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Attribute Importance in Multiattribute Transportation Decisions

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This report describes a study of the relative importance of various travel attributes as influences on commuters' choices among car, bus, and Bay Area Rapid Transit (BART) for traveling to work in the San Francisco Bay area. A sample of commuters were interviewed, and each was asked to rate his or her satisfaction with car, bus, and BART on each of the attributes studied. The relative importance of the attributes was inferred by examining these ratings and the relationships between the ratings and the usual choice of travel mode. The study differed from previous similar research in that attribute importance was measured with a statistic that estimated how much each attribute contributed to differences in utility among the choice alternatives. Most previous research failed to consider an essential component of the quantity measured by this statistic, namely, average differences in utility among alternatives caused by average differences among alternatives in the levels of each attribute. Among the attributes judged to be most important were safety from crime, seat availability, and dependable arrival, which are ordinarily not included in quantitative planning procedures such as travel demand forecasting and cost-benefit analysis.

To a large extent, the experience of urban travel by any method can be described in the abstract as a composite of varying travel attributes. This paper describes a study of ten different travel attributes and their relative importance as influences on commuters' choices among car, bus, and Bay Area Rapid Transit (BART) for traveling to work in the San Francisco Bay area. The attributes were (a) cost, (b) total travel time, (c) dependability, (d) relaxation, (e) safety from accidents, (f) time use while traveling, (g) flexibility, (h) seat availability, (i) safety from crime, and (j) waiting time.

A sample of commuters were interviewed and each was asked to rate his or her satisfaction with car, bus, and BART on each of the ten attributes. The relative importance of the attributes was inferred by examining these ratings and the relationships between the ratings and the usual choice of travel mode.

The research was intended to have some immediate applications as a general diagnostic tool in transportation planning for evaluating the relative importance of various attributes that might otherwise be misjudged or overlooked. Primarily, however, the research was considered exploratory, the first stage in a multistage research strategy. Applications to quantitatively detailed planning procedures—such as travel demand forecasting or cost-benefit analysis—require additional research to identify policy variables that underlie the attributes identified as important and to determine how these policy variables are related to utility and behavior (1).

In basic objectives and methodology, this research was similar to a number of recent studies (2, 3, 4, 5, 6, 7, 8). The study differed from previous research, however, in that attribute importance was measured with a statistic that estimated how much each attribute contributed to differences in utility among the choice alternatives, for the people in the study sample. Most previous research has failed to consider an essential component of the quantity measured by this statistic, namely, average differences in utility among alternatives caused by average differences among alternatives in the levels of each attribute.

To demonstrate the importance of this difference, one must consider some theoretical and methodological issues in detail. This is done in the following section of the report. Readers interested primarily in the substantive conclusions of the research could skip to the section on data collection without loss of continuity.

MEANING AND MEASUREMENT OF ATTRIBUTE IMPORTANCE

The theoretical concepts underlying this study can be summarized in the form of a linear utility model. For a detailed discussion of linear utility models and their applications to research on travel behavior see Domencich and McFadden (9). The model is

$$U_{mk} = \sum_j B_j X_{jmk} + e_{mk} \tag{1}$$

where

U_{mk} = utility of travel mode m for person k,
X_{jmk} = measured value of attribute j for mode m and person k,
B_j = coefficient representing the influence on utility of attribute j as measured with variable X_{jm}, and

e_{mk} = stochastic error term influencing the utility of mode m for person k.

The fundamental, virtually tautological axiom underlying the use of this model is that, given a choice among two or more alternatives, an individual will select the one with the greatest utility.

Given the assumptions embodied in the linear utility model and having estimated the utility coefficients B_j, it is possible to calculate one or more importance statistic for each attribute variable. These statistics would indicate the extent to which each attribute influences the utilities of and consequently choices among the alternatives in the choice set (10).

A simple importance statistic can be defined, in terms of a choice made by a particular individual between two alternatives, as

$$I_{jk}(m,n) = B_j |X_{jmk} - X_{jnk}| \quad (2)$$

This importance statistic reflects the extent to which the phenomena measured by variable j contribute to differences in utility between alternatives m and n for person k.

Note that the importance statistic in Equation 2 is calculated as the product of two factors: first, the utility coefficient, which indicates the extent to which one unit of the variable is related to utility, and, second, the number of units of the variable by which the two alternatives differ. As the value of either of these two factors increases, the value of the importance coefficient increases. If either factor has a zero value—i.e., either the variable has no influence on utility or the alternatives do not differ on the variable—the value of the importance coefficient is zero.

