficient on the time variable becoming insignificant. The model that was finally judged to be the best model includes the cost difference variable plus 3 variables that were used in earlier disaggregate model tests to represent the level of convenience and accessibility associated with the train journey. The variables are the cost of station access and egress, SUBCOS; the time spent walking and waiting on the train journey, WW TIM; and the difference in the number of journey units (segments) associated with the journey, JU DIF. The coefficients and t-values are as follows:

Constant and Variables	Coefficient	t-Value
Constant	1.038	10.88
CD REL	-0.312	-5.20
SUBCOS	-0.193	-3.010
WW TIM	-0.005	-2.199
JU DIF	-0.080	-3.92

$R^2 = 0.453$, and $F = 31.698$. This model is similar to the model derived in disaggregate tests for the group of social-recreational travelers, in which the inconvenient features of the train journey (SUBCOS, WW TIM, JU TRA) were contrasted with the best features of the automobile, i.e., its speed (TD REL). In this case, the model may be interpreted as meaning that the inconvenient features of the train journey are compared with the least attractive feature of the automobile, i.e., its cost (CD REL). This hypothesis does not seem at all unreasonable; thus, this model will be used as the best aggregate model to obtain the modal-split predictions that will then be compared with the predictions from the disaggregate model.

Comparison of Model Structure

The differences in the statistical significance of the variables tested on the aggregate data set led to an important conclusion. The disaggregate models are based on the behavioral hypothesis that the traveler makes his or her mode-choice decision on the basis of the relative times costs and other characteristics of the modes available to him or her. The statistical tests performed on the models fail to reject this hypothesis. It has been argued (2) that the aggregate models are also behavioral. However, the hypothesis that the proportion of travelers choosing the train depends on the relative characteristics of the modes is not confirmed by the statistical tests. Thus, although the aggregate models may be behavioral in concept, the behavioral hypothesis is rejected by the data and the behavioral nature of the aggregate models must be placed in doubt. Simply to choose variables on the basis of a behavioral hypothesis is not sufficient if the data do not support that hypothesis.

In summary, the data aggregation process conceals the behavioral basis of the mode-choice decision, and the disaggregate approach yields models that are both behaviorally and statistically sound.

PREDICTIVE POWER

The second stage of the comparison involves examining the predictive power of the disaggregate and the aggregate models. In the absence of a second, predictive data set, the prediction tests were carried out by using 2 data sets representing 2 random drawings from the original population; these data sets were obtained by randomly dividing the sample into 2 halves. It is acknowledged that this is a less than optimal testing procedure; it is, however, the best available under the circumstances and can provide useful insights into relative predictive abilities.

The intercity flows are regarded as a corridor, and the tests developed represent the relative accuracy of predicting the modal split for the corridor as a whole. The prediction error is presented in 2 forms. The first, ϵ_1, is defined as the absolute difference between the predicted and actual mode split; it may also be interpreted as the percentage of the sample for whom erroneous predictions of mode split are made. The second considers the error as a percentage of the actual modal split. Clearly, the second form will yield a higher error than the former, the difference being diminished as the actual modal split approaches 100 percent on one of the alternative modes. Both error measures are presented for comparative purposes.

Disaggregate Predictions

The properties of predictions of modal split from disaggregate models have been reported elsewhere (8, 9); therefore, these results are given in a somewhat abbreviated form in Table 1. These results require little explanation or comment. It is evident that the prediction errors associated with disaggregate models are low. The mean errors are presented together with the errors associated with summing the predictions from the 2 data sets to indicate that the errors tend to offset each other so that the total error is smaller than the errors for each data set. Thus, the better overall measure of error is the mean error.

Aggregate Predictions

To provide a broad picture of the errors associated with the aggregate model, 3 prediction tests were performed. The first 2 involve deriving predictions of the number of train travelers in each zone-to-zone pair; these predictions were then summed to yield a corridor prediction. The third test involves a different error concept. The tests were performed by using the models derived above. As it is based on the best statistical relation derivable from the aggregated data, model 2 is referred to in the following discussion as the best aggregate model. Model 1, which contains the best set of variables from the analysis of the disaggregate data, is referred to as the best disaggregate model. However, the terms "best aggregate" and "best disaggregate" refer to the derivation of the variable set in each model. The prediction tests are carried out on models built with the aggregated data.

Random-Split Predictions—The closest replication of the disaggregate model prediction tests involved randomly dividing the zone-to-zone pairs into 2 groups. The first data set contained 83 zone-to-zone pairs; the second contained 75. Each data set was used to calibrate the model: The data sets and coefficients were then interchanged and 2 sets of predictions were obtained. The predictions are given in Table 2.

Directional-Split Predictions—Since the procedure of randomly dividing the data into 2 sets for prediction tests has been criticized, a new method was derived that made use of the origin-destination characteristics of the zone-to-zone pairs to produce the 2 data sets: The first data set represents travel from Edinburgh to Glasgow (81 pairs), and the second data set represents travel from Glasgow to Edinburgh (77 pairs). Such a breakdown also provides some insight into the transferability of zonal models, i.e., the extent to which a model developed in one situation may be used to predict behavior in another. The results for the "best" models are given in Table 3.

Mean Prediction Errors—Since the effect of a transportation system improvement may be highly localized, the error associated with the prediction of modal split for a given zone-to-zone pair must be considered. The mean zone-to-zone prediction errors are given in Table 4 as indications of the errors associated with the prediction of mode split for the average zone. They were obtained by first calculating the absolute error in predicted modal split for each zone-to-zone pair; the mean of these errors was then obtained.

Comparison of Predictive Power

The predictions obtained from the aggregate models have much larger errors associated with them than the predictions from the disaggregate models. The results are particularly strong when one considers the different models and the different methods of obtaining the 2 data sets. Although the results from the random-split method are, as might be expected, better than the results from the directional-split method, the errors are still larger when compared with the errors from the disaggregate models. Moreover, the errors from the aggregate models improve only marginally when the best aggregate rather than the best disaggregate model is used. Moreover, the average prediction errors indicate that the ability to predict at a less than corridor level is suspect. (Regrettably, the data format is insufficiently flexible to allow the predictions from the disaggregate model to be broken down by zonal pairs without excessive data manipulation.) The fact that the errors are consistently high across models

Table 1. Disaggregate model predictions.

Item	Data Set 1	Data Set 2	Both Data Sets
Sample size, number	1,197	1,243	2,440
Predicted train, number	582	601	1,183
Actual train, number	589	595	1,184
ϵ_1, percent	0.59	0.48	0.04
ϵ_2, percent	1.19	1.00	0.08

Note: $\bar{\epsilon}_1$ = 0.535, and $\bar{\epsilon}_2$ = 1.095.

Table 2. Random-split data set predictions by aggregate model.

	Best Aggregate Model			Best Disaggregate Model		
Item	Data Set 1	Data Set 2	Both Data Sets	Data Set 1	Data Set 2	Both Data Sets
Sample size, number	902	1,040	1,942	902	1,040	1,942
Predicted train, number	434	595	1,029	435	659	1,094
Actual train, number	363	537	900	363	537	900
ϵ_1, percent	7.88	5.58	6.64	7.98	11.73	9.98
ϵ_2, percent	19.58	10.81	14.33	19.83	22.72	21.55

Note: $\bar{\epsilon}_1$ = 6.73 and $\bar{\epsilon}_2$ = 15.19 for aggregate models; $\bar{\epsilon}_1$ = 9.85 and $\bar{\epsilon}_2$ = 21.27 for disaggregate models.

Table 3. Directional-split data set predictions by aggregate model.

	Best Aggregate Model		Best Disaggregate Model	
Item	Glasgow to Edinburgh	Edinburgh to Glasgow	Glasgow to Edinburgh	Edinburgh to Glasgow
Sample size, number	582	1,360	582	1,360
Predicted train, number	253	931	240	946
Actual train, number	433	467	433	467
ϵ_1, percent	30.93	34.12	33.16	35.22
ϵ_2, percent	41.57	99.36	44.57	102.57

Note: $\bar{\epsilon}_1$ = 32.52 and $\bar{\epsilon}_2$ = 70.46 for aggregate models; $\bar{\epsilon}_1$ = 34.19 and $\bar{\epsilon}_2$ = 73.57 for disaggregate models.

Table 4. Mean zone-to-zone prediction errors by aggregate model.

	Error (percent)		
Model	Data Set 1	Data Set 2	Mean
Random split			
Best aggregate	18.51	25.18	21.85
Best disaggregate	20.48	24.04	22.20
Directional split			
Best aggregate	37.93	36.95	37.43
Best disaggregate	42.80	39.17	40.94

and data divisions is a clear indication that the errors result from more fundamental problems. Although the results cannot be used as direct evidence of this, the fundamental problem is more likely the information loss (1, 4) that is associated with the aggregate models. In the case of the disaggregate models, all the available data are used in the calibration of the models and the derivation of the predictions; in the aggregate approach, much of the information content of the data is lost when the mean values of the zone-to-zone pairs are used to represent the complete range of information. Although this information loss may be greater in this test than in a transportation study (because of the combining of zones), the prediction errors from the aggregate procedure are still extremely large and should cause serious concern.

CONCLUSIONS

The objectives of this paper are very simple: to produce comparable predictions of mode-choice behavior by applying aggregate and disaggregate methods to the same data. The results are unambiguous. The errors associated with the aggregate method are several times as large as those associated with the disaggregate method. Even taking into account the limitations necessarily imposed by the design of the test, these results must be interpreted as a clear demonstration of the predictive superiority of disaggregate models. These results, taken in conjunction with recent results (10) on the ability of disaggregate models to produce accurate predictions using no more data than are required by aggregate models, make it clear that disaggregate models of transport mode choice have made the transition from academic toys to serious transportation planning tools.

ACKNOWLEDGMENT

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PRELIMINARY ANALYSIS OF DISAGGREGATE MODELING IN ROUTE DIVERSION

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A study of route diversion in the Baltimore-Washington corridor is presented. A disaggregate model of individual route choice is used. The study investigates diversion from US-1 to I-95 through a license plate sampling technique employed before and after I-95 was opened to traffic. Regression and logit techniques analogous to those in modal-split research were employed to study individual diversion behavior. The research allowed tentative conclusions to be drawn about the use of this kind of study design.

A PROBLEM of continuing relevance to the transportation planner is the set of stimuli that affect choices travelers make and the implications of those choices in terms of facility usage and quality of service.

