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Comparison of the Predictive Ability of Four Multiattribute Approaches to Attitudinal Measurement

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In the past decade, attitudinal measurement techniques have been developed that measure the relative attractiveness of specific levels of transportation characteristics. These partial measures are then combined to form overall measures of attractiveness, which makes it possible to simulate market responses under varying conditions. Four techniques that have emerged as leaders in this area are functional analysis, conjoint measurement, trade-off analysis, and unidimensional scaling. Each of these techniques assumes a compensatory utility function; the techniques vary with respect to the assumed integrity of the data (interval or ordinal) and with respect to subject tasks. To test each approach, 300 subjects in Charlotte, North Carolina, were interviewed, then reinterviewed one year later. Each subject was asked four different sets of questions concerning preferences for different transportation alternatives, characterized by various levels of mode and waiting time, cost, and travel time, as well as the subject's background and current mode of travel. Each attitudinal question set was analyzed by the appropriate scaling technique. The analysis showed that relative measures of attractiveness derived from each technique differ somewhat and that these measurement differences have an impact on market simulation. It was also found that techniques that provide the highest predictive ability are those that use a conjoint data set consisting of modes described by all factors simultaneously. It was also found that modal choice is most closely a function of previous choice of mode and that attitudes toward mode and waiting time have the greatest influence on modal split.

Many studies have applied attitudinal measures to transportation. Most of these have used unidimensional analysis or multidimensional analysis of unidimensional responses to choice of mode, i.e., transit versus automobile. As early as 1968, the National Survey of Transportation Attributes and Behavior (1) analyzed feelings in that context. Studies have focused on revealed preferences (2,3), stated preferences (4,5), or simulated choices (6-8). This paper compares four techniques that analyze stated preferences and simulated choices: functional analysis, trade-off analysis, conjoint measurement (monotonic), and unidimensional scaling.

Each of these techniques analyzes decisions as a function of a set of evaluations of the attributes that make up an object. In an early study, Fishbein (9) proposed an additive decision model that relied on univariate scales. Multivariate decomposition techniques were suggested by Kruskal (10) (conjoint measurement), Johnson (11) (trade-off analysis), and Anderson (12) (functional analysis). These techniques are described more fully below.

Functional analysis analyzes attitudes and preferences of individuals toward specific items. Each item is created by combining different levels of a number of factors (in this case, transit characteristics such as cost and travel time). These items, when presented to subjects, are rated on an interval scale and part-utilities are derived from these ratings (7).

The conjoint measurement approach analyzes responses to the same items. However, preference rankings are obtained from individuals instead of preference ratings. Two assumptions are usually made in the approach: (a) that utility is a linear additive function of part-utilities and (b) that stated preferences are monotonically related to the part-utilities (13).

Trade-off analysis is a simplification of the above approach with all factors presented in paired combinations. Levels of each pair of matrices are ranked one at a time. The assumption that the models are additive still holds. The main advantage of this approach is that the data collection tasks are reduced (6,8).

A few studies have made some comparisons between these techniques. Anderson (14) discusses the differences between conjoint measurement and functional analysis in a case study. Green and Wind (13) compare unidimensional and conjoint scales applied in different research settings. Curry, Levin, and Gray (15) compared the analysis of the same conjoint data sets by monotonic (nonmetric) and functional (metric) techniques. Jain and others (16), in a consumer services context, compared different monotonic approaches. The study that is the subject of this paper differs from these studies in the techniques under comparison, the consistency between question format and data analysis, the use of a rigorous before-and-after study design, and the sample size.

This study was designed around stated and revealed preferences in a before-and-after design in conjunction with a transit service change in Charlotte, North Carolina. A population of 300 subjects was interviewed before the service change and again one year later. To test the four techniques, the same information was acquired in forms appropriate to each technique.

DEVELOPMENT OF QUESTIONNAIRES

Early work such as that by Quandt and Baumol (2) and Warner (3) has shown that a transportation mode can be thought of abstractly in terms of its components or elements. The elements that have been shown to be most important are those that affect cost and overall travel time. Attitudinal studies have, for the most part, confirmed these results. Therefore, items for each part of the study questionnaire were formulated from four levels of three factors: (a) mode and (for buses) waiting time between vehicles, (b) travel time, and (c) weekly travel cost.

Separate questionnaire sections were made for each technique, as summarized in Table 1. Questionnaire sections were ordered in each of the 24 possible permutations randomly assigned to subjects. Within each section, questions were also ordered randomly.

STUDY AND SAMPLE DESIGN

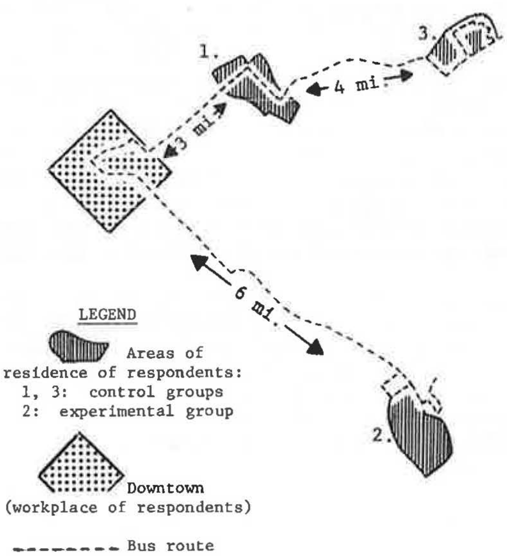
The major objective of this study was to test the four techniques against the impact of transit service changes on the attitudes and preferences of individuals. Another objective was to assess the kind and degree of reactions to increases in the cost of gasoline. A cluster sampling design was deemed most appropriate, and the data collection was designed for three clusters: an experimental group from a middle-income residential neighborhood (designated group 2) and two control groups, one from a low-income neighborhood (group 1) and the other from a middle-income neighborhood and similar in characteristics to the experimental group (group 3). All respondents worked in the downtown area. The major difference between the two middle-income groups was that the control group had transit service whereas the experimental group was scheduled to have services introduced during the period of the study.

The relative locations of the three clusters are

Table 1. Presentation of four measurement techniques in questionnaire.

Technique	Presentation	Response
Functional analysis	Presented as 16 combinations in each of the 4 components of a Latin Square design	Rated from 0 to 100 to indicate degree of preference
Conjoint measures (monotonic)	Presented as 16 combinations in each of the 4 components of a Latin Square design	Ranked from highest (1) to lowest (16)
Trade-off analysis	Presented as 16 combinations of 2 factors (4 levels) at a time (3 sets in all)	Ranked from highest (1) to lowest (16)
Unidimensional analysis	Each level of each factor presented, one at a time (12 elements in all)	Rated from 0 to 100 to indicate degree of preference

Figure 1. Workplace and areas of residence of study respondents in Charlotte, North Carolina.



shown in Figure 1. The round-trip distances to the downtown area from clusters 2 and 3 are about 13 miles, and the distance from cluster 1 is about 6 miles.

During the initial data collection, approximately 100 subjects in each cluster who worked in the downtown area were interviewed. Approximately one year later, the second-phase data were collected. The same respondents were contacted and, if they still lived at the same address and worked downtown, they were asked to complete at least part of a similar questionnaire. Because of the number of respondents who no longer qualified or refused to complete the second questionnaire, an additional random sample was selected to supplement the original sample. The numbers of original and supplementary respondents who were contacted in the second data collection are summarized below:

Group	No. of Original Qualifying Subjects	No. of Supplementary Subjects
1	68	32
2	61	39
3	53	47

PRELIMINARY ANALYSIS OF DATA

Background Descriptors of Subjects

For the initial respondents, the distribution by sex was as expected: Group 2 had fewer working women, which reflected the nature of the families residing in the neighborhood. Minority families were primarily represented in group 1 and to a lesser degree in group 3. Group 2 was in a slightly newer neighborhood and was less representative in its racial composition. Classification of respondent as head or nonhead of household reinforced the pattern of the sex of respondents. In all three groups, households of three or more appeared to predominate. The typically larger households in group 1 may consist more of multiple-family or non-nuclear-family units. The age distribution was as expected, with a bimodal distribution among groups 2 and 3. Data on education of respondents showed better-educated, younger respondents in group 2.

Perhaps the least expected results were found in the data on income distribution and present mode of travel to work. Group 2, the experimental group, appeared to have a lower average income than group 3. In addition, a substantial minority of group 2 used the bus, although no service was available in that neighborhood when the data were collected.

Modal-Choice Behavior

Modal choices of the complete samples for each group are summarized in Table 2. A shift toward bus travel is observed in each group. The experimental group (group 2) demonstrates a slightly smaller change than the control group (group 3), but this is easily explained by the unexpectedly high use of the bus before route modification. As expected, the highest overall use of the bus is by the low-income group (group 1), but the shift toward bus travel is smaller there.

These shifts are not apparent, however, from the data for the original sample summarized in Table 3. The shifts there are smaller, but the apparent stability in choice is misleading. The data given below demonstrate that the stable modal split in group 2 is the result of a complex set of changes:

Phase 1 Modal Choice	Phase 2 Modal Choice: Bus	Car	Other	Total
Bus	5	2	3	10
Car	4	43	0	47
Other	2	2	0	4
Total	11	47	3	61

It is the extent to which these changes can be forecast, as well as overall modal split, that is a true test of the ability of these techniques.

COMPARISON OF PART-UTILITIES ESTIMATED BY EACH TECHNIQUE

To enable comparison of the approaches, part-utilities were estimated for each level of each factor by using appropriate linear compensatory models.

A different analytic technique was used for each approach. Univariate scales were assumed to be interval scaled, and raw data were used in that case. For functional analysis, values for each factor level were found by averaging subjective evaluation scores of modes containing that factor level. For trade-off analysis the New York State

Algorithm (17) was used, and for monotonic conjoint measurement MONANOVA (10) was used.

The results presented here are for the initial respondents. This resulted in a separate estimate of part-utility for each level of each factor, for each technique, and for each subject. The estimates were averaged across subjects in each group, and these averages for the middle-income groups (groups 2 and 3) are presented in Table 4.

Each technique measures utility on a different scale. However, it is the intervals between values that are most important. These scales answer questions such as, Will a 10-cent decrease in fare compensate for a 10-min increase in waiting time? It should also be noted that conjoint measurement, or the monotonic approach, yields estimates that show "higher" utility when the values are more negative.

The range of part-utilities, then, indicates which factor is most salient. Cost has the widest range in virtually all cases. Travel time has the smallest range. However, results for the first factor (mode and waiting time) are bimodal, depending on transport modal preference. For average part-utilities calculated within modal preference groups, the largest range is for the first factor.

Table 2. Modal choice by group and time period: complete sample.

Modal Choice	No. of Respondents					
	Group 1		Group 2		Group 3	
	Phase 1	Phase 2	Phase 1	Phase 2	Phase 1	Phase 2
Car	65	74	86	73	76	77
Bus	21	28	11	18	8	20
Other	14	2	4	8	15	1
Total	100	104	101	99	99	98

Table 3. Modal choice by group and time period: original sample.

Modal Choice	No. of Respondents					
	Group 1		Group 2		Group 3	
	Phase 1	Phase 2	Phase 1	Phase 2	Phase 1	Phase 2
Car	44	48	47	47	45	44
Bus	14	17	10	11	1	4
Other	10	3	4	3	7	5
Total	68	68	61	61	53	53

Sensitivity of Techniques to Changes in Factors

Despite the consistency between techniques in the rank order of the average part-utilities, the intervals between part-utilities vary significantly. For example, in the experimental group (group 2) for functional analysis, a change in weekly cost from \$10 to \$4 had a value of 27, and this more than compensated for a change in mode from car to bus (with 10-min waiting time), which had a value of 9.2. On the other hand, for the same group, with trade-off analysis, a similar change in cost had a value of 0.20, which did not compensate for a similar mode change that had a value of 0.23. Similar differences were observable for all techniques, and these were consistently observed for each cluster.

