DISAGGREGATED BEHAVIORAL VIEWS OF TRANSPORTATION ATTRIBUTES

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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

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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

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

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.

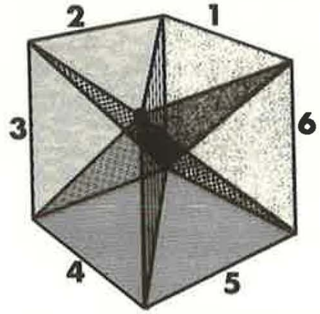
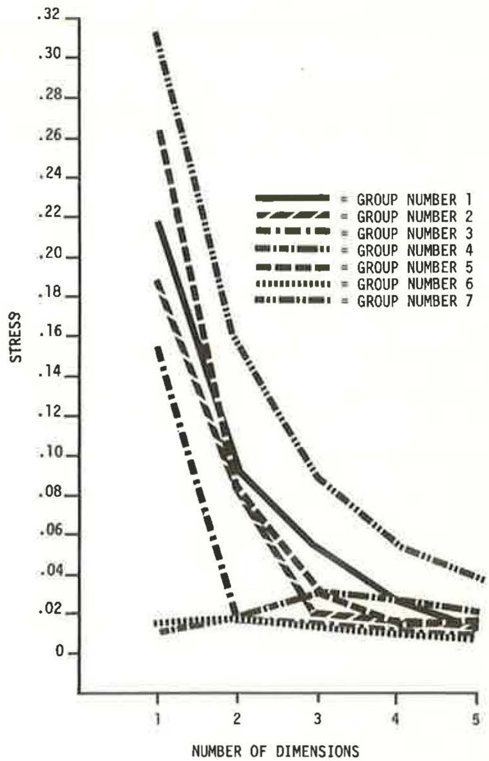


Figure 3. Stress values for 7 homogeneous perceptual groups for 1- through 5-dimensional solutions.



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).

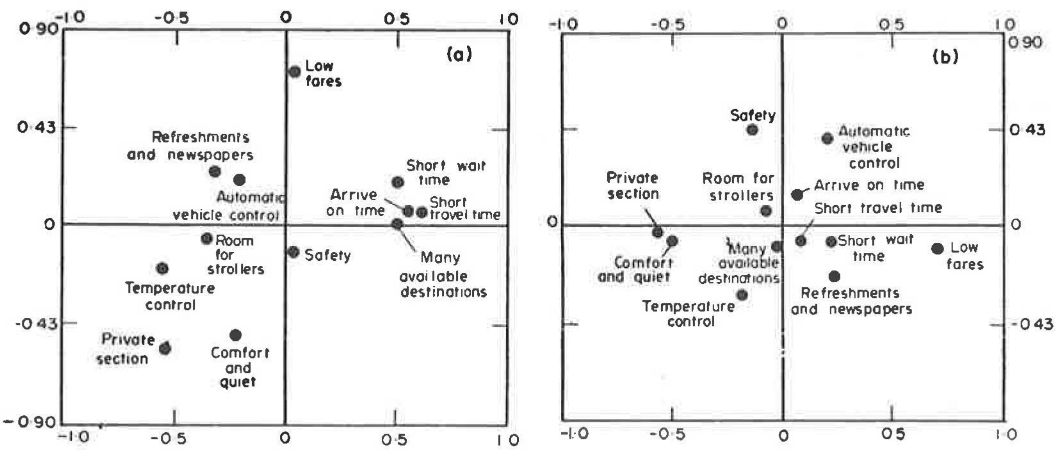
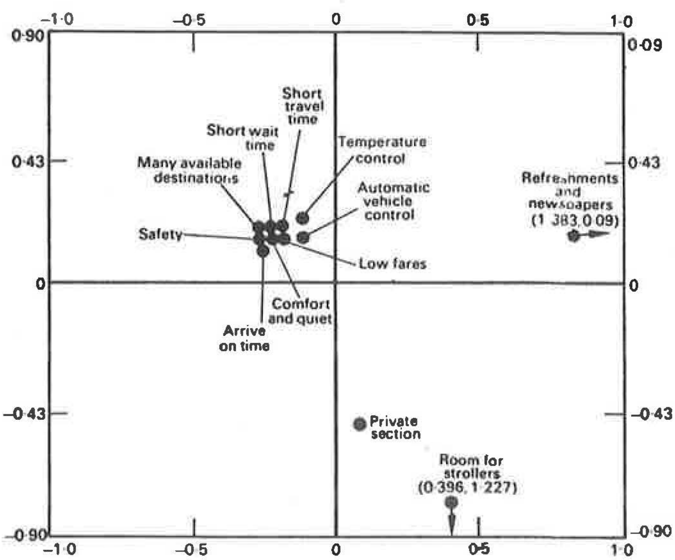


Figure 5. Perceptual space for group 3 in 2 dimensions, where stress = 0.015 (dimensions 1 and 2 are respectively horizontal and vertical axes).



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.

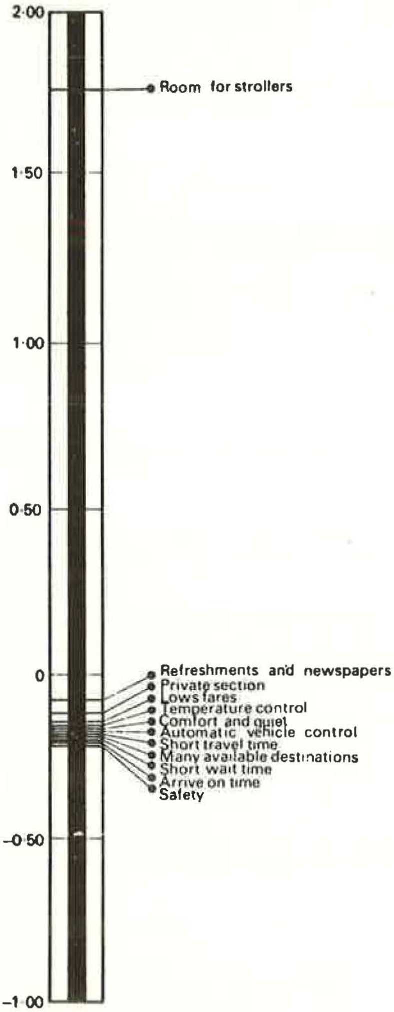


Table 4. Variables ordered by chi-square values for independence among perceptual groups.

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 χ^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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