Choices made by travelers are typically studied in the modal-split and assignment portions of the urban transportation planning modeling process. Classically, they have been studied in the aggregate (2, 3). Recently, however, efforts have been made to study modal choice at the disaggregate or individual level. Virtually all of this work has focused on the issue of mode choice and subsets of travelers in different socioeconomic groups (4). Little attention has been paid to stimuli that affect route choice of an individual automobile traveler and the resulting highway traffic assignment.

The objective of this paper is to report on a pilot study of the motivation for automobile route selection between 2 parallel routes in Maryland. The opening of a new highway during the study period provided an opportunity to develop before-and-after data relating to 2 parallel routes. The specific objectives of the research were

1. To assess the degree of applicability of certain behavioral, disaggregate modal-choice analysis techniques to the study of route choice;
2. To assess data and field study requirements as a learning process to determine future study designs of this type; and
3. To further the use of disaggregate models in all phases of the urban transportation planning process.

SITE SELECTION

Figure 1 shows the region in which the study area is located. Prior to July 1971, I-95 had not been completed between the outer belts of Baltimore and Washington (I-695 and I-495 respectively). Of the remaining 3 routes shown, US-1 was considered functionally to be the primary traffic arterial between Baltimore and Washington. Study timing was such that it was possible to gather information on volumes and use prior to the July 1971 opening of I-95 and then, after a sufficient stabilization period, to study the diversion of traffic to I-95. US-1 is a 4-lane undivided highway that has congestion and relatively high accident rates. I-95 has 4 lanes in each direction, wide grass medians, a high type of shoulders, and excellent design.

STUDY DESIGN AND DATA COLLECTION

Because of severe budget limitations on data collection, a study procedure was developed that would accomplish 2 objectives of data collection for later modeling efforts:

Figure 1. Location of study area.

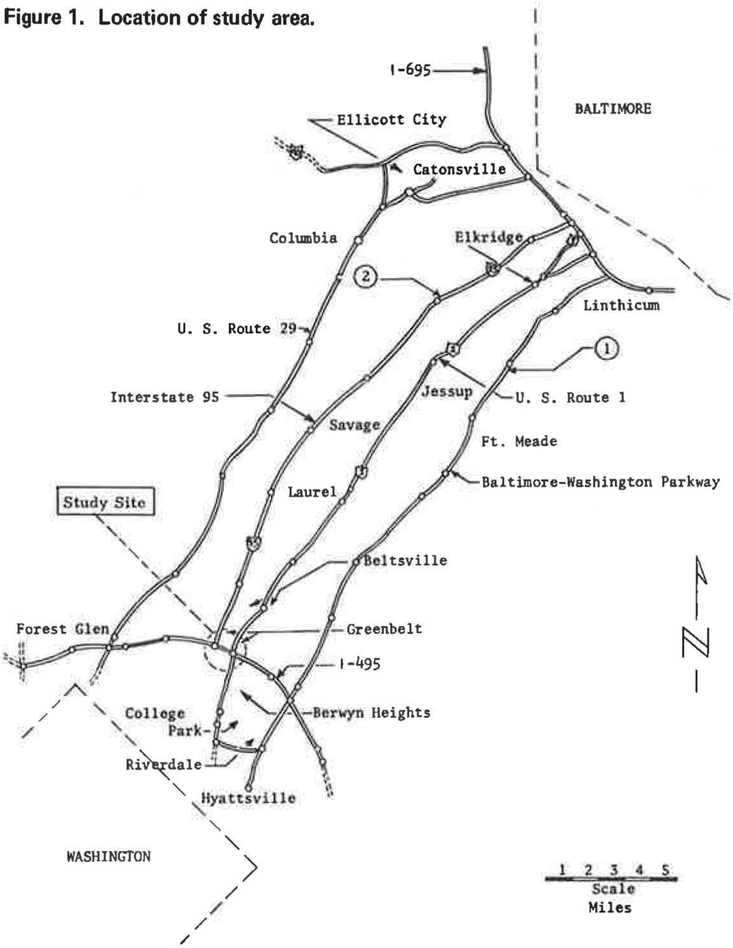


Table 1. Traffic on US-1 before and after opening of I-95.

Day	July 1971	June 1971
Sunday	9,158	11,560
Monday	15,628	19,152
Tuesday	16,940	19,456
Wednesday	16,019	19,672
Thursday	16,305	20,021
Friday	16,908	18,832
Saturday	12,961	15,496
Total	103,919	124,189

Table 2. Analysis of independent and dependent variables.

Grouping	P	R	R^2
1 min	$0.442 + 0.0397(X_1)$	0.76	0.58
	$0.430 + 0.684(X_7)$	0.55	0.30
2 min	$0.451 + 0.0389(X_1)$	0.79	0.63
	$0.439 + 0.665(X_7)$	0.57	0.33
5 min	$0.455 + 0.0370(X_1)$	0.86	0.74
	$0.438 + 0.672(X_7)$	0.67	0.45

1. Allow an inexpensive investigation of the volume changes of commuting traffic in the I-95—US-1 corridor, and

2. Allow further investigation of a subset of diverting and nondiverting commuter travelers with respect to a broad set of stimuli for route choices.

Before I-95 opened, license plates of northbound and southbound vehicles on US-1 were randomly recorded for 1 week in June 1971 during the morning and evening peak hours. Traffic volumes were also recorded on US-1 for 1 week shortly after I-95 opened. Between June and July, volumes dropped 18 percent (Table 1). Finally, license plates were recorded on both I-95 and US-1 in January 1972. Computerized comparison of plates yielded gross information on diversion.

This field procedure yielded an approximate 10 percent sample of peak-hour volumes. Sample sizes as 1-week totals of peak-hour vehicles in both directions are as follows:

Time	US-1	I-95
Before I-95 opened	3,550	—
After I-95 opened	3,224	4,665

Detailed questionnaires were sent to approximately 10 percent of the US-1 and I-95 sample for the after portion of the study. Accordingly, 585 questionnaires were sent to drivers of vehicles whose plates had been tracked through both the before and after portions of the study. The primary objective of the questionnaire was to investigate parallels between route selection and disaggregate mode-choice modeling wherein the driver makes a choice in response to an individual socioeconomic preference and to system characteristics and trip purposes. The questionnaire obtained information on origin-destination, travel time, travel cost, trip purpose, income, family size, number of drivers at origin, sex, and age. This set of data formed the basis for further quantitative analysis of the diversion problem.

ANALYSIS OF DATA AND MODEL DEVELOPMENT

Data from the questionnaires were used to help in understanding the decisions to use US-1 or I-95. The input variables for further quantitative analysis were defined as follows:

X_1 = travel time difference between US-1 and I-95;
X_2 = cost difference between using US-1 and I-95, valued at $3/hour (7);
X_3 = number of passenger vehicles owned at origin;
X_4 = persons residing at origin;
X_5 = number of persons of driving age at origin;
X_6 = annual income of household; and
X_7 = weighted travel cost, developed by factoring travel time difference with respect to household income.

This latter set of factors used were those developed from previous research on value of time by Thomas and Thompson (5).

Simple bivariate regressions were performed on each of the above independent variables against the dependent variable P, probability of diverting to I-95. This dependent variable was developed by the quotient (number of diversions in class i)/(total population of class i), where class i is a 1-, 2-, or 5-minute increment of travel time difference between the 2 routes over the range of travel time differences developed from the questionnaire response. Results are given in Table 2 and shown in Figures 2 and 3.

Travel time was a consistently fair to good estimator. Travel cost was not shown because, as defined, it is a linear transform of travel time. Weighted or perceived cost by income level was shown as being a potential indicator of diversion. However, reasonably poor-quality estimating capabilities exist for this variable from the equations shown, except at the 5-minute grouping level.

Figure 2. Probability of diverting to I-95 versus travel time difference.

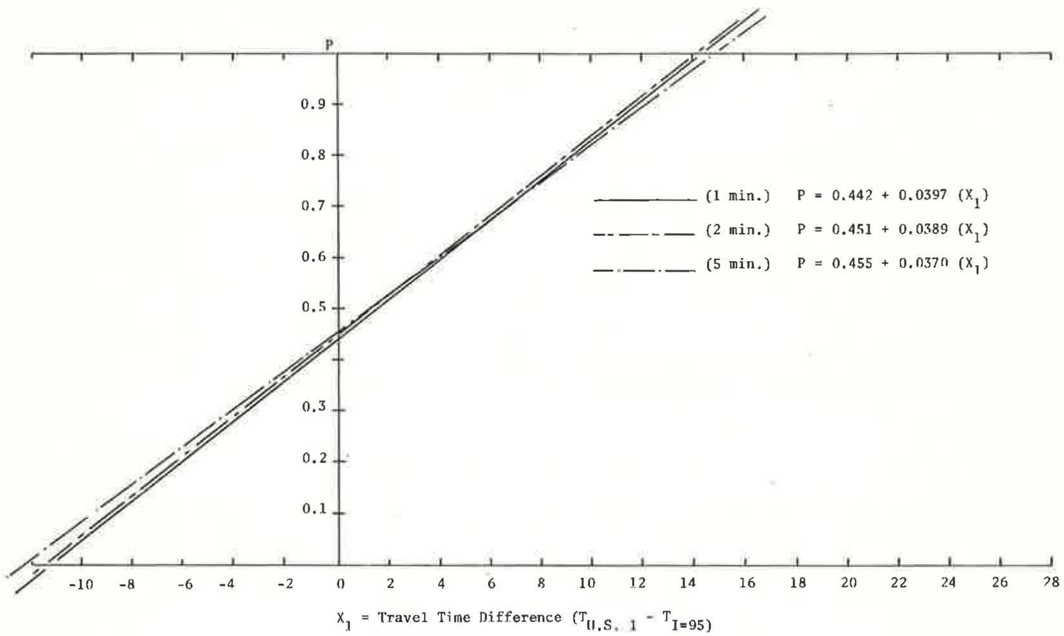
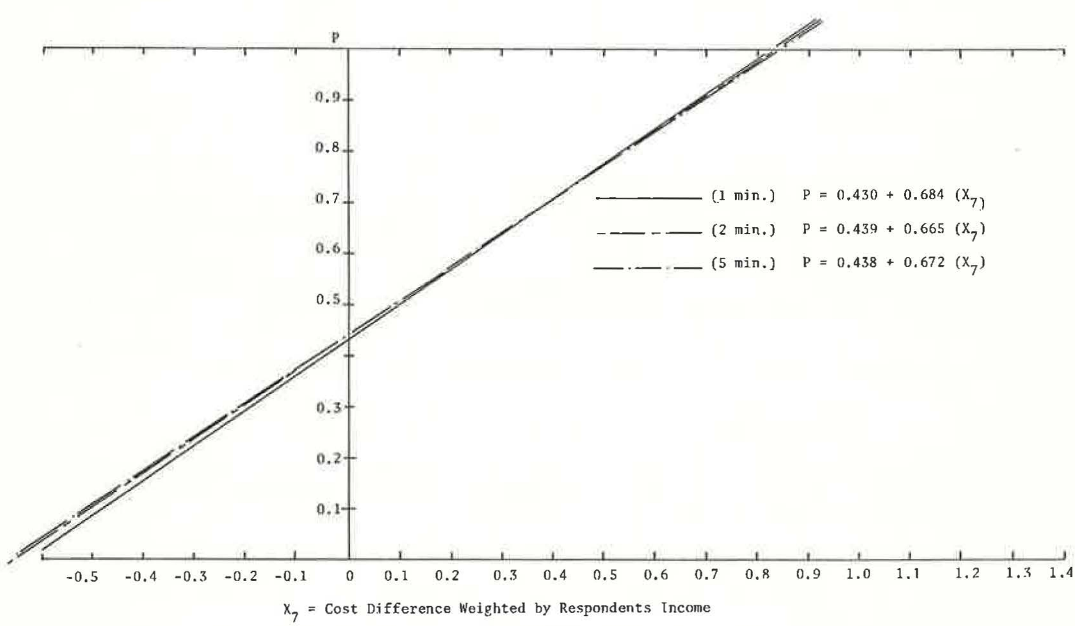


Figure 3. Probability of diverting to I-95 versus cost difference weighted by income.