Correlation of Part-Utilities Between Techniques

For the initial data, Benjamin and Sen (18) reported that the part-utilities derived from each of the four techniques do not correlate highly. Furthermore, those subjects whose decision processes were best described by a linear model did not respond more consistently than the other subjects. It was also found that familiarity with the factors and levels that described a mode led to more consistent results, although correlations between part-utility estimates were still somewhat low.

SIMULATED RESPONSES TO MARKET CONDITIONS

A further demonstration of the impact of the differences between techniques is a comparison of the forecasts of responses to various market conditions. To accomplish this, a simple simulation model was formulated. First, the overall utility was formulated by combining appropriate part-utilities for each mode under consideration. Then the overall utilities were compared and the mode with the highest utility was considered to be the selection of that respondent. The process was completed separately for each respondent and the results were tabulated.

The model was a linear compensatory model (chosen because it was consistent with the disaggregate data): Overall utility = (part-utility of mode and waiting time) + (part-utility of cost) + (part-utility of travel time).

For each simulation it was necessary to create a scenario in which the modes, waiting time, weekly cost, and travel time for each means of travel were described. The simulations forecast responses to the market conditions described by the scenario.

Table 4. Average part utilities for four measurement techniques: middle-income groups.

Factor	Level	Functional		Monotonic		Trade-Off		Unidimensional	
		Group 3	Group 2	Group 3	Group 2	Group 3	Group 2	Group 3	Group 2
Mode and waiting time	Car, 0 min	66.6	70.4	−0.80	−1.01	0.44	0.44	92.2	81.7
	Bus, 10 min	62.1	61.2	−0.18	−0.27	0.21	0.21	64.1	60.5
	Bus, 20 min	55.2	53.6	0.13	0.203	0.16	0.17	59.1	49.0
	Bus, 40 min	40.6	39.7	0.85	1.08	0.19	0.19	23.2	26.2
Weekly cost	\$4.00	71.8	68.2	−1.15	−0.94	0.42	0.39	93.4	84.5
	\$5.00	66.6	63.4	−0.63	−0.56	0.24	0.25	85.7	79.6
	\$8.00	50.2	52.2	0.41	0.38	0.16	0.17	59.7	61.7
	\$10.00	35.5	41.2	1.35	1.13	0.19	0.19	51.2	46.4
Travel time	22 min	59.5	58.3	−0.26	−0.19	0.34	0.32	80.7	78.0
	25 min	58.5	57.8	−0.12	−0.06	0.26	0.27	70.1	69.5
	30 min	54.6	56.1	0.13	0.02	0.22	0.22	58.3	61.6
	37 min	51.9	52.8	0.25	0.23	0.18	0.19	45.5	50.9

Note: Group 3 = control group; group 2 = experimental group.

Table 5. Comparison of simulated and observed modal splits for all data sets.

	Modal Split[a]									
	Simulated									
	Univariate Analysis		Monotonic Approach		Functional Analysis		Trade-Off Analysis		Observed	
Group	Bus	Car	Bus	Car	Bus	Car	Bus	Car	Bus	Car
1	0.17	0.83	0.14	0.86	0.20	0.80[b]	0.03	0.97	0.27	0.73
2	0.13	0.87	0.30	0.70	0.26	0.74[b]	0.13	0.87	0.20	0.80
3	0.04	0.96	0.28	0.72[b]	0.32	0.68	0.07	0.93	0.21	0.79
All (pooled data)	0.11	0.89	0.24	0.76[b]	0.26	0.74[b]	0.08	0.92	0.23	0.77

[a]Proportion of subjects who chose car or bus.
[b]No significant difference at $\alpha = 0.10$ significance level.

Table 6. Discriminant analysis of modal choice by panel: standardized discriminant function coefficients.

Variable	Definition	Univariate Analysis	Monotonic Approach	Functional Analysis	Trade-Off Analysis
ΔU_1	Mode and waiting time	-0.39	0.22	-0.24	-0.22
ΔU_2	Weekly cost	0.16	-0.17	0.10	0.04
ΔU_3	Travel time	0.29	-0.06	-0.02	-0.07
M′	Prior modal choice	0.96	0.95	0.94	0.96
Z_1	Residence zone 1[a]	0.19	0.09	0.07	0.04
Z_2	Residence zone 2[a]	0.05	0.00	-[b]	0.01

[a]Z_1 and Z_2 are 0-1 (dummy) variables representing residence in respective zones; $Z_1 = 0$ and $Z_2 = 0$ indicated residence in zone 3.
[b]Variable not included in analysis to permit convergence.

Results of Simulations of Responses to Existing Conditions for Initial Data Set

Benjamin and Sen (18) reported results of simulations under several scenarios, including a scenario corresponding to the current cost of gasoline and the existing transit service levels and costs. They found that the various techniques did correctly classify the majority of respondents but that each technique demonstrated a bias toward one of the modes.

Results of Simulations of Responses to Second-Year Conditions

By using the same simple simulation model but different part-utilities that correspond to second-year conditions (linear interpolations were used for values between estimated levels), responses to new services and prices were forecast from the original data set. Essentially, three changes had occurred: (a) The new service was introduced in zone 2, (b) bus fares increased from $0.40 to $0.50/trip, and (c) the average price of gasoline rose from $1.25 to $1.30/gal. For the middle-income groups (groups 2 and 3), transportation characteristics are as follows:

Mode	Waiting Time (min)	Cost ($) Weekly	Cost ($) Unit	Travel Time (min)
Car	0	5.20	1.30/gal	22
Bus	10	5.00	0.50/trip	37

The transportation characteristics of the low-income group (group 1) differed from these figures because zone 1 is a shorter distance from the central business district (CBD). For group 1, travel time by car was 10 min and by bus was 16 min. The cost of weekly trips by car was $2.60.

Modal splits forecast by each technique for each group are presented in Table 5 along with corresponding observed modal splits. Modal splits for the data pooled from all groups are also presented in Table 5.

Several trends emerge from that table. First, all techniques overestimate car use by group 1. This is an indication of intervening factors not represented in this simple simulation, such as an income constraint and car availability.

Another trend is that the techniques seem to perform equally well in both middle-income groups (groups 2 and 3). The initial lack of availability of transit service to group 2 did not adversely affect the ability of those subjects to perform the various survey tasks. Finally, the modal-split forecast for the pooled data reveals that two techniques were highly accurate. Monotonic conjoint analysis and functional analysis both predict a modal split that corresponds closely to the observed modal split. In fact, the difference between observed and predicted proportions is not significant at the 0.10 significance level. These techniques also performed well within each zone. At the 0.01 significance level, no significant difference was observed for functional analysis for any group, and for monotonic analysis only for group 1 (which, as mentioned earlier, can be explained by intervening variables). Although monotonic analysis performs a bit better overall, the functional approach seems to predict the modal split for each group more consistently.

The other techniques consistently underestimate the shift toward transit. The primary difference between the techniques that performed well and those that did not is that the former rely on representations of modes described by all key factors at once and the latter represent modes by only one or two factors at a time. Clearly, there is an advantage in representing the most complete picture possible.

ANALYSIS OF MODAL CHOICE FOR PANEL RESPONDENTS

Comparisons of Simulated and Actual Choices

Findings from a comparison of simulated and observed modal split for the panel respondents (those subjects who were interviewed in both the first and second years) were similar to findings for the total sample, which are summarized in a previous section of this paper. More precise than the estimation of modal split is the case-by-case prediction of modal choice. To investigate this, choices were simulated for the panel respondents. When cross-tabulated with the actual modal choice, for each group for each technique, results ranged from 63 to 84 percent correct prediction. Trade-off analysis and univariate analysis performed slightly better than the other techniques because of their tendency to classify the vast majority of cases as automobile drivers, which corresponded to the choice of most respondents. However, when the proportion of correctly classified bus and car users was used as a criterion, functional analysis and monotonic analysis performed best.

Discriminant Analysis of Modal Choice

A more complex simulation model was formulated by using discriminant analysis. In this model, it is assumed that decisions are a result of preference for a mode along with other situational variables (a linear function was assumed):

$$M = f(\Sigma a_j \cdot \Delta U_j + b \cdot M' + cZ) \quad (1)$$

where

M = mode chosen in the second year,
ΔU_j = difference in part-utility between modes for factor j,
M' = mode chosen during the previous year,
Z = variable (or set of dummy variables) representing zone of residence, and
a_j, b, and c = coefficients to be estimated by the discriminant analysis.

Coefficients a_j, b, and c represent the relative importance of each independent variable in predicting choice. The differences in part-utility for each characteristic (ΔU_j) were calculated by subtracting first-year part-utility estimates for car and bus. Model coefficients were estimated separately for part-utilities derived from each technique.

Prior choice of mode (M') was included as a surrogate for familiarity with and accessibility to either car or bus. It is well known to market researchers that people tend to continue to use the same products and brands of products for a variety of reasons. This is confirmed in Table 3 by the majority of panel modal choices over time.

Zone of residence (Z) was included to reveal any overall difference in responses from residents in each zone. Since income and proximity to the CBD were the primary distinguishing factors between zones, this is a surrogate for those factors.

The results of the discriminant analysis are summarized in Table 6. The standardized coefficients listed there reveal that prior modal choice was the dominating factor in this decision. However, other variables also contributed. Of the remaining variables, mode and waiting time affected choice most. Furthermore, coefficients of variables representing zone of residence were small, which indicated that responses of residents in the experimental zone (group 2) were virtually indistinguishable from responses of residents in the control zone (group 3).

The classifications of known cases for each technique were identical; 92 percent of known cases were correctly classified, and the predicted modal split was not significantly different from the actual modal split.

The dominant influence of prior choice is a useful guide where all alternatives are available to the subjects beforehand and only small system changes are planned. In that situation, a change in system attributes must lead to a corresponding change in preference that is large enough to overcome the influence of prior modal choice. For this panel, which included 161 subjects who chose either car or bus both years, 13 subjects reported a change in mode. The discriminant function was unable to correctly classify the majority of these cases.

Because of the small number of those who changed mode, the importance of modal preference in the choice process represented by the discriminant function is understated; a disaggregate simulation based on utility values is needed to discover those who changed mode in this case.

A simple simulation of these 13 subjects resulted in correct classification of approximately half. Once again, functional analysis and monotonic analysis performed best, accurately predicting modal split for this group.

CONCLUSIONS

An empirical study of this type is limited in several ways. Results reflect the sampling frame and procedure, both the content and the form of the questionnaire, and the system characteristics under study. Results are also affected by unexpected events, such as a large number of bus users in the experimental group (which had no bus service) and the large number of people who changed place of employment or who moved during this one-year interval.

Within these limitations, several conclusions can be drawn from these study results. First and foremost, results of attitudinal research are believable. Overall, observed behavior closely reflects attitudes toward these decisions.

Methodological implications also emerge. For example, the best results occur when alternatives are presented in the most complete and realistic manner possible. In other words, techniques that represent all factors simultaneously produce better results. This is particularly relevant when new and different service changes are anticipated and prior choice cannot be a guide.

On the other hand, simpler techniques are most economically administered. When prior choice is applicable, attitudinal measurement does not play as big a role in decision analysis and does not need to be as precise. In this case, univariate measurement performed just as well and is therefore most cost effective.

The development of an attitudinal research project has three critical elements: design of the questionnaire, administration, and analysis. Univariate analysis is simplest and most economical in all respects. The questionnaires for trade-off analysis are more easily developed and administered than those for conjoint analysis, but the results require analysis by special computer programs.

The most difficult questionnaires to develop are those for conjoint analysis (either monotonic conjoint measurement or functional analysis). In the monotonic approach, subjects are asked to rank modes, which is to say that one mode is judged to be better than another on the basis of some criterion. On the other hand, functional analysis requires subjects to rate modes, which implies two tasks: judging one object to be better than another and stating by how much.