A General Importance Coefficient

The simple importance statistic (Equation 2) can be generalized to apply to choices made by any number of people among any number of alternatives. To generalize the statistic to samples of more than one person, the average value of the statistic can be calculated over all people in the sample. Similarly, to generalize the statistic to choices among more than two alternatives, the average of the two-alternative statistics can be calculated over all possible pairs of alternatives in the choice set. Finally, to simplify the calculations, averages of absolute value terms can be approximated with root mean squares. Thus an aggregate importance statistic for variable j for choices made by k individuals among P alternatives is:

$$I_j = B_j \left(\left\{ \sum_{k=1}^{K} \sum_{\substack{m=1 \\ (m>n)}}^{P} \sum_{n=1}^{P} [(X_{jmk} - X_{jnk})^2] \right\} \Big/ K\binom{P}{2} \right)^{1/2} \quad (3)$$

Comparisons of this statistic for different attributes indicate, for the study sample, the relative extent to which each attribute contributes to differences in utility among the set of alternatives investigated (car, bus, and BART).

Components of the Importance Statistic

The aggregate importance statistic (Equation 3) can be partitioned into two components, $I_j = C_{j1} + C_{j2}$, where

$$C_{j1} = B_j \left(\left\{ \sum_{\substack{m=1 \\ (m>n)}}^{P} \sum_{n=1}^{P} [(\bar{X}_{jm} - \bar{X}_{jn})^2] \right\} \Big/ \binom{P}{2} \right)^{1/2} \quad (4)$$

$$C_{j2} = B_j \left[\left(\sum_{k=1}^{K} \sum_{\substack{m=1 \\ (m>n)}}^{P} \sum_{n=1}^{P} \left\{ [(X_{jmk} - X_{jnk}) - (\bar{X}_{jm} - \bar{X}_{jn})]^2 \right\} \right) \Big/ K\binom{P}{2} \right]^{1/2} \quad (5)$$

Thus

$$\bar{X}_{jm} = \left[\sum_{k=1}^{K} (X_{jmk}) \right] \Big/ K$$

and

$$X_{jn} = \left[\sum_{k=1}^{K} (X_{jnk}) \right] \Big/ K$$

The second of the two importance components, C_{j2}, is a standardized utility coefficient, which, for any variable, equals the utility coefficient that would be estimated if the variable were transformed such that the mean variance of the differences in variable values between pairs of alternatives was 1.0.

The standardized utility coefficient can be interpreted as a measure of partial attribute importance. It reflects the extent to which a change of one standard deviation in the attribute difference variable causes a change in the utility difference between two alternatives and, consequently, a change in the choice probabilities for the two alternatives. It indicates how much the attribute contributes to variations over the sample in the utility differences between alternatives. However, unlike the total importance coefficient (Equation 3), the standardized utility coefficient is not sensitive to the average utility differences between alternatives caused by the attribute. For example, the standardized utility coefficient would not reflect the extent to which choices among car, bus, and BART were influenced by average differences in travel time among the three modes.

This failure to reflect average differences also holds for two other statistics—t-statistics and correlation coefficients—that are commonly interpreted as measures of importance for variables in linear utility models.

Johnson (10, 11) discusses the properties of standardized utility coefficients, t-coefficients, and correlation coefficients, and derived their relationships to the coefficient of total importance for a simple case.

DATA COLLECTION

The Survey

The study was based on data obtained in the spring of 1975 from 258 people in the San Francisco-Oakland area. The sample was designed to consist of potential transit commuters living and working in areas well served by bus and BART. Operationally, this meant people who lived in areas accessible to bus and BART service and who worked in San Francisco, Oakland, or Berkeley—all cities well served by bus and BART.

At the time of the survey the BART system was operating on all lines of the system during the day on weekdays but had no evening or weekend service. The people in the study sample were interviewed by telephone. The sample was selected by using random telephone dialing (12).

As indicated in the following table, the characteristics of the study sample were generally comparable to census statistics (1970 census) for workers in the San Francisco-Oakland area. However, as expected from the sample design, the sample had a higher proportion of transit commuters than did the metropolitan area as a whole (24 percent versus 15 percent).