RELATION TO LOGIT ANALYSIS

The above bivariate equations were used in the logit format of

$$P' = \frac{eP}{1 + e^P}$$

where P′ is as defined in the bivariate regressions. The rationale of logit development is to exhibit a more rational stimulus-response conception of probability of diversion and to develop asymptotic limits on diversion at or near P = 0 and P = 1 (4). Three of these plots are shown in Figures 4, 5, and 6. In each case the smoothing or asymptotic effect has not been completely captured within the range of stimuli shown. The implication is that, for this particular study corridor, total assurance of diversion or nondiversion exists only in ranges of greater than 20 to 25 minutes of time lost or saved by use of a respective route, as shown in Figures 4 and 5. Figure 6 implies that high relative weighting of travel time by income is necessary to induce diversion.

MULTIVARIATE ANALYSIS

The variable input set included travel time difference, travel cost factored by income, number of vehicles at origin, number of persons of driving age, and number of persons readily at the origin. A step-wise regression yielded the following information with the final variables in the equation: $P = 0.43 + 0.05X_1 - 0.39X_7 - 0.01X_3 - 0.02X_5$. The following is a summary of explained variation.

Step Number	Variable	R	R^2
1	X_1	0.8610	0.7412
2	X_7	0.8810	0.7762
3	X_4	0.8859	0.7847
4	X_3	0.8870	0.7868
5	X_5	0.8870	0.7868

Seventy-seven percent of the explained variance results from travel time difference and travel cost difference weighted by income. However, even when these 2 or primary indicators are used, only 0.03 is added to the R^2 because of the inclusion of weighted cost difference. The correlation matrix shows an extremely high partial correlation between X_1 and X_7. As developed here, one must conclude that weighted cost difference is autocorrelated with time difference in the analysis. To pursue a logit curve with the above input was considered irrelevant. Further comment will be made on speculative issues of concern about this section in the conclusions.

CONCLUSIONS AND ISSUES FOR FURTHER STUDY

This study was a highly speculative, pilot investigation of route choices of automobile travelers. Its value is more in the enlightened direction provided for further research than in the specific end products obtained. Several items are apparent.

1. More sophisticated questionnaire design is necessary to provide responses that are meaningful for potential use in scaling and weighting socioeconomic preferences related to route choice.
2. More comprehensive field study and counting are necessary in a comprehensive study. The license plate matching survey technique is efficient, but should be employed for a large sample (perhaps 100 percent) of the peak hours during selected weeks before and after diversion. A sampling procedure for off-peak volumes should be designed through classical sampling approaches to yield, along with the peak-hour information, a diversion profile over all time periods throughout the study weeks. Seasonal variation, if important, should be considered.

Figure 4. Probability of diverting to I-95 versus travel time difference (1-min grouping).

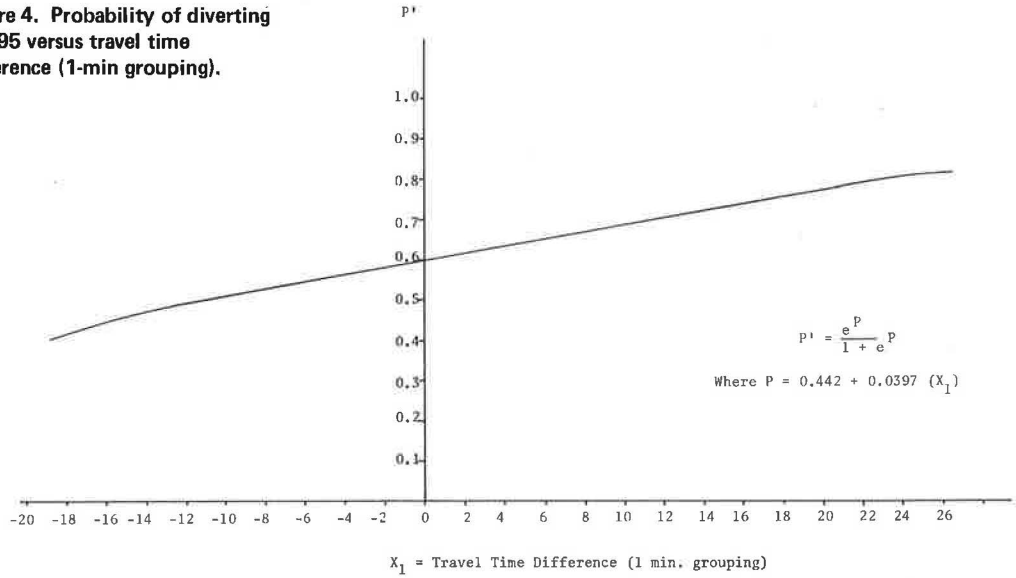


Figure 5. Probability of diverting to I-95 versus travel time difference (5-min grouping).

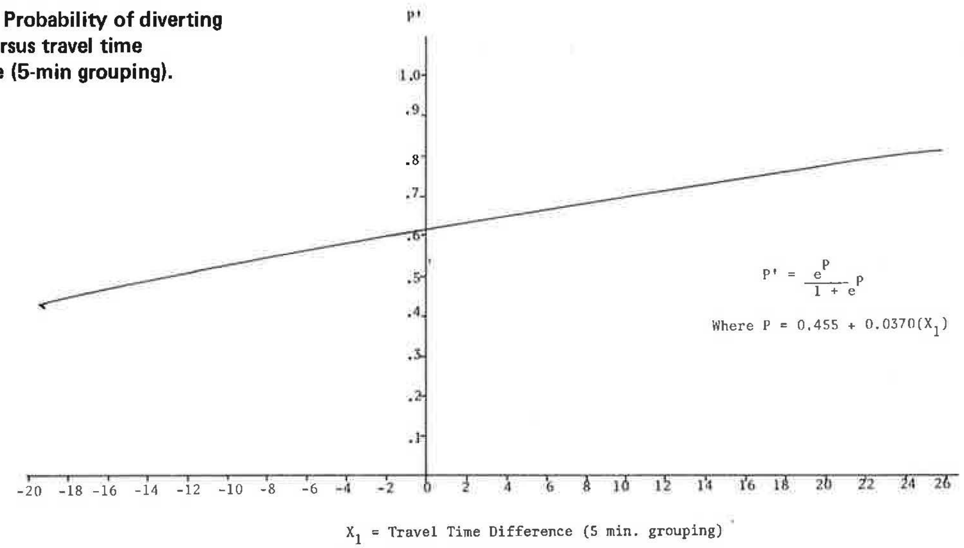
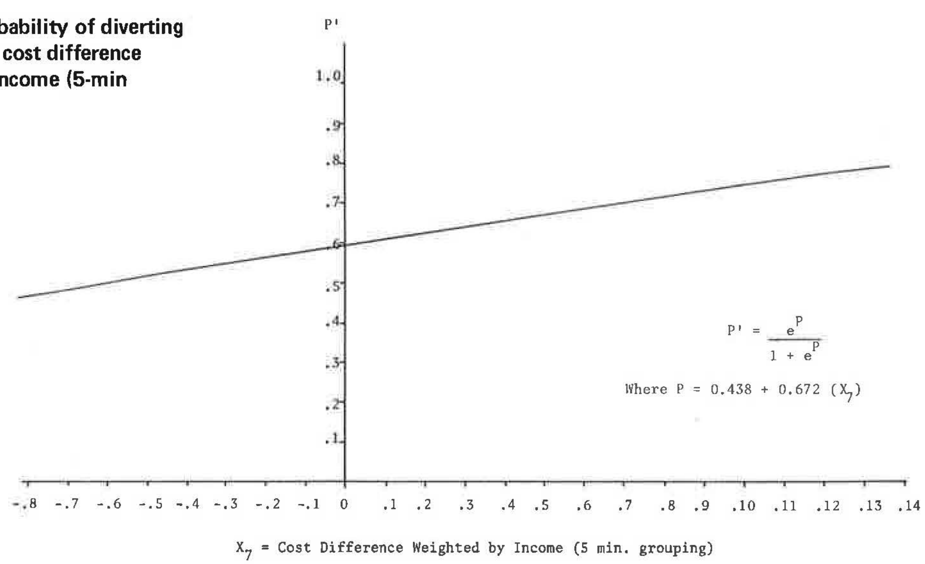


Figure 6. Probability of diverting to I-95 versus cost difference weighted by income (5-min grouping).



3. With respect to actual results obtained here, the most valid indicator is travel time difference as determined from the bivariate analysis and smoothed in a logit format. Although this would appear intuitively obvious, to more adequately investigate the socioeconomic aspects of the driving population is relevant. Although the multivariate analysis of X_1 and X_7, time difference and cost weighted by income, was rejected based on presumed autocorrelation, the authors speculate that perceived economic and social status of the driver may heavily influence his or her route choice and travel patterns generally. A more sophisticated questionnaire might develop the use of quantitative information relating to X_7, which is more indicative of the entire travel choice phenomenon than X_1, and yield X_7 or some other type of status-oriented weighting variable as a surrogate for many stimuli, one being travel time.