We hypothesized that rating is more difficult and time consuming than ranking, since ranking is simpler. However, throughout the research it was observed that the rating task is in fact easier because modes can be rated one at a time and then, when necessary, comparative ratings can be adjusted by the subject. Alternatively, ranking requires an initial overview of all modes before the best mode can be chosen and subsequently all can be ranked. Thus, it was actually easier to administer the functional questionnaire than the monotonic questionnaire. (The use of rankings is appropriate when the subjects are totally unfamiliar with objects and the validity of precise ratings is uncertain. In that case, monotonic conjoint measurement should be used.)

We therefore conclude that, when a conjoint data set is required, functional analysis should be considered, since in this study it was the most cost effective overall. (This statement assumes the validity of the use of rankings; this is a reflection of the modes being compared, as mentioned previously.) However, when precise estimates are not required, the univariate approach seems adequate.

Finally, it should be noted that the study was designed to allow analysis of interactions at the aggregate level. The analysis reported here was at the totally disaggregate level and was limited to linear functions. This is frequently the case with totally disaggregate data and, in this case, it did not seem to impair the predictive capabilities of these techniques.

The results reported here can only be verified by a continuing body of research to document the range of subjects and settings in which these techniques are applicable. Within the limitations of the study, the results confirm that careful attitudinal research provides valuable information for those who plan and design transportation systems.

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Modeling Travelers' Perceptions of Travel Time

JAMES E. CLARK

In order to better understand and model the way urban travelers make decisions, the relation between travel times as actually measured and travel times as reported by travelers themselves is examined. Stevens' Law, the psychological theory that the perception of a stimulus is related to the actual stimulus by an exponential function, is used to analyze the relation between a set of travel times reported by travelers and the corresponding travel times actually measured. A comparison of the measured and reported times suggests that Stevens' Law does apply to the perception of travel time and that travel times for different modes of travel are perceived in different ways. The effects of these differences between reported and measured travel times for planning models are then examined, and a suggestion is made as to how Stevens' Law can be used to overcome these differences and improve the accuracy of transportation planning models.

It has long been recognized that there are problems in choosing what values to use to represent variables such as travel times and costs in transportation planning models (1). The growing use of behavioral model forms (such as logit analysis) that are explicitly based on economic and psychological theories of how individuals make choices has brought these problems into clearer focus. In all theories of choice behavior, an individual's choices of such items as travel mode and destination are based on the individual's perception of the characteristics of various modes and destinations.

Unfortunately for transportation planners, information on travelers' perceived values of travel times, travel costs, and other such variables is not directly available. The two available methods of representing the perceived values of such variables are by the use of the actual, measured values and by the use of values reported by travelers in surveys. Both of these methods, however, have at least potential inaccuracies in comparison with the perceived values. In addition, it has recently been shown that there frequently are large differences between measured and reported values for travel times and costs (2).

As will be discussed later, the use of measured values in estimating models of the sort usually used in transportation planning requires the implicit or explicit assumption that the measured values of variables are a linear function of the perceived values or at worst that the perceived values are randomly distributed around the actual measured values. However, the psychological theory of perception, discussed in more detail below, suggests that the perceived values are likely to be nonlinear functions of the measured values. Although this would suggest that using reported values would be preferable to using measured values in transportation planning models (at least where reported values are available), it must be acknowledged that reported values may also not accurately reflect perceived values. In some cases, travelers may never have considered the value of some variables (for example, the travel time by bus for a trip the traveler always makes by car), so the reported values may well be largely guesses rather than perceptions. In addition, travelers may consciously or subconsciously distort their perceptions so that their reported values for travel times, costs, etc., make their own choices seem better or more logical than they really are. In the marketing literature, this phenomenon is known as "postpurchase bias", and it is commonly found that buyers of a particular product report more favorable perceptions of the product after the purchase is made than they did before the purchase. Although this paper recognizes the possibility that reported values may well differ from perceived values, reported values of travel times are used here as proxies for the unavailable perceived values.

The remainder of this paper is an exploration of the differences between reported and measured travel times and of the effects of these differences on the estimation of an urban transportation planning model. The first section outlines the general theory of perception that has been developed by psychologists. Next, the data set used is described. This is followed by a comparison of measured and reported travel times as a test of the applicability of the psychological theory of perception to travel behavior. The effects of the differences between measured and reported times on the estimation of a modal-split model of the logit type are then examined. Finally, the conclusions that can be drawn from the exploration are presented.

PSYCHOLOGY OF PERCEPTION

The basic concept of psychology regarding the relation of perceived values of a phenomenon to their actual values is summarized in Stevens' Law (3), which states that the perceived values are a power function of the actual values, or

$$PV = a \cdot (AV)^b \quad (1)$$

where

PV = perceived value,
AV = actual value, and
a and b = coefficients related to characteristics of the particular phenomenon involved.

In experiments by psychologists, Stevens' Law has been found to describe accurately the relation between the perceived magnitudes of various stimuli (as reported by those exposed to the stimuli) and their actual magnitudes (4). In the psychological literature and in the geography literature referred to below, reported values have been assumed to be equal to perceived values.

During the 1970s, geographers have used Stevens' Law to explore the relations between perceived physical distance ("cognized distance", in their terminology), as reported by groups of experimental subjects, and actual distance. In general, Stevens' Law has been found to apply to the reported perceptions of actual physical distances. For a sample of persons in Kingston, Ontario, Ericksen (5) estimated the following relation between perceived distance and actual distance: $a = 1.51$, $b = 0.91$, and $R^2 = 0.45$. For a sample from Columbus, Ohio, Briggs (6) estimated the following: $a = 1.55$, $b = 0.57$, and $R^2 = 0.76$. Other similar studies (7-9) have had similar results.

These efforts led to a study by Burnett (10) that related reported perceptions of travel times ("cognized time") to actual measured travel times for driving trips to various locations in the Dallas-Fort Worth, Texas, metropolitan area from the then new Dallas-Fort Worth Regional Airport. Information on drivers' reported travel times to their destinations was gathered by interview from drivers leaving the airport and was matched with measured driving times to the destinations. The data set consisted of 200 pairs of reported and measured travel times to various destinations.

Power functions in the form of Stevens' Law were then estimated by Burnett for the various subsets (different directions, destination types, and age and income groups) of the sample. Except for one subset, the estimated values of a fell between 1.31 and 3.65 and the estimated values of b fell between 0.60 and 0.89; R^2 values were between 0.52 and 0.84. Comparisons of the results for different subsets showed that, although the direction of travel (toward or away from the city center) has a statistically significant effect on the estimated coefficients, age and destination differences have no significant effects. Large differences in income also produce significant differences in estimated coefficients.

The research described in this paper can be regarded as both an extension and an expansion of Burnett's pioneering efforts. Whereas Burnett's data covered a relatively low-density geographic area, the data used here are from a much more densely populated area. In addition, the data cover not only automobile drivers but also automobile passengers and users of bus and rapid transit services. Finally, the variety of modes available allows the estimation and comparison of modal-choice models by using reported and measured travel times.

DATA DESCRIPTION

The data on reported travel times and other trip and traveler characteristics used in this study were collected from a sample of people who traveled to Evanston, Illinois, to shop. Evanston, a predominately residential suburb located on Lake Michigan immediately north of Chicago, had a population of 80 000 at the time the data were collected. The downtown area is typical of older North American cities and suburbs, with shop-lined streets rather than shopping malls. There are two large department stores and numerous specialty shops along with many restaurants and office buildings. Convenient and reasonably inexpensive parking, both on the street and in off-street parking lots and ramps, makes driving practical. The shopping area is served by several bus routes that connect the downtown shopping area with other parts of Evanston, other suburbs, and the northern parts of Chicago. A north-south elevated rapid transit line (the "L") provides service to the downtown area from a large part of Evanston and Wilmette (immediately north of Evanston) and connects with the Howard Street rapid transit line that serves northern Chicago. Although Evanston is also served by the Chicago and North Western commuter railroad and by taxi services, these are not included below due to insufficient data; walking and bicycling were also used by some of those surveyed to travel to the shopping area.

Data on travel times (both in-vehicle and out-of-vehicle), travel costs, trip origins, and other trip characteristics, both of the mode actually chosen by the traveler and of the mode the traveler gave as the alternative he or she would use if the chosen mode were not available, were obtained from self-administered questionnaires distributed to persons shopping in downtown Evanston on days with pleasant weather conditions in June 1975. The survey also obtained socioeconomic data on the travelers themselves.

Data on measured in-vehicle travel times by automobile were obtained by actually driving the reported trips and measuring the time required, by way of the fastest route available, for each trip. Each trip was driven twice in each direction at the same time of day as the reported trip; the measured time was obtained by discarding the fastest and slowest times and then using the mean of the two remaining times. Using the mean of all four trips noticeably changed the measured times of a few trips due to atypically high or low measured times on one of the four runs and resulted in a somewhat worse fit when the times were compared with the reported travel times.

A problem with developing the measured driving times arose from the manner in which the trip origin was obtained from questionnaire respondents. To preserve the respondents' anonymity, only the approximate address was requested on the questionnaire. During the coding of the returned questionnaires, the location of each trip origin was assigned to one of the 0.5-mile² zones into which the study area was divided. The actual driving times were measured from the most centrally located major intersection in each zone to the center of the downtown shopping area. To allow for the driving time from the actual trip origin to the zone center intersection, 2 min was added to each of the measured driving times. The figure of 2 min was obtained from trials in which runs were made from several randomly chosen locations in five zones to the downtown center. Using times of 1 or 3 min did not significantly change the results presented below.

Measured in-vehicle travel times for bus and L-riders were obtained from the timetables in effect at the time of the survey. Sample measurements of actual travel times show that these schedules are consistently met. The number of observations for which both a reported and a measured time are available is given below:

Mode	Chosen	Alternative
Automobile		
Driver	213	134
Passenger	59	72
Bus	82	147
L	32	79
Total	386	432

The totals for chosen or alternative mode do not agree due to the use by some respondents of taxi, train, walking, or bicycle as either their chosen or alternative mode.

Although this study does not focus on differences between reported and actual travel costs, due to the difficulty of accurately estimating a specific individual's driving costs for a particular trip, the data available do permit a few comparisons of reported and actual transit fares. Among those who actually used transit to travel to Evanston on the survey date, 98 percent of bus riders and 81 percent of L-riders correctly reported the fare paid; many of those reporting incorrectly were apparently confused between one-way fares (as requested in the questionnaire) and round-trip fares. However, of those who gave transit as their alternative mode, only 84 percent of the potential bus riders and 68 percent of the potential L-riders correctly reported the fares they would have paid if they had used transit. Most of the incorrectly reported fares--91 percent for bus and 96 percent for L--were higher than the actual fares.

COMPARISON OF REPORTED AND MEASURED TRAVEL TIMES

Initial comparison of reported and measured in-vehicle travel times was made by regressing the log of reported time on the log of measured time plus a constant term. This functional form is the equivalent of Stevens' Law [$PV = a \cdot (AV)^b$, where PV is represented by the reported time and AV by the measured time]. The resulting estimates of a and b are given in Table 1, along with goodness-of-fit measures, for the sample as a whole and for subsamples broken down by mode and by whether the observation is of the traveler's chosen or alternative mode.

In these regression estimations, all those with "yes" in the b < 1? column (all but regressions 7 and 15) have b coefficients that are less than 1 at the 1 percent level of significance. A b coefficient that is significantly different from 1 implies that there is the sort of nonlinear relation between perceived times (as represented by reported times) and measured times that Stevens' Law predicts, whereas a b coefficient of 1 would imply that reported travel times are merely proportional to actual travel times. There may be problems with using the usual methods of modeling and forecasting travel choices and behavior if there is a nonlinear relation between perceived and measured travel times. This is discussed in the next section of this paper.