Variable	Study Sample (%)	Workers in San Francisco-Oakland Area (%)
Sex		
Male	56	61
Race		
White	74	84
Age		
Under 45	69	63
45-64	29	35
Over 64	2	3
Income		
Under $8000	23	23
$8000-$14 999	36	40
Over $14 999	41	36
Autos in household		
0	13	8
1	39	42
2 or more	48	50
Usual mode to work		
Drive auto	61	65
Ride auto	5	9
Transit	24	15

Attribute Ratings

Survey respondents were asked to indicate their perceptions of commuting by car, bus, and BART by rating each of the modes available for their work trip on the ten attributes of interest. The rating categories were good, fair, and poor.

The wordings used to describe the attributes were

1. Cost: "the cost,"
2. Total travel time: "the total travel time door to door,"
3. Dependability: "knowing you can get to work on time,"
4. Relaxation: "how much you can relax,"
5. Safety from accidents: "safety from accidents,"
6. Time use: "the chance to do useful or pleasant things while traveling,"
7. Flexibility: "being able to travel when and where you want to,"
8. Seat availability: "your chances of getting a seat,"
9. Safety from crime: "safety from crime and being annoyed by the unpleasant behavior of other people," and
10. Waiting time: "the time you spend waiting."

Respondents were not asked to rate modes that they reported to be impossible to use in commuting.

The ratings were ordered by modes within attributes; i.e., all available modes were rated on cost, and then all available modes were rated on total travel time, etc.

Three of the attributes—seat availability, safety from crime, and waiting time—were rated only for bus and BART. Because of a misunderstanding of the interview instructions, ratings of these three attributes were made only if both bus and BART were reported to be possible for the respondent's trip. Consequently, the rating data on these attributes were available for a sample smaller than the one for data on the other attributes.

DATA ANALYSIS

Interrelationships Among Attribute Variables

The first step in the data analysis was to examine the intercorrelations among the attribute rating variables in order to identify any groups of highly intercorrelated variables. Matrices of Pearson correlation coefficients were calculated separately for the set of attribute rating variables for each of the three modes. Each matrix was then analyzed with a factor analysis procedure consisting of an image analysis (13) followed by an oblique Oblimin rotation (14).

The correlation matrices and factor analysis results were very similar for each of the three modes and identified three groups of highly intercorrelated variables: (a) time, dependability, waiting time, and, to a lesser extent, flexibility; (b) relaxation, time use, and, to a lesser extent, safety from accidents and seat availability; and (c) safety from crime and waiting time.

The correlation of transit ratings to safety from crime and waiting time is interesting. It suggests either a coincidental correlation of different underlying determinants—i.e., bus waits may tend to be longer in more dangerous areas—or the possibility that the ratings of both attributes reflect the common influence of perceived danger, meaning that a more dangerous situation may make waiting seem longer. For these three groups of variables and for selected subsets of these groups the average intercorrelations were calculated. The results are presented in the table below (attributes in the car column marked with a hyphen were not rated).

Attribute Groups	Rated Mode Car	Bus	BART
Time, dependability	0.44	0.54	0.56
Time, waiting time	-	0.63	0.36
Time, dependability, flexibility	0.37	0.49	0.42
Time, dependability, waiting time	-	0.54	0.42
Time, dependability, waiting time, flexibility	-	0.48	0.38
Relaxation, time use	0.50	0.54	0.28
Relaxation, time use, seat availability	-	0.50	0.23
Relaxation, time use, safety from accidents	0.42	0.45	0.30
Relaxation, time use, seat availability, safety from accidents	-	0.42	0.25
Safety from crime, waiting time	-	0.45	0.34
First seven attributes	0.26	0.35	0.21
All attributes	-	0.35	0.23

None of the groups of variables was sufficiently intercorrelated to suggest that the variables measured entirely the same phenomena. Nevertheless, the interrelationships among the attribute variables should be kept in mind when evaluating the results of subsequent analyses. It is possible that for intercorrelated variables the relationships to behavior may reflect the influence of a common set of underlying policy variables. Johnson (11) has discussed the problem of evaluating attribute importance when attribute variables are intercorrelated and has considered the advantages and disadvantages of several alternative methods of analysis.

Average Attribute Ratings

The next step in the data analysis was to compute the average rating of each attribute for car, bus, and BART. Other things being equal, the more alternatives differ, on the average, with respect to an attribute, the more influence the attribute has on preferences among the alternatives. The average ratings are illustrated in Figure 1.