4. The above point and the thrust of a study design such as this one are particularly relevant at this time because of energy shortages and extreme travel price alterations. These result in intensive stimuli for individuals to alter route choices and travel patterns and to reexamine these as entities centrally related to their life-style and perceptions of its quality. Travel is considered a derived demand, and excellent opportunity exists to use disaggregate analysis to study the sensitivity of this demand to life-style characteristics and the effect of exogenous forces on automobile travel behavior. To the extent disaggregate analysis yields adequate information on these items, it is a potentially viable modeling component in urban transportation planning in addition to its current use in pure modal-split analysis.

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PREDICTION WITH DISAGGREGATE MODELS: THE AGGREGATION ISSUE

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This paper describes the problem of aggregation in forecasts of travel behavior under conditions in which aggregate behavior is the accumulation of travel choice decisions by individuals or households. Failure to deal with this problem, which is explicit in the use of disaggregate models and implicit in the use of aggregate models, leads to predictions that have biases related to the heterogeneity of the group for which the prediction is made. Alternative approaches to the development of unbiased aggregated forecasts based on disaggregate choice models are described. The importance of forecasting the distribution of characteristics that influence individual or household choice is cited. The advantages of an explicit aggregation procedure are identified with respect to sensitivity to changes in the distribution of choice-influencing characteristics and to improvement in the sensitivity to changes in the average values of these characteristics. Directions for future research to overcome the aggregation problem are identified.

•DISAGGREGATE choice models have had rapid development in recent years. The improved understanding they have provided of the decision process influencing individual behavior has contributed to the refinement and modification of theories of travel behavior. More recently, attention has been directed toward the use of disaggregate models for the prediction of aggregate travel behavior. This approach to obtaining aggregate predictions is based on the principle that the travel behavior of large groups is the manifestation of the travel choice decisions of numerous individuals or households. The problem associated with aggregate predictions based on disaggregate models is the development of a procedure for expanding individual choice estimates over the population of interest to obtain a reliable, unbiased description of group behavior.

The construction of an aggregate forecasting model based on a disaggregate model depends on both the form of the disaggregate model and the shape of the multivariate distribution of characteristics that influence travel choice. If the underlying disaggregate model is linear over the range of interest, the aggregate forecasting model will have the same linear specification; averages of the variables will be substituted for the individual values. However, if the disaggregate model is nonlinear, the disaggregate functional specification, in which averages of the independent variables are substituted for individual values, will give a biased forecast of the average of the dependent variable, except in the special case where the population is homogeneous with respect to those characteristics that influence the choice under study. This is shown with an example in the following section.

In principle, the transformation of a disaggregate model into an aggregate forecasting model can be accomplished by integrating the relation over the distribution of the choice-influencing characteristics. In general, the explicitly aggregated forecast model will contain parameters of the relevant distributions as well as parameters of the choice process. Such models will therefore be adaptable to forecasting under conditions where different distributions prevail or where the distribution structure is expected to change over time.

On the other hand, a model that is calibrated with aggregate data and that does not explicitly take account of the distribution of choice-influencing characteristics will have biased coefficients and will be valid for forecasting only if the distribution of characteristics for the forecast situation is reasonably similar to the distributions in the groups on which the model was originally calibrated.

The transformation of a disaggregate choice model into an aggregate model by mathematical integration may be an intractable problem, depending on the form of the disaggregate model and the shape of the relevant distributions. However, to obtain approximate aggregate forecasts by use of numerical integration or grouping techniques is always possible. Any transformation method will require the forecast of the distribution of relevant characteristics in addition to representative values. Even if no forecast distributions are available, judgment may be used in a Bayesian sense to suggest modifications to existing distributions.

AGGREGATION PROBLEM

Consider a disaggregate model describing the probability of a decision-making unit, either individual or household, choosing an alternative from a set of possible alternatives (such as one of several modes to work or one of several destinations for a weekly shopping trip). The general form of this model is

$$P_t(i:A) = f(U_{jt},\ \text{all } j \text{ in } A) \tag{1}$$

where

$P_t(i:A)$ = probability of decision unit t choosing alternative i from the set of alternatives A,
$f(\ )$ = function of the enclosed arguments, and
U_{jt} = utility of alternative j to individual t.

For the purpose of this discussion we will assume that the utility of each alternative for individual t is a linear function of the attributes of that alternative. (We will refer to the decision unit as an individual henceforth. However, the discussion applies equally to any behavioral unit. The linear assumption does not place a significant constraint, for nonlinear relations may be expressed by defining attributes in terms of logarithmic, exponential, or power functions, and interaction of variables may be represented by creating variables that are functions of groups of attributes.) That is,

$$U_{jt} = \sum a_m X_m^{jt} \tag{2}$$

where

X_m = value of attribute m of alternative j for individual t, and
a_m = parameter that describes the influence of the associated variable on the utility value. (The assumption that parameters a_m are identical for each household will be used throughout. Differences in parameters representing differences in behavior may occur for different market segments. Aggregation over different market segments is discussed in a later section.)

In the special case where the choice model applies to a binary (2-choice) situation and the function of utilities is the difference between the utilities, that is,

$$\begin{aligned} P_t(i:A) &= f(U_{it},\ U_{jt}) \\ &= U_{it} - U_{jt} \\ &= \sum_m a_m(X_m^{it} - X_m^{jt}) \end{aligned} \tag{3}$$

it can be shown that the expected proportion of individuals who will choose alternative i is equal to the probability of choosing i for an individual who faces the average of the attributes of each alternative. That is,

$$\bar{P}(i:A) = P_{\bar{t}}(i:A) = \bar{U}_i - \bar{U}_j = \sum a_m(\bar{X}_m^i - \bar{X}_m^j) \tag{4}$$

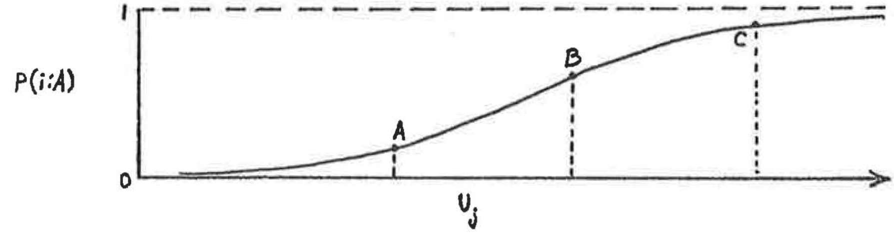
where

$\bar{P}(i:A)$ = expected proportion of people choosing alternative i,
$P_{\bar{t}}(i:A)$ = probability of choosing i for an individual facing average attributes for all alternatives,
$\bar{U}_j$ = average utility of alternative i, and
$\bar{X}_m^i$ = average value of attribute m of alternative i.

The aggregate model in Eq. 4 is identical to the disaggregate model of Eq. 3; average values of all the attributes are entered in place of the individual values. In this case, the influence of any attribute on the aggregate proportion choosing an alternative can be fully represented by the average value of the attribute to the group under study. The aggregate relation, Eq. 4, would give unbiased predictions for expected choice proportions. Unfortunately, the structural requirements of disaggregate choice models (probability of any choice must be within the 0 to 1 range) requires that the choice model be a nonlinear function of the relevant utilities. In this case, it can be shown that the corresponding nonlinear aggregate function with average values used to replace individual values will give biased results unless the individuals in the group are homogeneous with respect to all of the characteristics that influence the choice (binary or multiple) under study (1). That is, the average of the function (the average probability) is not equal to the function of the averages (the probability for an individual facing average attribute values). For example, consider the logit formulation of the binary choice model,

$$P_t(i:A) = \frac{e^{U_{it}}}{e^{U_{it}} + e^{U_{jt}}} \tag{5}$$

which can be represented as a function of $(U_{it} - U_{jt})$ by the following diagram:



(The binary choice logit model is used for ease of discussion. Essentially identical results may be obtained for the multinomial logit model.) The probability associated with any value of $U_{it} - U_{jt}$ for a single individual may be read directly from the graph, and the influence of a small change in U_{it} or U_{jt} is a function of the slope of the curve at the point of interest. If we consider a population with average utilities $\bar{U}_i$ and $\bar{U}_j$ represented by point B and assume that all $U_{it} = \bar{U}_i$ and all $U_{jt} = \bar{U}_j$, the average probability of choosing i and the sensitivity of that probability to changes in the difference between the utility functions will be identical to that for one individual represented by B. However, if the true population consists of subgroups represented by points A and C, both the estimated average probability and the sensitivity to changes in the attributes of an alternative will be biased. This analysis can be extended to multiple subgroups or continuous distributions of group members with similar results.

AGGREGATE PROBABILITY ESTIMATES

The best estimate of the proportion of the population that will choose alternative i from set A is simply

$$\bar{P}(i:A) = \frac{1}{N} \sum_{t \in N} P_t(i:A) \tag{6}$$

which is the average of the expected response probability of each individual in the population. (Equations 6 and 7 apply equally to binary- and multiple-choice situations.) Similarly, the expected change in the proportion choosing i due to a change in the value of one of the attributes of any of the alternatives in set A, say j, will be

$$\Delta\bar{P}(i:A) = \frac{1}{N} \sum_{t \in N} \frac{\partial P_t(i:A)\, \Delta X_n^{jt}}{\partial X_n^{jt}} \tag{7}$$

But the change in the selected attribute, ΔX_n^{jt}, and the responsiveness to change, $[\partial P_t(i:A)]/\partial X_n^{jt}$, may be different for different individuals. Since the responsiveness to change depends on the probability prior to the change, solution of the estimation problem for perfect prediction requires knowledge of the distribution of the choice probabilities, or all the attribute values from which the choice probabilities are determined, and of changes in X_n^{jt}. Obviously it will not be feasible to predict these values for each individual and to explicitly aggregate the results as implied by Eqs. 6 and 7.

The condition for consistent aggregation with nonlinear functions, homogeneity of individuals in the group, suggests that one method of approximating this representation is to group individuals in categories such that the assumption of a representative value of individual utility is an acceptable approximation for all individuals in the group. In this case,

$$\bar{P}(i:A) = \frac{1}{N} \sum_{T=1}^{NG} N_T P_T(i:A) \tag{8}$$

and

$$\Delta\bar{P}(i:A) = \frac{1}{N} \sum_{T=1}^{NG} N_T \frac{\partial P_T(i:A)}{\partial X_n^{jT}} \Delta X_n^{jT} \tag{9}$$

where

N = total number of individuals;
NG = number of groups;
N_T = number of individuals in group T;
$P_T(i:A)$ = probability function for the representative individual in group T;
$[\partial P_T(i:A)]/\partial X_n^{jT}$ = derivative of the probability response function with respect to a change in any attribute, X_n^{jT}, for the representative member of group T; and
ΔX_n^{jT} = representative change in attribute X_n^{jT} for group T.