The extremely low R^2 for regression 1 containing all the data, especially when compared with the R^2 values in the various subsets, seems to imply that different groups within the sample may perceive (or at least report) travel times in different ways or on different scales. This might come about because travel time is perceived differently for different modes or because those travelers who actually used a particular mode perceived (or reported) their travel time differently from those who did not use that mode.

As described by Williams (11), it is possible to construct a statistic based on the differences between the regression error sums of squares for a data set as a whole and for the various subsets; this statistic has an F-distribution. A significant F-statistic implies that the regressions performed on the various subsets have different coefficients, and an insignificant F-statistic would imply that the regression coefficients are not in fact very different. For each mode except automobile driver, there is no significant difference in the perception of travel time between those who actually chose the mode and those who gave that mode as their alternative; the difference between those who chose to drive a car and those for whom driving was their alternative is significant at the 1 percent level. There is also no significant difference between automobile drivers and automobile passengers.

However, there is a significant difference (at the 1 percent level) among the different modes in how the travel time by those modes is perceived. A comparison of regressions 8, 11, and 14 shows that the scale factor a is higher for both bus and L than for automobile, which suggests that, at least initially, a minute spent in an automobile seems shorter than a minute spent on a bus or on the L. The exponent b, however, is lower for bus and L travel than for automobile travel; the time spent traveling seems to increase at a slower rate on public transit than in driving or riding in a car.

APPLICATION TO TRANSPORTATION PLANNING MODELS

The analysis above strongly suggests that travel time is perceived by travelers in a manner different from actual measured travel time and that perceived time is related to measured time by Stevens' Law. This relation has at least the potential for creating inaccuracies in the types of transportation planning models commonly used.

As an example, consider the logit model, probably at this time the most frequently used model form for transportation research; logit analysis is also being applied more and more frequently in actual transportation planning and forecasting models. Where an individual is choosing between options i and j, the logit model has the following form:

$$P_i = e^{G(X_{j,i})}/[1 - e^{G(X_{j,i})}] \quad (2)$$

where P_i is the probability of choosing option i and $G(X_{j,i})$ is a function of the relative characteristics of choices i and j. The function G is usually assumed to be linear in the differences between the characteristics of the two choices. For example, if a person were to choose between bus (b) and car (c) for a trip and the travel times and costs of the two modes were used as the choice criteria, the function G would take the following form:

$$G = a_1(T_b - T_c) + a_2(C_b - C_c) \quad (3)$$

where

T_b and T_c = travel times by bus and car, respectively;
C_b and C_c = travel costs; and
a_1 and a_2 = coefficients to be estimated.

If it is thought that some inherent characteristics

Table 1. Regression estimations: reported and measured times.

Mode	Regression No.	Chosen or Alternative Mode	a	b	b < 1	R^2	No. of Observations
All	1	Both	5.37	0.101	Yes	0.016	818
Automobile	2	Both	2.03	0.721	Yes	0.278	347
driver	3	Chosen	2.61	0.604	Yes	0.224	213
	4	Alternative	2.01	0.645	Yes	0.191	134
Automobile	5	Both	1.91	0.711	Yes	0.309	131
passenger	6	Chosen	2.56	0.541	Yes	0.192	59
	7	Alternative	1.47	0.862	No	0.431	72
All automobile	8	Both	2.01	0.713	Yes	0.283	478
	9	Chosen	2.54	0.602	Yes	0.224	272
	10	Alternative	1.83	0.717	Yes	0.271	206
Bus	11	Both	3.09	0.481	Yes	0.254	229
	12	Chosen	3.70	0.355	Yes	0.146	82
	13	Alternative	2.88	0.536	Yes	0.305	147
L	14	Both	2.30	0.624	Yes	0.282	111
	15	Chosen	2.13	0.724	No	0.265	32
	16	Alternative	2.47	0.539	Yes	0.268	79
All transit	17	Both	2.51	0.588	Yes	0.379	340
	18	Chosen	2.79	0.516	Yes	0.245	114
	19	Alternative	2.42	0.619	Yes	0.440	226

of buses or cars affect the person's choice, a dummy variable in the form of $a_3(D)$ can be added to the function G.

Although the linear form for G both is intuitively appealing and has the weight of consumer choice theory (12) behind it, problems arise when this form, using measured values, is confronted with Stevens' Law. Other things being equal, the usual form of the logit model, estimated from actual travel times, would imply that a relative change in travel time of, say, 10 min will have the same effect on the choice probability between car and bus regardless of the length of the trip involved. Stevens' Law, however, with b coefficients estimated above as less than 1, implies that a change of 10 min will be perceived as becoming smaller the longer the trip.

Some of the effects of these differences between measured travel times and those reported by travelers can be seen by estimating logit models of modal choice by using first the measured travel times from above and then reported travel times. The results of such a comparison are given in models 1 and 2 in Table 2. The coefficients presented are the estimated a_i from Equations 1 and 2.

Table 2 gives the estimated coefficients for logit models based on the hypothesis that a traveler's choice of mode depends on relative travel costs, travel times, and specific characteristics of the modes available. Both models used a data set with 256 observations; these consist of those individuals surveyed as described above whose chosen and alternative modes were among the driver, passenger, bus, and L modes. The data are the same for both models except that travel time in model 1 is obtained by adding the measured in-vehicle travel times to the travelers' reported out-of-vehicle travel times whereas model 2 uses the sum of the in-vehicle and out-of-vehicle travel times reported by the travelers.

Travel time and travel cost would a priori be expected to have negative coefficients; the higher the cost or time of a mode, the lower the probability of choosing that mode would be expected to be. The insignificant coefficient on travel cost is not surprising for a data set based on relatively infrequent shopping trips; similar results have been found by others in similar situations (13). The negative signs on the coefficients for specific modes refer to their unattractiveness in comparison with automobile driver, the base mode for these equations.

As can be seen in Table 2, the results of the two models are somewhat dissimilar. In particular, model 1, using measured times, implies that travel time is not a significant factor in the modal-choice decision of those travelers surveyed (the t-statistic is not significant even at the 10 percent level). Model 2, using reported times, implies, on the other hand, that travel time is a highly significant determinant of modal choice (the t-statistic is significant at the 1 percent level). The other coefficients are also quite different. Although both are significant at the 1 percent level, the higher F-statistic for model 2 implies that model 2 fits the data better than model 1.

The foregoing analysis suggests that using reported rather than measured data on travel times to estimate demand models is to be preferred. But reported data are frequently not available. In particular, reported data will not be available for forecasting the future effects of changes in the transportation system. One possible way to counteract this problem is to modify the actual travel-time data according to travelers' perceptions of those times. Model 3 in Table 2 presents the results of a logit model run on the data discussed above for measured travel times, where the measured times are transformed according to Stevens' Law by using the a and b regression coefficients for each mode as estimated in the previous section. As can be seen, the estimates in model 3 agree quite closely with those in model 2 based on reported travel times.

CONCLUSIONS

In order to better understand and model the way urban travelers make decisions, this paper has examined the relation between travel times as actually measured and travel times as reported by travelers themselves by using reported times as proxies for perceived times. Stevens' Law, the psychological theory that the perception of a stimulus is related to the actual stimulus by an exponential function, was used to analyze the relation between a set of travel times and trips reported by travelers and the corresponding travel times actually measured. A comparison of the measured and reported times implied that Stevens' Law does apply to the perception of travel time and that travel times for different modes are seemingly perceived in different ways. The effects of these differences between reported and measured travel times on transportation planning and forecasting models were then examined.

Several useful conclusions can be drawn from this study. The first is that the way in which travelers perceive the characteristics of transportation systems is not described with complete accuracy by the engineering characteristics of the systems. Transportation planners and forecasters must be aware of how perceptions differ from reality; Stevens' Law seems to describe at least a major part of the connection between perception and reality. Second, if a planner knows or can estimate the a and b coefficients in the Stevens' Law equation that relate perception to reality, the accuracy of planning models can be improved by transforming the actual values of system characteristics, such as travel times, to reflect travelers' perceptions of these characteristics more closely.

These conclusions suggest several recommendations for future research on modeling travelers' perceptions. The testing of the applicability of Stevens' Law to other modal characteristics, such as travel cost and access and egress times, would be straight-

Table 2. Logit estimations.

Model No.	Travel Cost Coefficient	Travel Cost t-Statistic	Travel Time Coefficient	Travel Time t-Statistic	Passenger Coefficient	Passenger t-Statistic	Bus Coefficient	Bus t-Statistic	L Coefficient	L t-Statistic	F-Statistic	Correctly Predicted (%)
1	0.001 87	0.78	-0.0116	-0.90	-0.783	-3.08	-1.129	-3.71	-1.272	-3.86	66.8	73.0
2	0.002 29	0.94	-0.0526	-2.99	-0.756	-2.94	-0.408	-1.14	-0.703	-1.91	76.1	73.4
3	0.002 25	0.94	-0.0523	-2.98	-0.799	-3.10	-0.527	-1.60	-0.734	-2.02	75.9	73.4

forward as would testing the transferability of the coefficients of Stevens' Law among localities in different geographic areas and with different characteristics. Preliminary psychological research (4) suggests that it may be possible to develop a single equation that captures the relations between reality and perception for all types of travel characteristics.

Another potentially fruitful area for further research would be an integration of the Stevens' Law concept with the concept of cognitive dissonance. The usefulness for transportation choice modeling of the theory of cognitive dissonance, with its implications regarding the interrelation of attitudes and behavior, has been explored by Golob, Horowitz, and Wachs (14), Dumas and Dobson (15), and others. Further application of the insights into human behavior that are available in the literature on psychology and marketing should prove beneficial in improving both knowledge of travel behavior and the ability to forecast future behavior.

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Design and Analysis of Simulated Choice or Allocation Experiments in Travel Choice Modeling

JORDAN J. LOUVIERE AND DAVID A. HENSHER

A new approach for modeling traveler trade-offs and choices is proposed, described, and illustrated. Based on research in psychology, marketing, and economics, a method for developing discrete choice models from controlled laboratory simulation experiments is developed and presented. The method borrows statistical theory from discrete choice theory in econometrics and from the design of statistical experiments to marry work in trade-off analysis with choice analysis. The method is illustrated by means of several travel-choice-related examples that involve choice of mode and destination. Recent evidence of validity in forecasting the actual behavior of real markets is reviewed in support of the approach.

Since the early 1970s, the study of revealed-choice behavior based on the random utility derivations of discrete choice theory in econometrics (1-6) has gained a following in the analysis and forecasting of travel behavior. If real choice data satisfy the conditions assumed in the statistical choice models, it is possible to derive aggregate-level trade-offs and to simultaneously forecast choice behavior. Hence, methods based on revealed choice have high external validity and practical applicability to strategic policy problems.

Other approaches have recently gained attention--notably, laboratory simulation methods such as variations of conjoint measurement or trade-off analysis (7-9) and functional measurement (10-15), which are the primary methods of approach for developing quantitative descriptions of multiattribute individual and group judgments, trade-offs, or utilities. These approaches are based on the responses of travelers to hypothetical travel alternatives and not on their observed behavior. The former type of data is here called "intended choice" and the latter type "revealed choice".

The intended-choice approaches to trade-off analysis have limitations that hamper their applicability, including the following:

1. One is usually forced to make untestable assumptions about the functional form of the trade-offs in practical applications.
2. One must make assumptions about the relation between choice and utility that are untestable and are contrary to most assumptions in practical random utility choice models.
3. It is difficult to incorporate individual constraints on choice effectively except in an ad hoc or post hoc fashion.
4. External validity assessment is less obvious than with revealed-choice methods.

The revealed-choice methods, on the other hand, have major limitations:

1. One must make assumptions about functional form a priori and, in contrast to the intended-behavior methods, one cannot ever guarantee that it will be possible to test these assumptions adequately with real data.
2. One must make assumptions about mean utility parameters or at least segmented mean parameters that are known from evidence to be often false (10,12,13,15,16) and that are used for the sake of tractability rather than empirical reality.
3. Measurement errors and correlations among variables cannot be controlled to any satisfactory degree, or at least have not historically been well controlled (18).
4. The forecasting accuracy of the models has been disappointing, which suggests that external validity of observations of choice is insufficient to guarantee internal validity or forecast accuracy.