On the average, the car was rated as far superior to bus and BART on total travel time, dependability, and flexibility. On the other attributes, car commuting was rated as slightly inferior to transit travel, especially with respect to safety from accidents. The average ratings for bus and BART commuting were generally similar, the major differences being that BART commuting was rated as slightly better in terms of safety

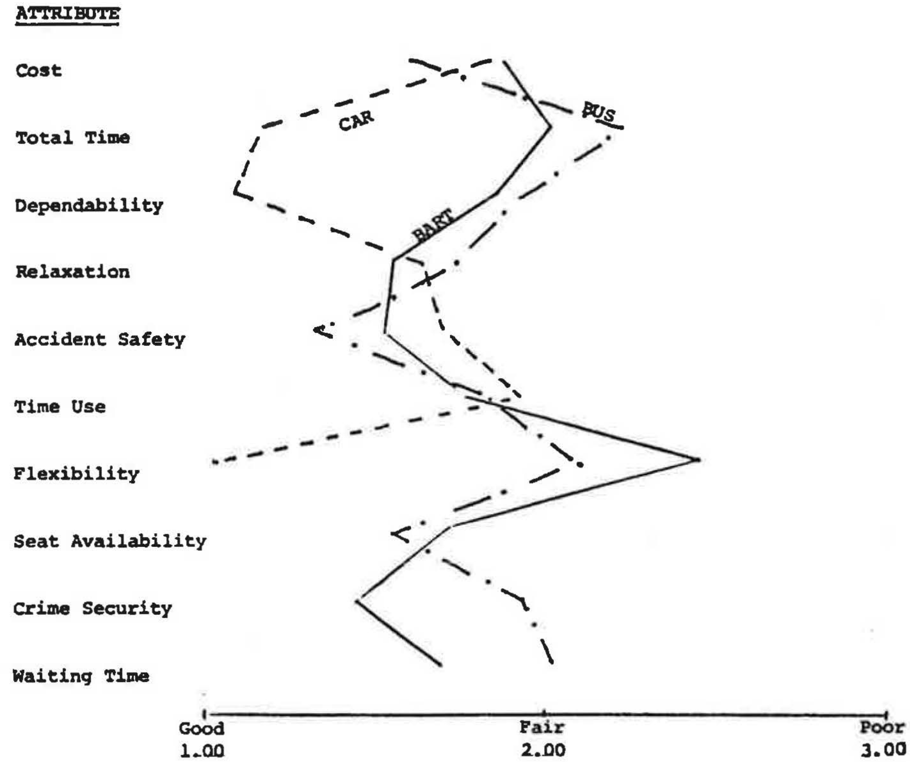


Figure 1. Average attribute ratings of car, bus, and BART for commuting to work.

from crime, waiting time, and relaxation.

Seat availability, crime safety, and waiting time were not rated for car travel. However, assuming, as seems reasonable, that car would have been rated good on these attributes, the differences in evaluations between the car and the two transit modes are substantial.

Relationships Between Attributes and Behavior

To evaluate the extent to which the average differences in ratings reflected average differences in utility and to estimate the other components of attribute importance, it was necessary to analyze the relationships, over the study sample, between the attribute ratings and preferences among the rated modes.

Graphs

As a preliminary step in the analyses and as a convenient means of visualizing the relationships between the attribute ratings and behavior, graphs were constructed by relating the probability of choosing among alternative modes to differences in attribute ratings for the modes. A separate graph was calculated for each attribute.

To simplify the graphical presentation and to increase the size of the sample reflected in each graph, the information on bus and BART modes was condensed to create a single "preferred" transit mode for each individual. If the person regularly commuted by one of the transit modes or if only one mode was possible, it was considered the preferred mode. Otherwise, the preferred mode was determined by a question in the interview on which mode the person would prefer to use if he or she did not drive to work. The graph for each attribute related the probability of choosing transit over auto to differences in attribute ratings for the two alternatives.

The graphs are presented in Figure 2. They indicate that the ratings for all the attributes were strongly related to reported behavior. For most of the attributes the sample proportions using transit ranged from between 0 and 10 percent when the differences value was minus two (auto rated good, transit rated poor) to about 50 percent when the difference value was plus two (auto rated poor, transit rated good). The relationships were somewhat weaker for the attributes of relaxation, time use, and safety from accidents, however.