In cases where the attribute change is not uniform, the selection of groups should provide a reasonable degree of homogeneity of this change within groups as well as for the attributes influencing individual choice probabilities. A variety of methods for grouping households can be suggested. Generally it will be most understandable to group them according to the variables that are relevant to the choice under study. The degree of stratification for each of the variables will depend on the range of the variable and the size of the parameter associated with it. In cases where the distribution can be described by continuous functions, the grouped summation may be replaced by a numerical or mathematical procedure (2, 3).

DISTRIBUTION OF INDIVIDUAL CHARACTERISTICS

The models of aggregate behavior represented by Eqs. 8 and 9—or corresponding methods based on numerical or mathematical integration—make explicit the dependence of the estimate on

1. The individual's response to the characteristics he or she faces (the individual choice function), and
2. The distribution of individuals according to their characteristics and the characteristics they face.

This explicit representation is the basis of 2 major advantages of explicitly aggregated predictive models based on disaggregate analysis over aggregate forecasting models based on correlative analysis of aggregate data.

1. Improved sensitivity to changes in individual behavior due to changes in environmental characteristics including policy controlled variables, and
2. Sensitivity to changes in the distribution of the characteristics that the population has or faces.

The structure of the aggregate models represented by Eqs. 8 and 9 requires a complementary population distribution model to be employed in conjunction with the disaggregate choice mode. Although this adds a potentially complicating dimension to the application of disaggregate models, it should be possible to develop simple models of distribution based on assumptions that are at least as good as the implicit assumptions embodied in models based on aggregate travel data. In addition, the possibility of developing improved representation of population distributions can be explored.

NEED TO FORECAST CHARACTERISTIC DISTRIBUTIONS

Each of the possible methods for obtaining unbiased aggregate forecasts of travel behavior requires explicit representation of the distribution of the characteristics of the population and the travel choices they face. This requirement places increased demands on the forecast of explanatory characteristics. Obviously it will be difficult to develop models capable of forecasting joint distributions of a wide variety of population and travel choice characteristics. The critical issue for modeling strategy is to improve the quality of distributional forecasts to a level that is compatible with the quality of other elements in the overall forecast process. Decisions must be made as to the methods of representation of the required distributions including assignment to groups versus continuous representation. In addition, those distributions that are to be represented with the greatest level of detail and accuracy must be identified. Primary attention should be directed toward improving the quality of forecasts for those distributions to which the required aggregate forecasts will be most sensitive.

The criteria for these decisions must be related to the objectives of the analyses to be performed, but would presumably include evaluation of the expected bias and standard error of the aggregate forecast. The levels of satisfaction of these criteria will be interrelated. For example, increasing the number of dimensions along which the population is stratified will tend to reduce the aggregation bias but may also increase the standard error of the aggregate forecast.

Decisions on the distribution forecast procedure to be used will depend on the particular situation under study, the type and quality of population distribution forecast models available, the range of the nonlinear function included in the disaggregate model, and the robustness of simplifying assumptions concerning the shape and interdependence of these distributions.

ALTERNATIVE DISTRIBUTIONAL FORECAST PROCEDURES

A range of procedures may be considered for use in forecasting the required distributions. Such procedures represent different assumptions concerning the process that underlies the development of the observed distribution (for example, the co-location aspects of residential location choice for different income groups) and the degree to which simplifications may be introduced. The acceptability of alternative forecasting procedures depends on their conformity with the underlying distribution process and the robustness of the aggregate behavioral forecasts to the simplifications used. Three general approaches are described below.

1. The simplest distribution forecast procedure would be to project the existing distribution in a zone unchanged over the period of interest except for already planned or in process changes that can be explicitly identified. This assumption will be best for short-term predictions. However, even for longer periods this assumption—with modifications based on available information and judgment—can provide better aggregate forecasts than those that could be obtained through the use of conventionally developed aggregate modes. For example, the near-term effect of a change in public transit service could be based on the existing distribution of household and highway service characteristics.
2. Another procedure would be to assume that the distribution of the population is systematically related to a small number of indexes (means, for example) that might be readily forecast. For example, one might assume a gamma distribution of income, 1 parameter (defining the shape of the distribution) fixed and the scale parameter determined from the mean (4) or both parameters simply related to the mean or more generally to directly predict both parameters of the distribution.
3. A more sophisticated procedure would be to develop a transition matrix for "growing" households from inception, through various life-cycle stages, to dissolution, including information on relevant characteristics. Such an approach would be most appropriate for relatively large areas where the effects of migration are relatively unimportant.

INTEGRATION OF HOUSEHOLD AND SPATIAL CHARACTERISTICS

The distribution of spatially related characteristics facing the household must be considered as well as the distribution of socioeconomic or household characteristics. Characteristics that are neighborhood or transport-system specific are examples. This suggests the need to spatially assign the household-characteristic distribution and to develop joint distributions over household and spatial characteristics. Obviously, this step will be much simplified if an assumption of independence can be justified between household and spatial distribution or if the dependence can be simply specified.

However, to argue that the distribution of household and spatial characteristics is related through the household location choice process is more reasonable. This relation could be modeled by first forecasting the regionwide distribution of household characteristics and then assigning households with specific characteristics to geographic locations as part of a residential location choice model that explicitly accounts for geographic, neighborhood, and transportation service characteristics.

In general, the entire problem of forecasting interrelated distributions of population and spatial characteristics could be simplified by designing spatial groupings (zones or districts) so as to highlight differences that are relevant to the analysis in question. Considering the spatial sensitivity of out-of-vehicle travel time and access to transit, for example, it would be useful to explicitly identify areas that are, or would be in the future, highly differentiated in terms of accessibility to transit service. Geographic aggregation of the population for areas with common service characteristics would simplify the aggregate prediction problem when compared to present zonal groupings.

MARKET SEGMENTS IN BASE MODELS

To this point, we have explicitly assumed that travel choice behavior can be represented by a single disaggregate model. That is, we have assumed that all groups of the population have the same behavioral response when they are confronted by identical conditions. However, in many cases the population will have to be segmented and different disaggregate models developed for each market segment. In this case, prediction requires the explicit distribution of the population into these market segments, and all further distributions must be conditional on them. The aggregation procedure would be applied to each market segment and then aggregated over all market segments. Suitable market segments might be related to household life-cycle, occupation of primary wage earner, or other characteristics that may be expected to influence taste patterns with respect to travel behavior.

SUMMARY DESCRIPTION OF ANALYSIS AND PREDICTION

Development of a behaviorally sensitive aggregate forecasting model based on individual or other behavioral unit responsiveness to external characteristics requires the development of procedures for forecasting the distribution of these external characteristics and the characteristics of the household and the development of the underlying disaggregate choice model.

The proposed procedure for obtaining aggregate predictions may be divided into 4 stages. The first stage is to analyze existing data to obtain a disaggregate travel choice model and a household characteristics distribution model. The second stage is to forecast future distributions of population characteristics. The third stage is to define alternative distributions of transportation service characteristics based on policies to be tested, and the fourth stage is to predict aggregate travel behavior.

Once the models have been developed (stage 1) and the distribution of population characteristics for the area has been predicted (stage 2), stages 3 and 4 only have to be repeated to test additional transportation service alternatives.

RESEARCH DIRECTIONS

The preceding discussion indicates that the development of behaviorally sensitive aggregate forecasting models depends on the availability of models for the prediction of the distribution of characteristics that influence travel behavior and the prediction of the probability of disaggregate travel choices when disaggregate characteristics are known. This suggests that, in addition to the ongoing research directed toward the improvement and extension of disaggregate choice models, research must be directed to the development of models that may be used to predict the multivariate distribution of population and service characteristics that influence travel-choice behavior. Specific areas of research are

1. Analyze existing distributions of population characteristics to identify their shape and interdependence;
2. Develop procedures to forecast parameters of the identified distributions on a spatially specific basis;
3. Identify the relation between the distributions of population and transportation service characteristics, taking account of the potential development and application of disaggregate models for household location choice;
4. Develop and apply procedures to test the robustness of simplified descriptions of characteristic and service distributions;
5. Identify those forms of choice models and distribution representations that are amenable to mathematical integration; and
6. Develop criteria to be used in the comparison of aggregate forecasting models based on disaggregate and aggregate analyses, perform a full-scale test of alternative aggregate forecasting procedures, and identify the circumstances under which the different procedures should be used.

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CONSUMER PREFERENCES FOR AUTOMATED PUBLIC TRANSPORTATION SYSTEMS

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This paper investigates the attitudes of a cross section of residents of a metropolitan area toward 3 automated transportation systems. Respondents to a home interview survey evaluated their satisfaction with each system according to 12 attributes such as travel time, comfort, automatic control, and privacy of the vehicle. Respondents also evaluated their overall satisfaction for each system and projected their possible use of these systems. In the first phase of the analysis, the interrelations among the respondents' perceptions of the system attributes are examined. Five latent factors are determined through factor analysis to describe the attribute satisfaction ratings: level of service, comfort and privacy, degree of automatic control, out-of-pocket cost, and options and amenities. These factors are consistent for both work and shopping trips. In the second phase, reported overall satisfaction for work and shopping trips is explained in terms of the attributes through the use of linear additive models. Level of service is a significant descriptor of overall satisfaction for work trips; comfort and privacy and options and amenities are added descriptors for shopping travel. The final phase of the analysis uses a nonlinear estimation technique to explain the allocation of work and shopping trips by the respondent. This technique revealed, as did the linear additive model, that satisfaction with a mode is dependent on trip purpose.

•KNOWLEDGE of the perceptions displayed by individuals toward alternative designs and operating strategies of existing and proposed transportation systems can be important to the successful planning, implementation, and operation of the systems. This study is an attempt to advance information on peoples' attitudes, specifically within the realm of models for automated urban public transportation systems.

The models developed here are concerned with a better understanding of how peoples' attitudes with respect to certain attributes (i.e., waiting time, comfort, and fare) affect their perceived overall satisfaction for 3 proposed automated transportation systems. The knowledge of those attributes that influence the attitudes of an individual toward a particular transportation mode are desirable inputs to both the design of system components and the planning of specific applications. The primary purpose of this study is not to develop a demand model per se for automated transportation systems but to construct models that will identify those attributes perceived by the respondents as important for determining their satisfaction for particular modes.