Recently, the consequences of failure to satisfy a number of these assumptions have been examined by Horowitz (18,19). Suffice it to say that the intended-choice approach can guarantee satisfaction of many of the assumptions by design while sacrificing immediate external estimation validity, whereas the revealed-choice approach cannot guarantee satisfaction of its assumptions with real choice data but does have immediate external estimation validity.

This paper attempts to partially bridge the gap between the two approaches by developing a method for estimating intended-choice models that satisfies to the extent possible the necesssary statistical conditions for a variety of econometric choice models and can be used to make forecasts to test external validity. Evidence in support of external validity is presented later in the paper. In this regard, the approach represents an improvement in the ability to analyze choice behavior with intended-choice data because it actually involves observations on choice or allocation behavior in controlled situations. Because the models derived are estimated from experimentally observed choices, they directly forecast choice behavior rather than judgments, utilities, or rankings. Although it is not explored in this paper, the approach also has the ability through the use of statistical principles in experimental design to rigorously test various assumptions inherent in, or deductions derived from, discrete choice models in econometrics (18,19). This permits one to rigorously test various aspects of choice models that at best can be tested only weakly with revealed-choice data.

THEORY

It is assumed that the derivations of discrete choice theory based on random utility notions are approximately true--that is, that the random utility version of the Luce (20,21) choice axiom as derived by McFadden (5) and Yellot (22) holds for aggregate choices or allocations:

$$p(a|A, \forall j\epsilon A) = e^{U_a} / \sum_{\forall j\epsilon A} e^{U_j} \tag{1}$$

where

$p(a|A, \forall j\epsilon A)$ = probability of selecting alternative a from choice set A, of which a is a member, defined over all j members of A, including a;
U_a, U_j = utilities or scale values of a and j, respectively; and
e = base of the natural logarithms.

One normally assumes that the scale values (utilities) may be expressed as a linear in the parameters and additive function; e.g., for alternative a,

$$U_a = b_{0a} + b_{1a} X_{1a} + b_{2a} X_{2a} + \ldots + b_{na} X_{na} \tag{2}$$

where

U_a = scale value of the ath alternative,
b's = constants to be estimated from the data, and
x's = attributes of the ath alternative.

Equation 1 states that the probability of choosing any particular alternative from a set containing at least one other is expressible strictly as a function of conditional probabilities. Equation 2 imposes a linear in the parameters and additive structure on the conditional probabilities to describe each alternative. In general, the attributes are specific to a particular alternative (e.g., alternative a), but it is possible in some contexts to treat the attributes as generic--i.e., attributes that are common to all or some subset of alternatives. Other problems require mixtures of generic and alternative specific attributes.

If one assumes Equation 1 to be true, it is possible to develop straightforward methods for collecting data and estimating the parameters of the choice models derived therefrom. The results of such choice studies are similar to those of conjoint analysis, trade-off analysis, functional measurement, or the like in that estimates of levels of utility can be derived, various algebraic forms of utility (or decision) models can be tested, and policy-relevant parameters such as elasticities can be obtained (1,7-10,12-17). More important, however, the choice models derived forecast choices directly without the necessity of developing a simulation routine combined with a number of assumptions (such as "highest" ranked equals first choice) that are required to predict choices from rankings or ratings data (16). The approach to this problem is discussed in the next section of this paper.

CONSIDERATIONS ON DESIGN OF CHOICE EXPERIMENTS

Equation 1 implies that any experimental design that ensures the independent estimation of conditional effects (scale values) should suffice as a choice design. Although we readily admit that in theory random samples of choice sets will satisfy this criterion, in practice it is impossible a priori to know the statistical properties of such designs. Hence, we favor the use of controlled statistical experiments that can be designed a priori to have certain statistical properties of interest. This paper concentrates on two such design properties:

1. The condition that the probability of a choice alternative being in a choice set and the probability of choosing the alternative given that it is in a choice set be independent and balanced across all sets of choice sets so that one can determine whether alternative a has a higher probability of being chosen over b because it is preferred to b or because it is available to be chosen more often than b, and
2. The condition that the attributes of the choice alternatives be as independent of one another as possible (i.e., orthogonal) both within and between alternatives.

In practice, it is possible to guarantee the satisfaction of these two conditions by the appropriate choice of an experimental design plan (9,12,17,23-27). In particular, it is always possible to satisfy these two conditions by treating each attribute as a factor "nested" under the appropriate alternative. By judicious choice of design plan, it is also possible to test for violations of Equation 1 by using some of the ideas contained in Horowitz's various tests for choice model adequacies (18,19). Most such tests require one to be able to estimate certain interactions in addition to main effects; however, one can almost always design such conditions a priori so that they will be satisfied by the data (24-26).

In general, main-effects plans that treat each attribute of each alternative as a factor will suffice for model estimation if Equation 1 is approximately true. Louviere and Woodworth (25) have shown these design plans to be near optimal for parameter estimation in terms of efficiency. The next section of this paper outlines parameter estimation for aggregated choice data. We concentrate on aggregated data for the sake of exposition of ideas; future papers will explore individual-level models, repeated-measures designs, and covariance analyses.

PARAMETER ESTIMATION FOR AGGREGATED CHOICE DATA

For many applications, such as sketch planning, aggregated choice data are sufficient to derive policy implications. If sample sizes permit, the choice data may be disaggregated into various policy categories of interest (assumed to be mutually exclusive) and aggregates of choices may be developed for analysis. So there is some limited flexibility for market segmentation with this approach. If disaggregated results are desired, the data must be treated as a series of discrete choices at the individual-respondent level and maximum likelihood estimation used to derive parameter estimates. Such methods are now well-known in travel analysis and need not be pursued here (1-6). However, because the problem of repeated measures on individuals has yet to be treated, caution should be used in any applications of traditional logit choice algorithms to the types of data described in this paper.

It is important to note that each individual is asked to make choices (or allocate choices, money, time, etc.) from a series of choice sets. The experimental designs briefly outlined in the previous section generate the appropriate choice sets to be administered to each individual, and each individual makes a sufficient number of choices to permit estimation of a separate, individual-specific choice model. Unfortunately, the theory of maximum likelihood estimation developed for multinomial logit choice models (4,5) only holds for large-sample problems, and the properties of the estimates for individual-level choice models are currently unknown. However, because each individual makes a series of discrete choices from statistically designed sets of choice sets, there is likely to be more than enough choice data in the aggregate across a typical sample (say, 400 individuals) to satisfy the large sample requirements. By "aggregate" we mean both (a) the total of discrete choices available (the number of individuals times the number of choices in all choice sets) and (b) the aggregated choice frequencies obtained by calculating the total number of choices made by individuals for all alternatives in all choice sets.

We now illustrate the method of estimation for aggregated choice data; Louviere and Woodworth (25) have demonstrated its asymptotic efficiency for large samples, as have others (4,28,29). The estimation method involves weighted least-squares regression in which Equation 1 is put in linear form as follows.

The relative frequency with which alternative j (= 1,2,...,J) is chosen in choice set i (= 1,2,..., I) is denoted as Rf_{ij}. This relative frequency is taken as an estimate of the unknown choice probability, and Equation 1 is rewritten as follows:

$$Rf_{ij}(a|A, \forall j\epsilon A) = e^{U_{ia}}/K_i \quad (3)$$

where κ_i is $\sum_{\forall j \epsilon A} e^{U_{ji}}$ and all other terms are as previously defined. That is, for the ith choice set, the denominator is a constant for all j alternatives. Taking logarithms to the base e of both sides yields

$$\ln[Rf_{ij}(a|A, \forall j\epsilon A)] = U_a - \ln(k_i) \quad (4)$$

Equation 4 implies that the U_a can be estimated by creating dummy variables for each j and for each i--in particular, a weighted multiple linear regression analysis in which each choice response (relative or absolute choice frequency) is associated with a design matrix of (1,0) dummy coded indices so that, if the choice observation (Rf_{ij}) pertains to choice alternative a, the dummy index for alternative a is coded one, otherwise zero. Similarly, if the choice observation appears in choice set i, the dummy index for choice set i is coded one, otherwise zero. In practice, of course, only (J - 1) and (I - 1) dummy indices can be used in estimation unless one "centers" the regression about the origin. Another estimation method (29) permits one to dispense with choice set constants by using the log odds with respect to some base alternative as the dependent variable. It is easy to demonstrate that the denominators or choice set effects cancel out for this case. As in disaggregate multinomial logit estimation, one choice alternative serves as a base alternative--the "origin" of the scale values.

Weighted least squares is used because the dependent variable is a proportion (the relative frequency of choices in choice set i), which does not conform to classical homoscedasticity assumptions in multiple linear regression. Louviere and Woodworth (25) and Grizzle, Starmer, and Koch (28) discuss weighting for this condition. The method yields modified minimum chi-square estimates that are asymptotically efficient and consistent in large samples.

EXAMPLE APPLICATIONS

This section illustrates the application of the approach to three travel-choice-related examples and also provides evidence from three validity tests that suggests the approach is predictive of the actual behavior of people in real markets.

Simple Destination Choice Problem: Choosing a Fast-Food Restaurant for Lunch

Example A involved 99 upper-class undergraduates in marketing at the University of Iowa, who were shown 10 different choice sets consisting of various combinations of the five major hamburger chains in Iowa City: Wendy's, Burger King, Hardee's, McDonald's, and Burger Palace. The choice sets were developed by treating each restaurant as a factor with two levels: available or unavailable. All possible sets of choice sets would be the 2^5 combinations of availability of each restaurant. This is a factorial design. We selected 8 choice sets from the 32 possible according to an orthogonal main-effects plan (24). One of the 8 sets selected is the null set (all unavailable); hence, there is a target group of 7 sets for analysis. Subjects were shown 3 preliminary sets of no analytic interest to acquaint them with the task.

Subjects indicated which restaurant they would be most likely to choose for lunch given that only the ones listed in a particular set were available. Subjects were informed that some restaurants could fail or others enter the market, and we wished to know what they would do if some now present were closed. The discrete choice data were aggregated to relative frequencies for analysis by weighted least-squares regression:

$$\begin{aligned}Rf_\kappa &= \beta_0 + \beta_1 \text{Wendy's}_\kappa + \beta_2 \text{Burger King}_\kappa + \beta_3 \text{Hardee's}_\kappa + \beta_4 \text{McDonald's}_\kappa \\ &+ \beta_5 \text{Set } 1_\kappa + \beta_6 \text{ Set } 2_\kappa + \beta_7 \text{Set } 3_\kappa + \beta_8 \text{Set } 4_\kappa + \beta_9 \text{Set } 5_\kappa + \beta_{10} \text{Set } 6_\kappa \qquad (5)\end{aligned}$$

where

Rf_κ = observed relative frequency for the κth ($\kappa = 1,2,\ldots,$ K = 40) choice possible in the task;
Wendy's, Burger King, etc. = (1,0) dummy variables to represent (J - 1) alternatives (restaurants) (each choice observation is coded one if it is the alternative in question, zero otherwise);
Set 1, Set 2, etc. = (1,0) dummy variables to represent the (I - 1) different denominators or "choice set effects" (each choice observation is coded one if it was observed in the ith set, zero otherwise); and
β_0, β_1, etc. = empirical regression parameters to be estimated from the data.

The statistical results are as follows:

Restaurant	Estimated Scale Value	Standard Error
Burger Palace	0.00	--
Wendy's	2.56	0.11
Burger King	1.82	0.11
Hardee's	1.08	0.11
McDonald's	2.39	0.11

The F (14,26) = 48.36, which has a probability of occurring by chance of less than 0.0001. The R^2 value is 0.98. The model appears to give a good account of the aggregated choice data.