Logit Analyses

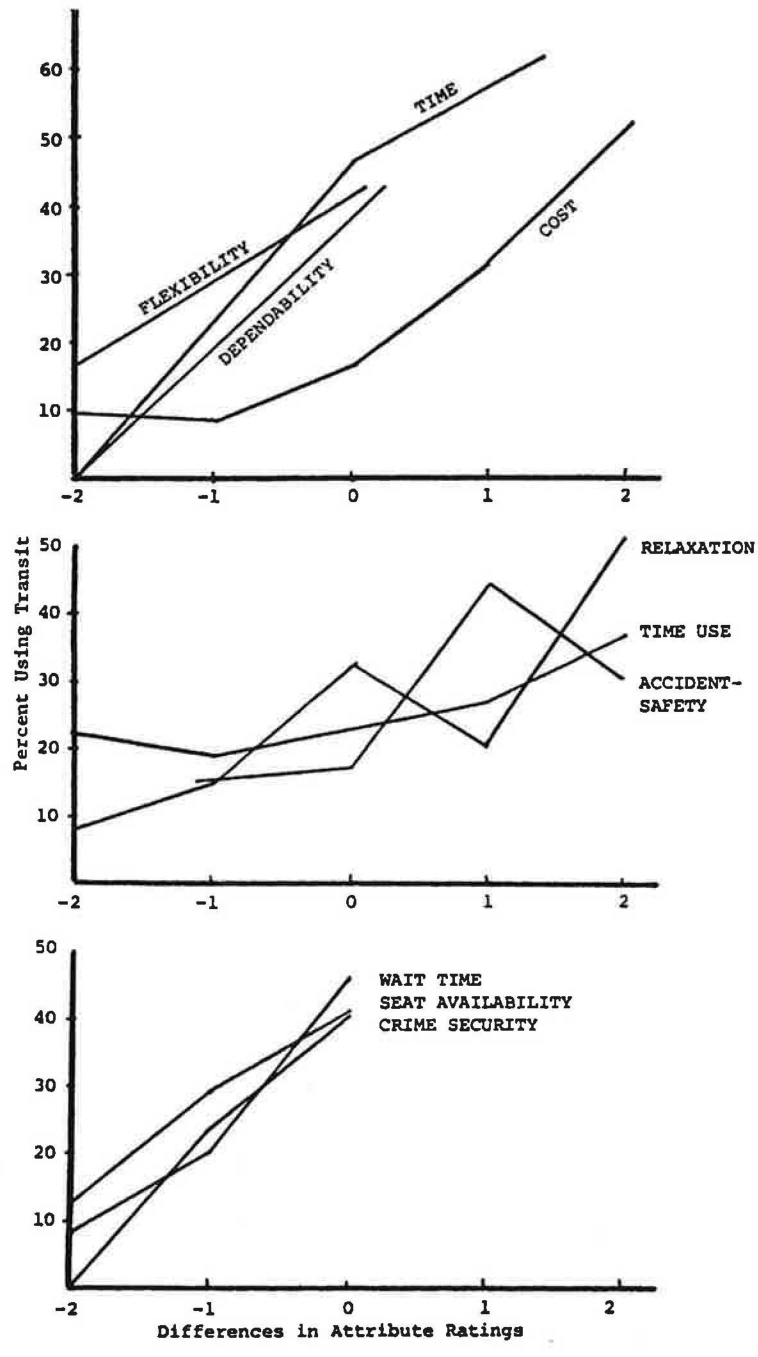
To provide a more sensitive and theoretically appropriate analysis of the relationships between the attribute ratings and behavior, maximum likelihood logit analyses (15) were done that related the attribute ratings to the choices among car, bus, and BART over the study sample. The analyses were carried out on the QUAIL system of computer programs (16).

The results are shown in the following table, where B_z is the standardized utility coefficient and LRI is the likelihood ratio index of "pseudo r^2."