The 3 automated urban public transportation modes and the guideways on which they operate are described in the next section. The questionnaire and subsequent data base are also presented in that section, and the 12 attributes used to describe each mode are detailed. The results of the factor analyses of the interrelations among peoples' perceptions of these attributes are presented in the following section. Linear regression models are developed in a third section to explain the overall satisfaction rating given each mode by the respondents. Perceived differences in overall satisfaction between modes are also examined in that section. In the final section, the allocation of trips among the modes is explained in terms of the attribute ratings through the use of a binary-choice logit model.

DATA BASE

The sample of observations for this study came from a survey assessing attitudes for hypothetical new urban transportation modes designed to serve the arterial transportation needs of a large metropolitan area. The survey is detailed by Dobson and Kehoe (3). Three transportation modes—dual-mode transit (DMT), people mover (PM), and personal rapid transit (PRT) are the subject of the research reported here. The personal rapid transit mode involves a small vehicle that individuals can use on a private basis. It remains on the guideway at all times and holds as many as 4 people. PRT vehicles are designed to provide comfort, privacy, and to a large extent the flexibility of the private automobile. They are routed from origin to destination with no stops, and passengers must board and disembark at transit stations. The people mover is a vehicle designed to accommodate approximately 25 passengers. It resembles a bus, but operates exclusively under automatic control on a guideway. PM operates on a regular schedule and stops to load and discharge passengers along the route. Dual-mode transit operates under driver control on regular city streets or by automatic control along the guideway. The dual-mode transit vehicle holds about 12 people and resembles a small bus in appearance. In manual mode, the DMT vehicle operates as a demand-responsive bus. Thus, in order to use DMT, a person places a call to a dispatcher and requests a DMT vehicle. The vehicle operates along regular streets picking up and discharging passengers and then enters a guideway, where it is controlled automatically without a driver.

Specifically the survey provided respondent evaluation for the 3 automated transportation modes. Socioeconomic and demographic characteristics of the respondents were also collected. The survey was implemented in the form of an in-home interview of approximately 1-hour duration. The final sample consisted of approximately 500 respondents systematically sampled from the population of the Detroit Standard Metropolitan Statistical Area (as defined in the 1970 Census of Population).

The interviewer first ascertained whether the pre-selected respondent made 1 or more work trips per week. If so, a work trip questionnaire was presented. Otherwise, a shopping trip questionnaire was administered. After receiving an explanation of the design and operation of each mode through the use of diagrams and scenarios, respondents were asked to give a satisfaction rating of 1 to 7 for that mode on each of 12 attributes. These attributes are shown in Figure 1. In addition, respondents were requested to evaluate their overall satisfaction with each mode. The respondents were also asked to allocate 10 hypothetical trips among the public transportation modes of the Metro Guideway and their present means of transportation. Figure 2 shows the question that requested the allocation of trips. To keep the interview and questionnaire within the attention span of the respondent, each questionnaire was directed to only 2 of the 3 modes. All respondents were asked to answer questions relating to DMT, but only about either PM or PRT, not both. This limited the sample sizes for much of the analyses reported here to approximately 250 observations (one-half of the total survey sample of 500). Additional data items from this survey have also been analyzed (4).

SATISFACTION RELATIONS

Factor analyses were performed on the data matrices of satisfaction ratings for the 12 system attributes shown in Figure 1. Analyses were conducted separately for each of the 3 automated modes and for each of the 2 travel purposes of work and shop. The objectives of these 6 factor analyses were twofold. The first objective was to identify the latent or underlying dimensions (i.e., linear combinations of the original attributes) that best describe the interrelations between satisfaction ratings. The second objective was to select a relatively independent subset of the original 12 attributes for use in models designed to explain respondents' overall satisfactions and modal choices (10).

From an examination of the variance accounted for by successive factors, it was decided to retain 5 factors for interpretation in each of the 6 analyses. Two factor analyses were performed for each mode: one for a work trip and the other for a shopping trip. Selection of the number of latent factors was accomplished through subjective evaluations of a number of statistical criteria (7).

Figure 1. Response form for judgments on dual-mode transit.

I think I would be this satisfied with this feature if I made my usual trip in a dual mode transit vehicle:	Extremely Satisfied	Very Satisfied	Somewhat Satisfied	Neither Satisfied Nor Dissatisfied	Somewhat Dissatisfied	Very Dissatisfied	Extremely Dissatisfied	
The ability I think I would have to get where I want to go on time	7	6	5	4	3	2	1	9
The safety I think I would have from harm by others and from vehicle accidents	7	6	5	4	3	2	1	10
The room I think there would be for strollers and wheel chairs	7	6	5	4	3	2	1	11
The ability I think I would have to get to many places in the Detroit area using the guideway	7	6	5	4	3	2	1	12
The ability I think I would have to buy refreshments and news-papers at the transit stations	7	6	5	4	3	2	1	13
The amount of control I think I would have of the temperature in the vehicle	7	6	5	4	3	2	1	14
The time I think I would have to wait for the vehicle	7	6	5	4	3	2	1	15
The time I think it would take to get to where I'm going	7	6	5	4	3	2	1	16
The fare I think I would have to pay	7	6	5	4	3	2	1	17
How comfortable and quiet I think the ride would be	7	6	5	4	3	2	1	18
The automatic control feature of the vehicle	7	6	5	4	3	2	1	19
The amount of privacy I think would have in the vehicle	7	6	5	4	3	2	1	20
Over-all, taking everything into consideration, how satisfied do you think you would be if you make your usual trip in a dual mode transit vehicle?	7	6	5	4	3	2	1	21

Figure 2. Instructions read to respondent for mode-choice task.

22. Still thinking about the future, assume that you could choose among the types of transportation we have been talking about. . . (LAY OUT BLUE CARD FOR EACH OF THE FOLLOWING). . .

Card #4
(Dup 1-8)
2 9

The type of transportation I use now, but with longer travel times

Dual mode transit

Personal rapid transit

Here are 10 cards. Each one of these cards represents one of your usual trips (to work/to go shopping). Please divide up these 10 trips the way you think you would make them by each of these types of transportation (POINT TO BLUE CARDS). You may take all of the trips using the same type of transportation or you may take some trips with one type and some with other types of transportation. Just show me which types of transportation you think you might use for 10 trips if you could choose any of these.

	Number of Trips				
		10			11
Present type	______	12			13
Dual mode transit	______	14	–	–	15
Personal rapid transit	______	16			17
Total Trips:	10				

Tables 1, 2, and 3 give the rotated factor loadings matrices for the 6 analyses. The factor loadings are correlation coefficients that relate each original attribute to each latent factor. The absolute value of each loading is thus proportional to the degree of correspondence between the factor and the attribute. Only loadings with absolute value greater than 0.50 are given in the tables. The tables also give the commonalities for each variable. These commonalities are coefficients of determination, R^2, expressing the proportion of variance of each variable that is explained by the latent factors taken together. The average of the commonalities for each of the 6 analyses ranged between 0.75 for DMT work trips to 0.82 for PM work trips. Thus, in all 6 cases a linear combination of 5 latent factors accounted for a large proportion of the variance in the original 12 attribute ratings.

Most of the factors are readily interpretable and are consistent across the 6 analyses. Consequently, a common set of 5 factors was chosen to represent the interrelations in the respondents' satisfaction ratings. Thus, the structure of perceptions toward the attributes for the 3 automated modes is relatively similar for both trip purposes. The 5 factors (and attributes chosen to represent each) are then as follows: (a) level of service (waiting time for vehicle), (b) comfort and privacy (comfort and quietness of ride/amount of privacy in vehicle), (c) degree of automatic control (automatic control feature of vehicle), (d) out-of-pocket cost (fare), and (e) options and amenities (temperature control in vehicle).

COGNITIVE STRUCTURE OF ATTITUDES

In theories relating attitudes to behavior, an important role is played by an individual's overall conscious, subjective feeling toward an object or set of objects. The concept of such an overall feeling, or overall satisfaction as it is measured in the present survey, is thoroughly developed in the psychological literature. The research reported in this section deals with the testing of specific hypotheses that relate individuals' overall satisfactions with a transportation mode to their beliefs about the attributes that define the mode. Kotler (15) defined such descriptive attributes for market research purposes as "a bundle of physical, service and symbolic particulars expected to yield satisfaction or benefits to the buyer." This division into attributes, moreover, provides a direct linkage to the new economic approaches to consumer theory (16) in which the objects of utility (benefit to the individual) are specified as the properties of the consumer good, as opposed to the good itself.

A multiple regression approach for explaining overall satisfaction in terms of separate attribute satisfaction scores has been introduced (22). This model is similar to the cognitive summation theories advanced in the field of psychology (4, 20). However, a number of issues involving conceptualization and measurement differentiate various versions of these psychological theories employed in market research. A recent paper (29) summarizes many of these issues. The form of the attitude hypotheses tested here is

$$A_j \cong \sum_{k=1}^{h} B_{jk}S_{jk} + \text{constant}$$

where

A_j = overall satisfaction associated with mode j,
S_{jk} = satisfaction associated with attribute k for mode j, and
B_{jk} = regression coefficient of the kth attribute for mode j.

Linear regression models were calculated for each mode. The attributes chosen to be used in the regression analyses were obtained from the factor analyses in the previous section of the paper. Responses to these satisfactions were solicited on a 1 to 7 semantic differential scale (1, 5, 24, 27).

The results of the regressions of overall satisfaction on the 5 attributes representing the latent factors are given in Tables 4 and 5. b refers to the actual regression

Table 1. Rotated factor loadings for dual-mode transit satisfactions.

	Work Trips						Shopping Trips					
	Factor						Factor					
Variable	1	2	3	4	5	Common-alities	1	2	3	4	5	Common-alities
Waiting time			0.85			0.84	0.76					0.77
Travel time			0.81			0.84	0.75					0.78
Fare		-0.68				0.64	0.87					0.79
Comfort	0.65					0.73		-0.77				0.75
Automatic control					-0.84	0.86					0.89	0.89
Amount of privacy	0.76					0.71		-0.65				0.68
Arriving on time					-0.60	0.66		-0.61				0.80
Safe from harm					-0.79	0.74						0.68
Room for strollers	0.60					0.80		-0.59				0.70
Able to get places				0.82		0.85				-0.78		0.81
Refreshments	0.78					0.68			0.90			0.84
Temperature control	0.76					0.65			0.55			0.67
Proportion of variance	0.23	0.18	0.17	0.10	0.09	75.00	0.22	0.19	0.13	0.13	0.10	76.60

Table 2. Rotated factor loadings for people-mover satisfactions.