Only the scale values are of interest in the examples; the choice set parameters are needed merely to ensure that the probabilities sum to one in each choice set and because they are algebraically necessary in the model form to be estimated. One could recover the original choice proportion data (the relative frequencies) by using the scale values estimated in the regression. Thus, the degrees of freedom necessary to account for the choice data are always much less than indicated in the regression analyses. Nonetheless, it should be noted that Equation 1 implies a constant cross elasticity for all attributes of all alternatives and the choice set constants contain all cross-elasticity effects. If one suspects that this hypothesis is not true, more detailed analysis of each choice alternative will be necessary.

Simple Modal-Choice Problem: Bus Versus Automobile Versus Other

A modal-choice task was developed by manipulating three attributes of bus systems and three attributes of automobiles in an experimental design. The attributes of bus (and their levels) were fare (25¢ and 50¢), travel time (15 and 40 min), and walking distance (1 and 5 blocks); the attributes of automobile were gasoline cost per gallon ($1.35 and $1.75), travel time (10 and 20 min), and parking costs per hour (20¢ and 50¢). In other words, the experimental design was created by treating each attribute as a factor with two levels and selecting a fraction of the 2^6 complete factorial design. The orthogonal fraction selected from Hahn and Shapiro (24) has 16 treatment combinations, each of which is a choice set. That is, a choice set consists of a description of the levels of the three bus attributes and the levels of the three automobile attributes; subjects were requested to indicate whether, given their present circumstances, they would choose to travel to the University of Iowa for regular morning classes by the described automobile, bus, or other (left unspecified). Subjects were the same 99 undergraduates involved in example A.

The discrete choice data were aggregated to relative frequencies for analysis by weighted least-squares regression. The following model was estimated:

$$\begin{aligned}Rf_\kappa &= \beta_0 + \beta_1 \text{bus}_\kappa + \beta_2 \text{auto}_\kappa + \beta_3 \text{fare (\$) if bus}_\kappa + \beta_4 \text{time (min) if bus}_\kappa \\ &+ \beta_5 \text{walk (blocks) if bus}_\kappa + \beta_6 \text{gasoline (\$/gal) if auto}_\kappa \\ &+ \beta_7 \text{parking (\$/h) if auto}_\kappa + \beta_8 \text{time (min) if auto}_\kappa \\ &+ \sum_{i=1}^{15} \alpha_i C_i \qquad (6)\end{aligned}$$

where

Rf_κ = kth relative frequency of choice observation (k = 1,2, ...,K;K is I x J);
bus, auto = alternative specific constants, derived by treating each as a (1,0) dummy variable;
fare, time, etc. = alternative specific attributes that have their numerical values if the choice observation pertains to the mode in question or are zero otherwise;
C_i = 15(I - 1) (1,0) dummy variables used to represent choice sets; and
$\alpha_i, \beta_0, \beta_1, \beta_2$ = empirical constants to be estimated from the data.

The results of the analysis are as follows (choice set results suppressed):

Variable	Parameter Estimate	Standard Error
Bus	1.26	0.55
Auto	-1.30	1.07
Other	-2.31	0.57
Bus time	-0.07	0.01
Bus fare	-2.58	0.85
Bus walk	-0.17	0.05
Auto gas ($)	-0.10	0.48
Auto parking ($)	-0.57	0.64
Auto time	-0.01	0.02

The F (24,24) was 36.97; the probability of an F-value that large occurring by chance is less than 0.0001. The R^2 is 0.95, so this model also gives a reasonably adequate account of the logs of the relative frequencies of choice data. Results indicate that, whereas University of Iowa students in marketing prefer buses to other modes, they are particularly sensitive to bus attributes in comparison with automobile attributes. It is notable that the travel-time coefficient for bus is almost nine times larger than that for automobile, which clearly indicates that time is not the same via either mode. With the bus equation, the implied value of travel time is about $1.65/h; however, these are student subjects.

Intraurban Modal-Choice Example: Bus Versus Air

An intraurban modal-choice task was developed by asking Iowa City individuals to make choices between the regular air service operating from Cedar Rapids, Iowa, to Chicago, Illinois (which requires Iowa City residents to drive approximately 26 miles to the Cedar Rapids Airport) and several different bus services proposed to operate directly from Iowa City to Chicago. At the time this paper was written, regular air service was offered by Ozark, Midstate Air, and Mississippi Valley Airlines. All operate nonstop services with flying times that range from 54 min to an hour and 45 min. All airlines had beverage but no in-flight food service.

Individuals were asked to choose among six alternatives: (a) regular air service at a particular price, (b) a bus service with drink and food service at a particular price, (c) a bus service with drink service but no food at a particular price, (d) a bus service with food service but no drink at a particular price, (e) the current bus service with no food or drink service at a particular price, and (f) some other method of travel, such as private vehicle. Respondents were asked to make choices in 16 different choice sets, which were developed by considering the air and four bus modes as factors with four levels of price; other was not given a price because it would vary from respondent to respondent.

Respondents consisted of a sample of 99 individuals chosen for convenience and willingness to participate and were drawn from three groups: (a) 33 Iowa City air travelers interviewed in the departure areas of the Cedar Rapids Airport; (b) 33 bus travelers interviewed at the Iowa City Bus Terminal, and (c) 33 students chosen because they declared that they made at least occasional trips to Chicago from Iowa City. All respondents participated in all choice sets. Data were aggregated to relative frequencies of choice for analysis by weighted multiple linear regression. The following model was estimated from the data:

$$\begin{aligned} Rf_\kappa = {} & \beta_0 + \beta_1 \text{air}_\kappa + \beta_2 \text{bus}_\kappa + \beta_3 \text{other}_\kappa + \beta_4 \text{air cost}_\kappa + \beta_5 \text{bus cost}_\kappa \\ & + \beta_6 \text{bus food}_\kappa + \beta_7 \text{bus drink}_\kappa + \beta_8 \text{bus food x drink}_\kappa \\ & + \beta_9 \text{choice set } 1_\kappa + \beta_{10} \text{choice set } 2_\kappa + \ldots + \beta_{23} \text{choice set } 15_\kappa \end{aligned} \tag{7}$$

where all terms are as previously defined or self-evident.

This model implies that there are different effects for dollar costs depending on whether the mode is bus or air and that food and drink have (potentially) nonadditive effects within bus. The results are as follows:

Variable	Parameter Estimate	Standard Error
Air	0.344	0.403
Bus	1.208	0.254
Other	-1.464	0.169
Air cost	-0.019	0.004
Bus cost	-0.127	0.010
Food	0.140	0.057
Drink	0.043	0.056
Food x drink	0.135	0.057

These results indicate that bus is preferred to air, which is probably the result of the preponderance of the sample of bus travelers and students and the larger number of different bus choices. In this respect, it is important to note that the sample is six times more sensitive to bus cost than to air cost and is much more influenced by the provision of a food service than a drink service. The (food x drink) interaction implies that having both is better than having either separately but having neither is considerably less preferred. If the sample were representative, it would imply that considerable leverage on patronage could be gained by the food-drink option and by offering air or bus travel cost specials.

SELECTED EVIDENCE OF EXTERNAL VALIDITY

This section briefly outlines the results of three recent tests of intended-choice-based models derived from controlled experimental manipulations of choice alternatives as described in previous sections of this paper. Other evidence of validity is reviewed by Levin, Louviere, Norman, and Schepanski (13) and elsewhere (8,11,12,14,15,25,30) and is therefore omitted in the interests of brevity. Suffice it to say that since 1975 intended-choice-based methods have compiled a consistent record of empirical successes in validity trials in the United States, Australia, and The Netherlands. The results reported here are representative of these other findings.

The first choice study to use the methods described above was conducted on behalf of a major pet food manufacturer. Because the results are proprietary, we provide only sufficient description to assess the outcome.

Random samples of pet food users were selected from several major markets in the United States in such a way as to be representative of the market. Subjects interviewed were shown 16 different choice sets consisting of combinations of 13 target pet food products based on a main-effects plan (23,24, 26,27) drawn from the 2^{13} factorial. Subjects were asked to allocate 11 points across the alternatives in each choice set so that the allocations reflected the proportion of each product that they would be likely to purchase in a typical month. Allocation data were aggregated to develop relative frequencies of choice, and a choice model similar to that represented by Equation 5 was estimated by weighted least-squares regression.

Market share forecasts were then made by using the scale values of the products derived from the regression. Data on U.S. national inventory withdrawal shares were obtained from a commercial company for the validity test. These data reflect distribution outlet withdrawals from inventory sources, which is not the same as aggregate sales share data but should be closely related. The results of this test revealed an obvious linear relation between observed and forecast national shares. The correlation was 0.83; some calibration (linear adjustment) would be necessary to apply the choice model developed in the interviews directly to the share data.

The second test involves a similar type of experimental design administered to a sample of 100 residents of Iowa City. The eight major supermarkets in Iowa City were treated as factors with two levels (available and unavailable), and 12 choice sets were constructed by developing a main-effects plan from the 2^8 factorial (23,24,26,27) to generate choice sets. First, those interviewed were asked to estimate how much of their grocery shopping budget they had spent in each of the eight stores over the preceding month. They were then shown the 12 choice sets and asked to indicate in which store they would be most likely to spend most of their budget if they could choose only from those listed in each choice set.

The choice data were aggregated to relative frequencies for analysis, and a model similar to Equation 5 was estimated from the data. The estimated scale values for each store were used to forecast their market share, and this was compared with the reported share data for the previous month's shopping obtained in the interview. The relation was again linear and the correlation was substantial (0.96). Again, a linear adjustment would be required to calibrate the laboratory model to the actual reported choice data.

The final example involves a transportation modal-choice problem in Australia. For policy reasons, it was desired to assess the sensitivity of choice for travelers to and from Tasmania and mainland Australia to changes in costs and types of service by sea and air. A sample of Tasmania and mainland residents completed a choice experiment that elicited (among other things) respondents' choices among an air service at a particular price, three different sea services (overnight with berth, overnight with chair, and fast daylight) at various prices, or "no travel". Respondents were shown 12 choice sets consisting of the four modal alternatives at different costs and the no-travel option. Three different questionnaires were created to permit all possible two-way interactions among the cost components of each mode to be estimated. Respondents were randomly assigned to the different questionnaires, and their choices were aggregated for a multiple linear regression analysis somewhat similar to Equation 6.

The model derived from the choice data was then used to predict the current known shares by air and sea (0.82 and 0.18, respectively). The derived model forecast the shares to be 0.78 and 0.22, respectively. This result suggests that the model requires minimum calibration and produces results consistent with actual observation.

DISCUSSION AND CONCLUSIONS

Many strategic research questions involve behavior for which either there are no current observational data or there is insufficient range and/or variation in independent variables of interest. Forecasting the response to introductions of new technology is but one of many examples of such research questions; others involve changes in existing transportation systems for which there is no historical precedent, such as a bus system that has historically operated all lines on a 30-min headway changing some to 15- or 60-min headways. In such instances, one usually tries to transfer knowledge from cognate problems or sites. It is well-known that such transfers have usually been disappointing. This paper proposes a new approach to the problem that involves observations of behavior under hypothetical, controlled simulation conditions.

The approach proposed in this paper produces models that are compatible with existing methods and technology; hence, no new educational or technical developments are required to implement the analysis. Of course, training would be required in the design of experiments and in the theoretical backgrounds in psychology and economics. The approach, however, has the advantages of being very flexible and inexpensive and providing quick response compared with more traditional methods. Cost savings accrue because so much more data can be obtained per individual. Moreover, experience with the procedures in academic and commercial applications has shown that the tasks for respondents are relatively straightforward and can be completed rapidly. Furthermore, analysis of the data is easy and inexpensive.