	Statistic				
Attribute	B_z	t	LRI	Correct (%)	df
Cost	0.89	4.22	0.34	75	218
Time	1.26	5.34	0.40	78	218
Dependability	1.37	4.97	0.40	78	218
Relaxation	0.63	3.25	0.30	76	218
Safety from accidents	0.60	3.09	0.30	74	218
Time use	0.35	1.91	0.27	76	218
Flexibility	0.49	2.54	0.28	74	218
Seat availability	0.79	2.35	0.28	68	138
Safety from crime	1.19	3.39	0.34	70	138
Waiting time	1.51	3.84	0.38	71	138
All attributes	–	–	0.57	79	129

Although the primary purpose of the logit analyses was to obtain a utility coefficient for each attribute, as an input to calculating attribute importance coefficients, the logit results also included values of the LRI, which reflected the strength of the relationship between the

Figure 2. Relationships between travel mode choice and attribute ratings.



attribute measures and travel mode choice.

For the individual attributes, the values of the LRI ranged from 0.27 to 0.40. For a multiple logit analysis using the entire set of variables simultaneously, the value of the index was 0.57. These LRI values are equal to or larger than most values that have been reported for similar research on travel mode choice, using either subjective or objective data. The logit results thus corroborate the evidence, shown in the graphs, that the attribute ratings were substantially related to reported behavior.

Importance Coefficients

For each attribute, the estimated utility coefficient was combined with values of the attribute ratings, over the sample, into an importance coefficient, based on Equation 3 above, that reflected the extent to which the attribute contributed to differences in utility among the alternative travel modes. Waiting time, safety from crime, and seat availability were not rated for the car alternative, so calculation of the importance coefficients was based on the assumption that car would have been rated good on these attributes by all respondents.

Three sets of importance coefficients were calculated in order to see how the importance of each attribute as an influence on choice is reflected among the three pairs of modes (car-bus, car-BART, and bus-BART). An additional set of coefficients was calculated to reflect the overall importance of each attribute, for choices among all three modes. The importance coefficients are presented below.

Attribute	Sets of Travel Modes Car-Bus	Car-BART	Bus-BART	Car-Bus-BART
Cost	0.95	0.98	0.74	0.91
Time	1.78	1.74	1.44	1.69
Dependability	1.83	1.82	1.56	1.76
Relaxation	0.67	0.68	0.51	0.64
Safety from accidents	0.61	0.71	0.57	0.63
Time use	0.37	0.40	0.25	0.36
Flexibility	0.97	1.10	0.64	0.94
Seat availability	0.89	1.01	0.95	0.95
Safety from crime	2.01	1.27	1.53	1.64
Waiting time	2.30	1.78	1.92	2.02

In terms of overall importance and considering choices among all three modes, the attributes seemed to cluster into several groups having roughly equal importance statistics. Waiting time, dependability, total time, and safety from crime appeared to be the most important attributes. Cost, seat availability, and flexibility appeared to be next in importance, followed by relaxation and safety from accidents. Time use appeared to be the least important attribute.

For choices among the different pairs of alternatives, the relative importance of the attributes appeared to be about the same as for choices among all three modes. The major differences were that waiting time and safety from crime appeared relatively less important for choices between car and BART, that flexibility appeared relatively less important for choices between bus and BART, and that seat availability appeared relatively less important for choices between car and BART.

CONCLUSIONS

Most of the attributes investigated in this study appeared to be important influences on travel mode choice. Respondents tended to rate the modes differently for most attributes, and the differences were strongly related to reported behavior. Among the attributes judged to be important were safety from crime, dependability, and seat availability, which are not typically included in quantitative planning procedures, such as travel demand forecasting or cost-benefit analysis.

The results suggest that these attributes should be taken more into account in transportation policy decisions. However, the conclusions must be qualified by the uncertainties discussed above regarding the extent to which the observed relationships to behavior of the different attribute variables actually reflected the influence of different underlying policy variables.

As discussed at the beginning of this paper, the conclusions from this research may have some immediate policy implications as general diagnoses. For example, safety from crime appears to be an important influence on choices between car and bus travel and may have some direct policy implications to transit managers serving the studied population (or similar populations elsewhere). Primarily, however, the research should be viewed as the first stage in a multistage research strategy. Subsequent research stages should identify policy variables that underlie the attributes identified as important and should determine how these policy variables are related to utility and behavior. The results of these later stages can be applied to more quantitively detailed planning procedures.

The major benefit of first-stage research on attribute importance is that it allows the relatively expensive and time-consuming research on objective policy variables to be focused on the most essential attributes.