	Work Trips						Shopping Trips					
	Factor						Factor					
Variable	1	2	3	4	5	Common-alities	1	2	3	4	5	Common-alities
Waiting time	0.62		0.55			0.78	-0.81					0.84
Travel time			0.73			0.85	-0.81					0.88
Fare			0.84			0.85					0.84	0.92
Comfort				0.71		0.86	-0.60					0.72
Automatic control					0.85	0.91				0.90		0.90
Amount of privacy				0.83		0.87		0.72				0.74
Arriving on time	0.82					0.85	-0.72					0.75
Safe from harm	0.65					0.78	-0.78					0.79
Room for strollers		0.83				0.77		0.55				0.73
Able to get places	0.78					0.78	-0.67					0.73
Refreshments		0.78				0.77		0.86				0.76
Temperature control		- 0.71				0.74			0.73			0.83
Proportion of variance	0.22	0.19	0.17	0.14	0.11	81.90	0.31	0.17	0.12	0.10	0.10	80.00

Table 3. Rotated factor loadings for personal rapid transit satisfactions.

	Work Trips						Shopping Trips					
	Factor						Factor					
Variable	1	2	3	4	5	Common-alities	1	2	3	4	5	Common-alities
Waiting time	0.89					0.85	-0.80					0.76
Travel time	0.87					0.83	-0.71					0.72
Fare					-0.82	0.91	-0.84					0.76
Comfort	0.53	0.52				0.64		0.59				0.74
Automatic control				0.92		0.92		0.76				0.74
Amount of privacy		0.86				0.80		0.76				0.81
Arriving on time	0.89					0.84			0.69			0.79
Safe from harm	0.69					0.66		0.64				0.61
Room for strollers			0.86			0.82					0.86	0.90
Able to get places	0.69					0.79			0.67			0.71
Refreshments		0.60	0.62			0.87				0.77		0.84
Temperature control		0.76				0.74			0.64	0.60		0.81
Proportion of variance	0.33	0.18	0.12	0.10	0.08	80.60	0.21	0.19	0.14	0.13	0.10	76.80

Table 4. Results of regression analysis.

		Work			Shop		
Mode	Variable	b	t	Beta	b	t	Beta
DMT	Wait time	0.32	5.7	0.34	0.36	6.3	0.34
	Fare	0.22	4.0	0.27	—	—	—
	Privacy	—	—	—	0.12	2.3	0.13
	Automatic control	0.14	3.2	0.19	0.16	4.0	0.21
	Temperature control	—	—	—	0.14	2.8	0.15
PM	Wait time	0.24	2.4	0.24	0.42	5.3	0.39
	Comfort	0.27	2.8	0.26	—	—	—
	Privacy	—	—	—	0.27	3.9	0.27
	Automatic control	0.25	3.1	0.29	0.16	2.2	0.17
	Temperature control	—	—	—	—	—	—
PRT	Wait time	0.50	5.9	0.50	—	—	—
	Fare	—	—	—	0.27	4.5	0.30
	Comfort	—	—	—	0.25	3.0	0.21
	Privacy	0.17	2.3	0.19	—	—	—
	Automatic control	—	—	—	0.27	5.2	0.34
	Temperature control	—	—	—	0.15	2.6	0.16
DMT-PRT	Wait time	0.48	5.6	0.49	0.24	2.8	0.24
	Fare	—	—	—	0.20	2.7	0.22
	Automatic control	—	—	—	0.21	2.8	0.22
	Arriving on time	0.26	3.0	0.27	—	—	—
	Temperature control	—	—	—	0.20	2.5	0.19
DMT-PM	Wait time	0.29	3.5	0.32	0.39	4.8	0.24
	Privacy	—	—	—	0.29	3.8	0.29
	Automatic control	—	—	—	0.16	2.3	0.16
	Room for strollers	—	—	—	0.15	2.1	0.16
	Temperature control	0.32	3.0	0.28	—	—	—

Table 5. Statistical tests of regression analysis.

Mode and Purpose	Constant	R	R^2	F-test	Number
DMT					
Work	1.74	0.60	0.36	36.65	194
Shop	1.25	0.64	0.41	46.83	280
PM					
Work	1.21	0.58	0.34	19.83	96
Shop	0.78	0.67	0.45	39.77	149
PRT					
Work	1.65	0.56	0.32	22.60	98
Shop	0.20	0.73	0.54	29.33	131
DMT-PRT					
Work	0.35	0.46	0.21	12.82	96
Shop	0.27	0.63	0.40	23.29	149
DMT-PM					
Work	-0.11	0.56	0.31	21.26	98
Shop	-0.11	0.62	0.39	20.33	131

coefficient, and t is a statistical test to determine whether the regression coefficient differs significantly from zero. The set of explanatory attributes for each regression model reported in the table is limited to that set of independent variables that are significant at the 0.05 level or higher. Beta is a measure of the relative contribution the variable makes toward accounting for the variation, or R^2. The F-test is a statistical test on the regression equation designed to accept or reject the null hypotheses. Disaggregation by trip purpose was incorporated into the analyses, for it was postulated that a person's perceived attitude toward a particular mode would differ according to the function of the trip. In this study the choice of trip purpose is a binary one: work or shop.

The attribute exhibiting the greatest importance in explaining overall satisfactions for both work and shopping trip purposes on DMT was waiting time. The concept of door-to-door service probably resulted in the respondents' attaching a high level of importance to the attribute that measured the unique in-home wait at one end of a trip. The only other variable found to be important in both trip purposes on DMT was automatic control. DMT is the only one of the 3 modes that is not fully automated since the demand-responsive portion of the DMT trip is operated manually. Consequently, one possible reason for the level of importance given automatic control is that respondents tended to feel uncomfortable with a totally automated system and preferred a mode that they can observe being operated for a portion of the trip. This high level of importance could also be traced to the flexible routing and scheduling of the DMT system, for respondents might have equated the level of automatic control associated with DMT to the desirable door-to-door service provided by such routing and scheduling. The question of how a respondent perceived automatic control calls for further research into perceptions toward this attribute-system relation. The only other variables that entered significantly into the DMT model were fare for the work trip and privacy and temperature control for the shopping trip. These results suggest that the work trip purpose is indeed perceived as being different from the shopping trip purpose for DMT. The significant attributes in the work trip were those concerned with level of service and cost. However, for the shopping trip, those variables representing additional conveniences, such as privacy and temperature control, were highly important.

The perceptual differences between the trip purposes for people movers were less evident. As with DMT, a high level of importance was attached to waiting time for both trip purposes. Comfort was perceived as important for the work trip and privacy for the shopping trip. Both privacy and comfort, however, are measures of the same factor. There is a slight distinction between the 2 variables, and in the case of PM comfort is perceived as more important for the work trip and privacy for the shopping trip. Automatic control entered the PM model for work trips because it was perceived as a service variable, and temperature control was included for shopping trips. For people movers, respondents' perceived differences between trip purposes were not extreme. However, the somewhat different variables for each trip purpose suggests that amenities such as temperature control are perceived as more important for the shopping trip.

In the case of personal rapid transit, the 2 trip purposes were considerably different. The only explanatory variables included in the work trip were waiting time and privacy, where the latter attribute accentuates the small vehicle, personal destination control of the PRT. The lack of importance with regard to automatic control is somewhat perplexing. For the PRT shopping trip, all variables were significant with the exception of waiting time. This was the only instance in which the waiting time attribute was not an important explanatory variable.

A large difference in the percentage of variance explained by the 2 PRT trip purpose models was also evident. A conclusion is that the work trip model was underspecified. This would suggest that variables of importance for the perceived PRT work trip are not included in the model, and further research is needed to uncover these variables.

The results suggest that the respondents perceived work and shopping trips differently, regardless of mode. A high level of importance was allocated to the level-of-service variable for all work trips, while other variables such as temperature control and privacy or comfort were consistently significant for shopping trips. The implication is that the amenities plus convenience might play an important role in designing systems that will attract shoppers; such amenities are not so significant as level-of-service performance for the work trip.

A second set of attitudinal hypotheses tested dealt with the respondents' perceived differences between modes. It was postulated that

$$\Delta OS_{ij} \cong \sum_{k=1}^{n} B_{ij,k}(\Delta S_{ij,k}) + \text{constant}$$

where

ΔOS_{ij} = difference in overall satisfaction between mode i and mode j,
$S_{ij,k}$ = difference between satisfaction rating given attribute k for mode j for each individual, and
$B_{ij,k}$ = regression coefficient for difference in satisfaction rating between mode i and mode j for attribute k.

These multiple regression models attempt to explain the difference perceived by the respondents in overall satisfaction between pairs of modes: DMT-PRT and DMT-PM. The independent variables consituted the differences between the scaled ratings assigned to each attribute by the respondents for DMT-PRT or DMT-PM, while the dependent variable served as the difference in overall satisfaction. The results of these regressions are also given in in Tables 4 and 5. As before, only those variables that revealed significance at the 0.05 level or higher were included in the final model.

The 2 work trip variables that the respondents perceived to differentiate between DMT and PM were waiting time and temperature control. The waiting time might be explained by the advantage in service that DMT has over PM: DMT provides door-to-door service. For PM, the rider must have a means of transporting himself to a station to board the vehicle. However, the DMT-PM work model is less fully specified and, therefore, substantial conclusions on perceived differences between these modes cannot be drawn.

Waiting time, comfort, and automatic control were all perceived as important attributes for differentiating between DMT and PM for shopping trips. These attributes can be associated with physical differences in waiting time and automatic control between the 2 modes and also with a physical comfort difference. The comfort difference is more subjective, however, probably ranging from the nature of the at-home pickup (via station pickup) to vehicle design and operation variances. Another attribute that affected the perceived difference between DMT and PM was room for strollers. For PM, as opposed to DMT, a person with a stroller still faces the problem of getting to and from the station.

A much larger multiple correlation coefficient was associated with the shopping trip when compared to the work trip. Waiting time was the only variable common to both trip purposes. Amenities and convenience and room for strollers entered to a much larger extent in the shopping model.

The final regression model expressed the overall satisfaction difference between DMT and PRT. By releasing the constraints of the 5 latent factor variables, the work trip model had 2 significant variables: waiting time and arriving on time. As with the DMT-PM model, the DMT-PRT work model was underspecified, and additional attributes beyond the 5 latent-factor ones were necessary to explain the perceived difference between DMT and PRT for the work trip. Arriving on time was found to be an important differentiating variable.