Based on external validity tests conducted with the proposed method and similar approaches developed in psychology and marketing, it is now clear that judgment and choice simulation methods can and do predict external behavior well. Indeed, it would be possible to argue, based on the evidence discussed in this paper and elsewhere (8,11,12,14,15,25,30), that judgment and choice models do no worse than econometric or other revealed-behavior models and most often perform considerably better. The additional advantages of being able to consider policy variables not now in place and to forecast responses to new innovations are also noteworthy. It now appears that judgment and choice models have matured to the point where they deserve the serious attention of practicing planners and others interested in strategic policy analysis and behavioral simulation modeling. At least one major planning group, the Wisconsin Department of Transportation, has adopted the approach in concert with its statewide road planning efforts, and the Australian Bureau of Transport Economics of the Australian Department of Transportation is now completing its third major study involving these techniques. In addition, we have conducted several dozen major commercial studies involving the methods discussed here, and there have been hundreds of other studies that have used trade-off methods.

This paper calls further attention to the complementarity of the judgment and choice approaches and more traditional revealed-behavior-based methods of data collection and analysis in transportation. Planners in the 1980s will require new and innovative solutions at low cost to solve problems effectively. The judgment and choice methods offer significant advantages that should not be ignored. The old argument that judgmental methods or methods based on behavioral intentions are less valid than methods based on observations of real behavior is now known to be false. Hence, validity arguments should no longer serve as a barrier to application of judgment and choice methods in travel choice modeling. Rather, it is time for researchers in both areas to begin to work together on common and complementary problems in travel choice behavior.

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Commuter's Versus Analyst's Perception of Automobile Travel Cost

AARON ADIV

A study that attempts to narrow the gap between objective and perceptual measures of travel costs is discussed. The study is based on telephone interviews of working people in the San Francisco Bay Area, who reported at length their perception of automobile cost. In turn, their reports were compared with objective measures used in the calibration of travel demand models. The accuracy of the reported costs and their relation to objective measures commonly used in transportation studies are determined in two ways: (a) by comparison of point estimates (i.e., cents) of the total daily cost (or cost per mile) reported by the respondents with data based on engineering computations and (b) by comparison of cost factors, or items of expenditure that the respondent considered including in his or her total daily cost estimate (e.g., fuel, parking, and maintenance), with cost factors commonly used in transportation studies. The results obtained by each method seem ambiguous. The first method showed a tendency to overestimate, whereas the other showed a tendency to underestimate with respect to objective measures. However, when the results are examined in their entirety, the ambiguity is resolved. The study explains why the second method is more reliable and leads to the conclusion that people perceive the costs of travel by automobile to be lower than what analysts dictate. Analysis of reported factors, the actual line items that influence the commuter's modal choice, indicates that modelers may inflate "perceived" cost by as much as 65 percent.

Travel time and travel cost by alternative modes are the basic ingredients of any model of modal choice and trip distribution. It seems, then, that these ingredients should have deserved the special attention of researchers; however, very little work has been done to clarify the question of the relations between time and cost values used by analysts and those that are considered by the individual traveler in evaluating his or her travel choice. The definition of perceived costs is of special importance to disaggregate behavioral models, which claim to capture the inner psychological trade-offs made by individual decisionmakers. In practice, there seems to be a gap between what the models claim to do and what they actually do. Capture of inner psychological determinants calls for calibration of the models with psychological perceptual data. In reality, however, most models are calibrated with objectively measured data based on engineering and economic computations. Only the earliest attempts to apply disaggregate behavioral models to travel choice used reported values (1,2). All recent models were calibrated with objectively measured data.

The limited amount of work on perception of travel impedances concentrates more on the question of travel time than on that of travel cost. In most cases, this was a by-product of a larger research effort that focused, for the most part, on the question of the value of time. Quarmby (2), Lisco (3), and Johnson (4) reported relatively high correspondence between reported and objectively measured travel time. Lansing and Hendricks (5) also found similar results. In addition, they made an attempt to study the perception of travel cost. However, their analysis is rather limited because they predetermined the "appropriate" automobile cost. Watson (6) made a systematic effort to categorize expected bias in reported travel data. He defined several types of biases. This categorization, as well as an empirical work on travel time by Johnson (4), provided a methodological guideline for this paper. More recent attempts to study the perception of travel costs have been made by Malecki (7) and Brög (8). Malecki concentrated on the study of fuel costs, and Brög studied distance, costs, and travel time and related them to wider issues of policy-sensitive planning models. As for perception per se, much of the pioneering work was done in psychophysics (9). Engel, Kollat, and Blackwell (10) present a basic review of perception. A more comprehensive review concerning the broader questions of belief, attitude, intention, and behavior is given by Fishbein and Ajzen (11).

STUDY OBJECTIVES AND METHODS

This study is an attempt to narrow the gap between objective and perceptual measures of travel costs. The paper is based on telephone interviews of working people in the San Francisco Bay Area, who reported at length their perception of automobile cost. In turn, their reports were compared with objective measures used in the calibration of travel demand models.

The impetus for this paper lies in the hypothesis that the commuters in the Bay Area overwhelmingly choose the automobile over rail (87 versus 2.4 percent) because of subjective underestimation of automobile cost. The specific rail system under study was the Bay Area Rapid Transit (BART) system. A more detailed analysis of reasons for BART's low patronage is presented elsewhere (12).

The uniqueness of this study lies in the fact that it extends beyond the narrow question of evaluating only the accuracy of a point estimate such as total reported daily cost. The study investigates questions concerning estimates of cost by the user: Do or can people estimate the cost of travel to work? How do they make the estimates? What expenditures (cost factors) do they include in their cost estimates? How do these expenditures correspond to engineering models? Are users perceiving "out-of-pocket" cost, total cost, or perhaps some other cost? Are there differences in the perception of cost that could be explained along socioeconomic, travel behavior, or geographic lines? A detailed definition of these discriminating variables is available elsewhere (12).

Before the analysis of cost, distance and time estimates were examined. This was done to ensure that cost estimates were not distorted by an inaccurate perception of travel distance and time. In general, reports estimating travel distance and automobile travel time were highly accurate. Moreover, people even tended to overestimate them consistently. These results are similar to those observed in other studies cited above.

The accuracy of the reported costs and their relation to objective measures commonly used in transportation studies are determined in two ways:

1. Comparison of point estimates (i.e., cents) of the total daily cost (or cost per mile) reported by the respondents with data based on engineering computations and
2. Comparison of cost factors, or items of expenditure that the respondent considered for inclusion in his or her total daily cost estimate (e.g., fuel, parking, and maintenance), with cost factors commonly used in transportation studies.

Table 1. Average objective costs per mile of automobile operation, maintenance, and ownership by automobile size: fall 1975.

Designation	Cost Factor	Cost (¢/mile) Standard	Compact	Subcompact	Automobile Fleet in BITS-2[a]
A	Operation and maintenance				
	Gasoline	4.33	3.68	2.75	3.82
	Oil	0.19	0.17	0.14	0.17
	Repair and maintenance	4.09	3.33	2.96	3.66
	Tires	0.45	0.39	0.35	0.41
	Accessories	0.09	0.09	0.09	0.09
	Total	9.15	7.66	6.29	8.15
	Ownership cost				
B	FHWA naive depreciation method[b]				
	Depreciation	4.08	3.70	3.20	4.20
	Insurance	1.07	1.60	1.50	1.60
	Registration	0.32	0.32	0.32	0.32
	Total	6.82	5.62	5.02	6.12
C	IURD economic depreciation method				
	Depreciation	7.97	6.29	5.25	6.97
	Insurance	1.70	1.60	1.50	1.60
	Registration	0.32	0.32	0.32	0.32
	Total	9.99	8.21	7.07	8.89
	Total A + B	15.97	13.28	11.31	14.27
	Total A + C	19.14	15.87	13.36	17.04

[a]Based on 54.49 percent standard-sized cars, 21.96 percent compacts, and 23.15 percent subcompacts.
[b]In general, difference between buying and selling price after subtraction of financing costs.

DATA BASE

BITS-2 Survey

This paper is based on an analysis of a telephone survey of 689 individuals who resided and worked (at least 20 h/week) in the San Francisco Bay Area and who were considered, a priori, to represent feasible potential BART users. The survey was conducted during the fall of 1975 after BART was fully operational. This survey, BART Impact Travel Study-2 (BITS-2), was carried out by the Urban Travel Demand Forecasting Project (UTDFP), University of California, Berkeley. The UTDFP attempted to explain and forecast the demand for urban transportation by using disaggregate behavioral models. BITS-2 emphasized detailed documentation of the work trip by usual and alternative travel modes. The final report and an annotated code book of BITS-2 are presented elsewhere (13,14). For model calibration, the UTDFP developed a large data set of objective system supply variables (15) that was used in evaluating the accuracy of reported data.

Objective Engineering Estimates of Automobile Cost

Objective costs were adopted from biannual reports of the Federal Highway Administration (FHWA) on the costs of owning and operating an automobile in the years 1972, 1974, and 1976. These figures are based on the average cost per mile of operating three sizes of cars--standard, compact, and subcompact--in a typical U.S. metropolitan area. The figures were adjusted to reflect costs in the San Francisco Bay Area in the fall of 1975. In general, the adjustments followed the methodological frameworks suggested by Keeler and Small (16) of the Institute of Urban and Regional Development (IURD), University of California, Berkeley.

Table 1 summarizes the results. In the table, costs per mile are broken down into several factors: (a) operation and maintenance and (b) two categories of ownership costs. The difference between B and C is in the method used to account for depreciation costs. The FHWA method (B) is a naive method that essentially accounts for the difference between buying and selling price after subtraction of financing costs. The IURD economic depreciation method (C) is an economic method that uses a capital recovery factor at a 10 percent annual interest rate over 10 years. The FHWA method is a layman's method of accounting for automobile ownership costs. It seems likely that as a perceived cost the FHWA method would have been the method used by respondents who claimed to include depreciation in their cost estimates.

RESULTS

Do People Estimate Automobile Costs?

A most striking result was that less than one-third of the BITS-2 sample (31.6 percent) had ever estimated the daily costs of driving to work by car before the encounter with the interviewer. The overwhelming majority--more than two-thirds--was not concerned enough with automobile costs to be stimulated into conscious cost evaluation. The rationale for this phenomenon is highly speculative. Respondents were not asked to explain why they had not estimated these costs if they had not estimated them before. Probable explanations are that automobile travel is habitual and an integral part of life in modern America, that automobile costs relative to personal income are negligible, or simply that there is no real alternative to a car in certain suburban areas of the San Francisco Bay Area. Similar results were reported by Lansing and Hendricks (5). They reported that, out of all usual automobile users in their sample, only 28 percent had ever estimated the cost of the automobile work trip.

People who had never estimated were asked to try to think through and make estimates during the interview. Even so, about one-fourth of those interviewed could not come up with any estimate. Hence, analysis of travel costs was based on only about three-fourths of the original sample--466 instead of 689 respondents.

In contrast to initial expectations, there was no significant difference in effort (had or had not estimated before) or ability (had not estimated but tried during the interview) to estimate daily costs among those who usually, frequently, or never used the automobile (χ^2 significance level = 0.6161). As a rule, purely transportation or geographic variables did not show a significant difference with respect to motivation to estimate cost, whereas traditional socioeconomic variables such as sex, income, and education did. Males and people with higher education and income showed a greater tendency to make estimates. For example, 37.4 percent of the males had estimated costs before the interview compared with only 24 percent of the females. Almost 50 percent of the respondents with a college degree had estimated costs before the interview versus about 20 percent of the people with only a high school diploma. Only 18.7 percent of respondents in the lower-income brackets had ever estimated cost compared with almost 40 percent in the upper-income group.