For some travel attributes—such as safety from crime or social status—it may not be possible to identify a manageable set of policy variables underlying the attribute ratings. To evaluate the consequences of policies with respect to such attributes, subjective methods could be used in which people were asked to indicate the influence of contemplated changes on their attribute ratings. The changes in ratings could then be used to evaluate consequent changes in utility and behavior, using previously determined utility coefficients for the rating variables. A disadvantage of this procedure is that it requires a special research effort to estimate rating changes for every contemplated policy change.

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Intercity Rail Travel Models

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Using a 1975 aggregate data base of 31 pairs of cities, forecasts are made of 1975-1980 rail patronage in the New York City-Buffalo corridor. A two-stage modeling process is used to estimate total city-pair volume by purpose, using gravity formulations relating annual volume to city size, government employment, and hotel and motel sales receipts. Binary logit models are then developed in which rail competes differentially with air, auto, and bus in order to avoid independent irrelevant alternatives assumptions. Rail service and terminal quality variables are included with time, cost, and frequency. The total rail share is then determined algebraically from the binary models. Pivot-point analysis is used to increase the accuracy of the forecasts. Results show that rail competes differently with each mode. Against air, the key variables are frequency and time ratios; against auto, the frequency, cost, and time ratios and terminal quality are important; against bus, train service quality, frequency ratio, and time difference are important. Elasticities of demand vary considerably by mode and distance. Forecasts show that if train, track, service, and terminal improvements are implemented as planned in the corridor over the next 5 years, 1980 link volumes will increase 58-105 percent over 1975 levels, with most diversion coming from short-distance auto trips. The net effect of this diversion will be to reduce 1980 corridor energy requirements by 9 percent over 1975.

The Planning Research Unit of the New York State Department of Transportation (NYSDOT) recently cooperated with Union College to study the energy efficiency of train service in the New York City (NYC)-Buffalo corridor. NYSDOT's role was to develop a workable model of train passenger demand and to analyze energy and passenger-kilometer efficiencies of alternative train, track, and service improvements in the corridor. This report summarizes the rail passenger demand models developed in the study. It briefly describes the data used, the developed models, and the pivot-point and normalization procedures used to increase the accuracy of forecasts. Rail demand forecasts and the potential for modal energy savings in the corridor are also discussed.

DATA

The data collection effort (1) concentrated on cities within the NYC-Buffalo corridor (Figure 1), with selected other city pairs included for continuity or availability or both of data. In total, 31 city pairs were included in the data base. Each city pair is described by a wide range of data elements (1) that include city size and spatial separation variables and modal service variables such as travel times, costs, and frequencies. In addition, the following quality-of-service data describing train and terminal service characteristics were also included:

Quality of rail service—snack car availability, sleeper car availability, lounge car availability, baggage service, package express, on-time performance, schedule match, dining car availability, and car type.

Terminal quality—parking availability, number of spaces, parking fee, parking lot lighting, terminal snack bar, local transportation, distance to downtown, and modernness of terminal.

Three central findings of the preliminary research conducted for the study (1,2) were as follows. First, when all factors are considered, a hybrid modeling approach—forecasting total intercity volume and then separate modal shares—appears to be the most productive. Second, care must be taken to avoid formulations that contain the so-called independence of irrelevant alternatives assumptions (IIA assumptions). Third, since quality of service influences modal choice, models developed should consider quality-oriented data on the rail system, including rail terminals. Ideally, such data should also be available for the other modes.

These principles led to the development of a new approach to intercity rail passenger demand modeling, which has been fully documented (3). The approach is to use two total travel models that forecast travel via all four modes between each city pair. These were developed for business and nonbusiness travel. The models have a simple gravity format. Estimates of total volume, however, will not replicate observed total volume because of residual errors caused by incomplete model specification. The slippage between estimated and true total volume in the base year (1975) can be eliminated for future forecasts, using pivot-point procedures.

Within each trip purpose, three separate competition models are developed for rail versus air, auto, and bus. The model form is binary logit. Each model includes only those variables relevant to the binary choice, for example, rail versus bus. These models are then used to derive a consistent estimate of the rail share. These rail shares, however, will not replicate the observed rail shares because of residual errors caused by incomplete model specification. The slippage between estimated and true rail shares in the base year (1975) can also be eliminated using pivot-point analysis.

The future modal volumes, in particular the rail volumes, are then obtained by multiplying the total volumes (as computed by the total models) by the modal share (as computed by the share models). Pivot-point analysis, described later, is used to reduce forecasting