The DMT-PRT shopping trip model included waiting time, fare, automatic control and temperature control, and arriving on time. These 5 variables are perceived to differentiate between DMT and PRT. These attributes differentiate between the 2 modes on the basis of their physical characteristics. PRT is a totally automated personal vehicle, and amenities and on-time performance can be considered prominent features of a PRT system.

As with the DMT-PM model, there were significant differences between the 2 trip purposes in the DMT-PRT models. Only level of service and arriving on time were significant in the work model, but other variables such as temperature control and automatic control were perceived as having the differentiating effect between DMT and PRT in the shopping model. This relation is similar to the DMT-PM model and to the overall satisfaction models.

CHOICE MODELS

For the purposes of application to transportation planning, it is important to attempt to establish a link between individuals' affect and their likely use of a new mode of travel. By this means, the information obtained from the psychological measurements, discussed thus far in this paper, may be used in determining the likely acceptability and use of a new mode of travel. This would add a much needed tool to those currently available to the transportation planner and would also provide a procedure to assist in system design.

Such a tool will require a 2-stage process. First, since the travel mode in question is not likely to exist as a fully operational system, data can be gathered only on the behavioral intentions of people in relation to use of the system. This behavioral intention should be related to the measurement of satisfactions with various attributes of the system. Second, actual behavior would be related to behavioral intention. This second step would need to be carried out after one or more systems were introduced. This research collected information on behavioral intention, and this part of the research is concerned with attempting to relate behavioral intention to measured satisfactions with system attributes.

The intention of the analysis reported in this section was to determine the extent to which the respondents' allocation of trips between alternative modes could be explained by differences in satisfaction ratings revealed for various attributes of the 2 modes. The hypothesis was that the relation between choices and differential satisfactions of attributes would be nonlinear in a form identical to recent disaggregate mode-choice models (13, 19, 25, 28). This form is the multiple logistic function: a sigmoid curve relation between probability of choice and a linear function of satisfaction differences. (Linear models were tried but were abandoned after interpretations of the results showed that a significant nonlinear effect was present in each case as hypothesized.)

The measure of behavioral intention employed was an allocation of 10 hypothetical trips among the respondents' present mode of travel, dual-mode transit, and either people mover or personal rapid transit (Fig. 2). Although the trip allocations included the respondent's existing mode, satisfactions for the existing mode on the 12 attributes were not obtained. Hence, the choice models were concerned with the allocation of trips only between DMT and either PM or PRT. Each trip allocation was considered to represent 1 observed choice. Thus, if the probability in the choice model is defined as the probability of choosing DMT, a respondent who allocated 3 trips to DMT and 5 trips to PRT (and 2 trips to his or her existing mode) would be considered as having been observed on 8 occasions, yielding 3 observations with a choice value of 1 and 5 observations with a choice value of 0 (the 2 trips to the existing mode being omitted).

Using this form for the dependent variable, we sought 4 binary-choice models: DMT versus PRT and DMT versus PM for each of work and shopping trip purposes. The 5 attributes identified by the factor analysis were used as explanatory variables to construct 4 models (Tables 6 and 7).

Some variables in each of these models are not significant, suggesting that the models constructed are not optimal. (Since a stepwise procedure is not available for logit models, a systematic exclusion of nonsignificant variables is not readily achievable.) However, all models are significant at the 95 percent confidence level (the 95 percent chi-square distribution table value with 5 degrees of freedom is 11.07). The pseudo-R^2 measure has a maximum value that is different for each model and is generally substantially less than 1.0. (The departure of the maximum value of the correlation coefficient indexes from 1.0 is a measure of the degree of nonlinearity in the model as well as the goodness of fit.) Therefore, the pseudo-R^2 serves only as a comparative measure between models.

Table 6. Results of logit analysis.

	Work				Shop			
	DMT-PRT		DMT-PM		DMT-PRT		DMT-PM	
Variable	Coefficient	t-score	Coefficient	t-score	Coefficient	t-score	Coefficient	t-score
Five set								
Wait time	0.276	3.67	0.356	4.58	0.111	1.68	0.134	2.16
Fare	0.243	-3.40	0.052	0.66	0.251	3.69	0.157	-2.76
Privacy	0.059	0.87	0.088	-1.11	0.195	3.02	0.082	-1.14
Automatic control	0.060	0.99	0.057	-0.83	-0.120	-1.81	0.230	4.56
Temperature control	-0.151	-1.93	0.171	2.78	0.363	4.56	0.136	2.22
Final set								
Wait time	—	—	—	—	—	—	-0.181	-2.36
Travel time	0.343	3.94	0.293	3.94	—	—	0.439	4.64
Fare	0.344	-4.34	—	—	0.301	4.90	-0.151	-2.59
Automatic control	—	—	—	—	-0.105	-1.61	0.285	5.45
Privacy	—	—	—	—	0.175	2.77	-0.245	-3.10
On time	—	—	—	—	0.244	2.96	—	—
Strollers	—	—	—	—	—	—	0.139	2.54
Temperature control	-0.182	-2.37	—	—	0.385	4.86	—	—
Retirement	—	—	0.300	3.63	—	—	—	—
Safety	0.244	3.18	—	—	—	—	—	—
Able to get places	0.216	2.31	—	—	—	—	—	—

Table 7. Statistical tests of logit analysis.

Mode and Purpose	Constant		Pseudo-R^2	Chi Square		
	Coefficient	t-score	Coefficient	Coefficient	t-score	Number
DMT-PRT						
Work	0.521	5.68	0.042	19.73	5	98
Shop	0.408	4.94	0.134	87.84	5	131
DMT-PM						
Work	0.937	9.63	0.097	41.36	5	96
Shop	0.675	9.08	0.056	41.34	5	149
Final						
DMT-PRT						
Work	0.484	5.30	0.109	52.10	5	98
Shop	0.390	4.76	0.130	84.97	4	131
DMT-PM						
Work	0.945	9.81	0.116	49.77	2	96
Shop	0.687	9.12	0.121	91.59	7	149

Given the poor statistical performance of most of these models, constraints on the variable set were relaxed, and more significant models were sought through the inclusion of additional attributes. These are also shown in Tables 6 and 7.

These models show a high degree of heterogeneity, with a range of 2 through 7 significant variables. In terms of both inclusion of variables and signs of coefficients, little consistency is found among the models. For shopping trips, DMT is superior to PRT for fare, privacy, and temperature control, but inferior for automatic control; for work trips, DMT is superior to PRT for travel time, safety from harm, and ability to get places, but inferior for fare and temperature control. Clearly, the modes are perceived differently for different purposes.

Similarly, for work trips, only travel time and refreshments are significant for comparing DMT and PM, both apparently favoring DMT; for shopping trips, 7 variables are needed to compare DMT and PM, and all but fare, waiting time, and privacy favor DMT. Of the signs on the attributes in this model, only the negative sign for privacy appears to be inconsistent with expectations and may be due to intercorrelations among the explanatory variables. This is a topic for further research, for the effects of interrelations among variables in logit models have largely remained uninvestigated.

As with the linear models of overall satisfaction differences, automatic control is a consistent variable of importance in the shopping trip models, but does not appear in the work trip models. Unlike the linear models, waiting time appears to have little importance in these models, entering significantly in only one model. On the other hand, fare and travel time, both of which were of little or no significance in the overall satisfaction models, appear in 3 of the 4 choice models. Room for strollers appears as a significant variable for the DMT-PM choice for shopping trips, as it did for the overall satisfaction differences for the same trips.

All of the choice models show evidence of considerable underspecification, which is demonstrated by the size and significance of the constant term. In the logit formulation, the linear function (the function specified in Tables 6 and 7) must be 0 for indifference between 2 alternatives. When satisfactions with all significant attributes are equal for each model pair, a significant constant yet remains, giving a non-0 value to the linear function. For no difference in satisfactions in each of the 4 models, the probability of choosing DMT will be 0.619, 0.598, 0.722, and 0.667 respectively for the 4 models. Hence, it may be concluded that additional variables are needed in the models to specify more fully the behavioral intention of the respondents and to remove the bias indicated by the significant constant terms.

In conclusion, it may be stated that mode choices can be explained by an examination of differences in satisfactions with various attributes. However, there is considerable scope for further development of such models. Such developments would include improvement of the specification of the models, estimation of more useful statistical measures of the models (e.g., the correlation ratio and associated F-statistic), and investigation of the effect of demographic characteristics on the choices (25).

CONCLUSION

This paper has presented a series of models concerned with the effect attitudes have on explaining overall satisfaction with a particular mode, perceived differences between modes, and trip allocation among modes. It was hypothesized that an understanding of the preferences and perceptions of individuals toward proposed forms of urban transportation is important to the successful implementation and operation of those systems. This study examined the respondents' perceptions toward 3 proposed automated systems: personal rapid transit, people movers, and dual-mode transit.

Interrelation among respondents' satisfactions of the attributes yielded 5 latent cognitive factors when factor analysis was applied: level of service, comfort and privacy, degree of automatic control, out-of-pocket cost, and options and amenities. The factors were stable for both shopping and work trips.

The findings developed from the regression models explaining overall satisfaction with the modes suggested that people perceive trip purposes differently. For the work trip associated with each mode, the level-of-service variable—waiting time—was perceived to be highly important; for the shopping trip, amenities and added conveniences—temperature control and comfort—were more important. The work trips were not so fully specified as the shopping trips, suggesting that additional attributes be incorporated in the work trip models. The success of the models confirms the validity of recent disaggregate extensions of psychological attitude summation theories to the explanation of consumer behavior.

The extent to which the allocation of trips by the respondent could be explained by differences in satisfactions with various attributes was then determined. A binary-choice logit model was used. As with the regression model, it was found that people perceive trip purposes differently. However, a higher degree of heterogeneity was evident in the choice models than in the satisfaction models. The results of the logit analysis suggest that the attitudinal information collected for the attributes included in the study is insufficient by itself for explaining allocation of trips among modes. The large size and significance of the constant term further imply that the models are underspecified.

These models show that peoples' satisfactions with respect to certain attributes have an effect on explaining overall satisfaction, satisfaction differences between modes, and allocation of trips among modes. However, stratification by socioeconomic and demographic variables, a more thorough process of attribute selection, and a clearer understanding of how the respondents perceived each attribute (e.g., automatic control) would improve the models presented. Improvements in these attitude behavior models are necessary if they are to serve as a basis from which transportation planning decisions are made. This research does indicate, however, that the use of perceptual judgments for generating transportation planning models is both feasible and useful in providing policy information for decision-making.

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