Methods People Used to Estimate Automobile Travel Costs

Unfortunately, the questionnaire allowed the potential respondent only three predetermined ("close-ended") choices for the method of estimating automobile travel cost: "cost-per-mile basis", "cost-per-mile and other basis", and "some other basis only". The majority of the respondents (51.8 percent) reported that they used some other basis only--in other words, any method other than cost per mile. About one-third (31.7 percent) reported that they estimated based on cost per mile, and an additional 10.9 percent reported that they used some undefined combination of cost per mile and other basis.

Knowledge about the way people perceive the costs of travel and the methods by which they arrive at their personal estimates is essential for applications of policies that use a price mechanism. However, the structure of the BITS-2 questionnaire limited insight into the workings of the methods by which individuals determined cost.

The semantic emphasis on cost per mile in the response pattern is attributed to the questionnaire designers' predetermined conviction that cost per mile was the appropriate method (13, p. 483). This conviction lacked any empirical evidence. One finds that in spite of the suggestive language of the questionnaire--"Did you arrive at your total daily cost by estimating a certain number of cents per mile, or did you make your estimate some other way?"--most people resorted to "some other basis only". Furthermore, it could be argued that the methods that include cost per mile are inflated due to a solicited favorable response.

The superficiality of the cost-per-mile method is demonstrated in an analysis that compares objective data with the reported estimates given by 184 people who claimed to use cost per mile. Most people who reported using this method quoted a figure of 15¢/mile, which "happened" to correspond to the allowable deduction for tax purposes in the year of the interview (mean = 15.14¢/day). Obviously, 15¢/day, which accounts for both variables and fixed costs, could not correspond to marginal costs: It was about 55 percent larger. It is even more revealing to find that there was no correspondence between this base figure and the reported total daily cost, adjusted for (divided by) the travel distance. The correlation coefficient (R) between these two subjective measures was extremely small (0.1075) and insignificant.

In summary, even this limited information indicates that the cost-per-mile method is an artifact used by analysts and accountants. It should not be confused with the actual method by which people estimate their cost. Apparently, they estimate cost (if at all) by some "gestalt" method. The question of how the gestalt takes place deserves further investigation.

Similar to the question of whether people made efforts to estimate costs, the difference in the reported method of estimating them held only for the core socioeconomic variables of sex, income, and education (χ^2 significance level = 0.02). It did not hold for geographic and transportation variables. In addition, there was no significant difference between respondents who had estimated prior to and those estimating during the interview (χ^2 significance level = 0.1151).

The so-called more sophisticated, or more experienced with automobile driving, tended to report more use of cost per mile and both cost per mile and some other method than their counterparts. They responded more positively to the suggestive language of the questionnaire. When the results are broken down by gender, 33.8 percent of males reported using cost per mile versus 28.5 percent of females and 13.3 percent of males reported using both methods versus only 6.9 percent of females. Similarly, about 40 percent of respondents with four or more years of college reported using cost per mile compared with less than 30 percent of those with less formal education. About 45 percent of the respondents in the highest income bracket reported that they estimated on a cost-per-mile basis versus less than 20 percent of the lowest income bracket. The pattern of this distribution can be explained by the fact that the "sophisticated" travelers are more aware of the existence of estimates of automobile cost in general and of a cost-per-mile method in particular. They are probably using this method on some regular basis when reimbursed for travel or when they exempt travel expenses from income tax.

Accuracy of Reported Costs

A direct comparison of a single reported attribute with a single corresponding objective measure, as has been done in studies of travel time, does not suit the more complex issue of travel cost. Here the answer depends on the definition of the appropriate combination of objective cost factors with which the report is compared.

Another analytic problem was derived from the fact that reports showed a strong tendency to be given in round figures and in multiples of 5. This phenomenon is well illustrated in Figure 1, which shows the distribution of reports on total daily cost. Most daily reports gave a cost of $1 (14 percent) or $2 (12 percent). Overall, 68 percent of all reports were given in multiples of 50¢; 98.3 percent were given in multiples of 5¢. A similar tendency (not shown here) was found in reports on cost per mile. About 56 percent of the reports were given in multiples of 5¢. There were no reports in fractions of cents, and the norm was 15¢/mile, reported by 23 percent. The strong tendency to round reports in multiples of 5¢ and/or 50¢ implies that direct correspondence between reported and objective measures is unattainable.

Daily cost estimates were "pure"--i.e., they were given instinctively. They were not biased by suggestive language and were reported by all subjects irrespective of their estimation method. As a result, in this paper they are considered more meaningful. The average value reported for total daily travel costs by automobile to work was 232.9¢/day. The accuracy of such a report is debatable, depending on what one considers to be the appropriate objective bench mark for comparison. For analytic purposes only, the reports of total daily cost are

Figure 1. Reported daily cost of home-to-work travel by automobile for 466 cases.

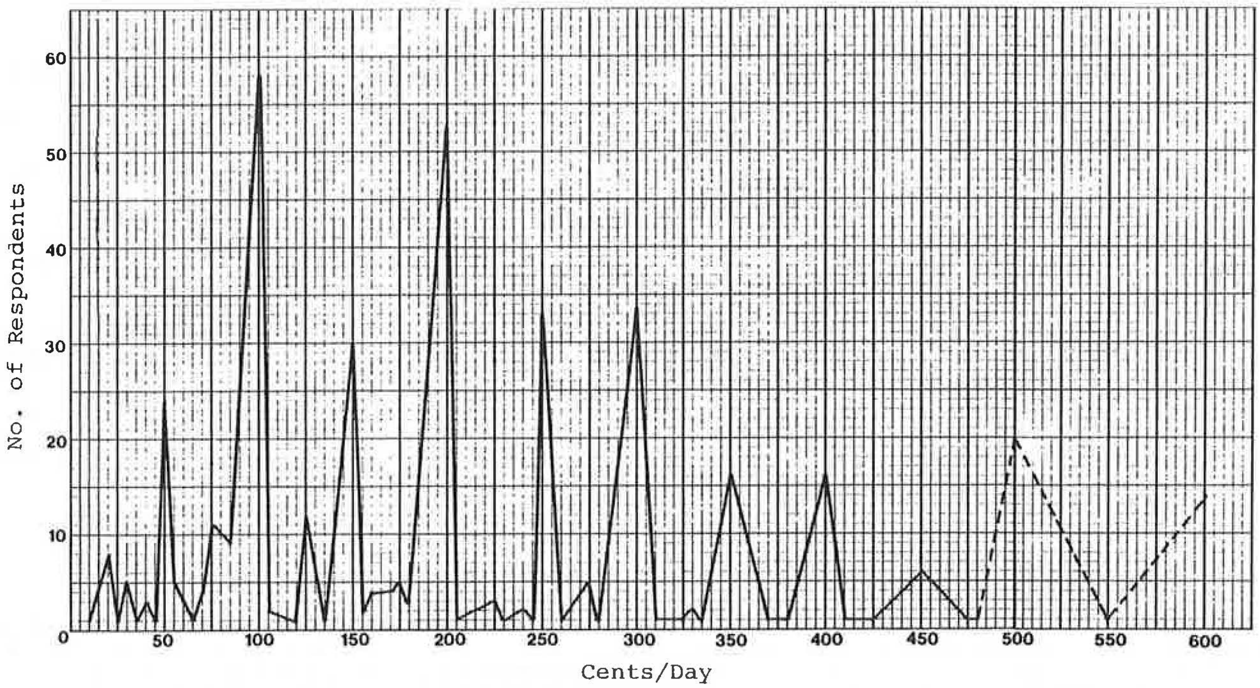

Table 2. Mean reported and objective cost per mile of driving to work for all respondents.

Category	Cost (¢/mile) Mean	SD
Reported cost		
Derived		
Objective (¢/day network distance)	12.71	13.12
Subjective (¢/day reported distance)	13.82	19.40
Original reports (¢/mile)[a]	15.14	14.74
Objective cost		
Operation and maintenance		
Excluding parking and tolls	8.15	1.00
Including parking and tolls[b]	10.55	6.36
Total cost of ownership[c] (operation and maintenance including parking and tolls[b])	16.65	6.50

[a] Given only by 184 respondents who reported on some cost-per-mile basis and revealed their base figure.
[b] Based on average parking cost of 2.29¢/mile and toll cost of 0.168¢/mile (reported daily cost network distance).
[c] FHWA.

converted here, via division by travel distance, into a derived cost-per-mile figure. This eliminates the problem of accounting for different travel distances by each traveler. Table 2 gives the means of several objective and subjective measures. The means provide an overall indicator for the general magnitude of the reports and their objective counterparts.

Because of the strong correlation between reported and objective travel distance, it is not surprising to find that the average values of derived cost per mile--objective or subjective--are very close, about 13¢/mile. The average cost per mile from original reports, given by only 184 respondents, was larger than either derived measure--more than 15¢/mile.

If one assumes that the appropriate objective measure is the sum of operating and maintenance cost--out of pocket--a simple comparison of means indicates a tendency of respondents to overestimate cost. All three reports made on a per-mile basis had larger means than either measure of objective marginal cost. Objective out-of-pocket cost, excluding terminal cost (parking and tolls), was only 8.15¢/mile. Even when terminal costs were accounted for, marginal cost was only 10.55¢/mile. A 95 percent confidence interval for any of the three reported costs per mile did not include the mean objective cost. This tendency to overestimate is in line with previous findings concerning distance and time.

In an analysis of variance, only geographic variables that capture the spatial relations between home and workplace showed a significant difference among respondents' estimates. For example, those traveling short distances, less than the average distance of 11.3 miles, substantially overestimated their cost. They reported, on the average, a cost of 22.06¢/mile. The long haulers reported only 9.25¢/mile. In contrast, none of the socioeconomic variables that influenced the ability to estimate--such as sex, income, or education--showed a significant difference. In addition, none of the transportation variables other than those that referred to inclusion of a specific cost factor showed significant impact on the cost estimates. Experience with automobile use, previous attempt to estimate cost, size of car used for the work trip, and availability of transit made no significant difference.

Further analysis of the relation between reported and objective daily costs was obtained by correlation analysis. The coefficients of determination (R^2) are intuitively appealing because they indicate the percentage variation, in reported cost, explained by the objective data. The following table gives the results of correlation between reported daily cost and several objective measures:

Objective Cost Measure	R^2
Implied cost of reported factors	0.4661
Total ownership (naive) and operating costs	0.2139

Objective Cost Measure	R^2
Total ownership (economic) and operating costs	0.2085
Marginal (fuel, maintenance, parking and tolls)	0.2277
Only fuel costs	0.1608
Only parking and tolls	0.1528

Several observations can be made about these results: First, all of the correlation coefficients above were statistically significant (probability value = 0.001). Second, the objective cost measure--be it total, marginal, or any combination between these two (other than only fuel or only parking and tolls) explained 20-22 percent of the variation: R^2 = 0.2085 to 0.2268. All of these correlations between objective and perceived measures were relatively weak. The similarity in correlation results from the way in which these objective measures were constructed. Other than their pure merit (measure of association), these similar coefficients signal a methodological problem concerning evaluation of reported daily cost.

All operation costs other than terminal costs (tolls and/or parking) are eventually a linear function of distance and of vehicle fuel efficiency. So, for example, the relatively low coefficient of "only fuel cost" (R^2 = 0.1608) actually captures the association between reported costs and automobile size plus travel distance. Once parking and tolls enter the equation, the information is exhausted, and the coefficient remains practically unchanged (R^2 approximately 0.22). It seems that a failure to recognize this problem led Quarmby (2) to suggest that a given cost per mile was the best internal perception of cost per mile by the user.

Reported Cost of Parking and Fuel for Daily Work Trip

Parking

A striking result that has a significant impact from the public policy viewpoint is that most of the respondents who usually used the automobile to go to work did not pay for parking at the workplace. Only about 10 percent of the "usual" automobile users reported paying for parking. About two-thirds of the usual users received free parking from their employer as part of their employment benefits. Another quarter of them parked free on the street. These results were further reconfirmed by the trip diaries (17) in which respondents to the BITS-2 telephone interview kept records of all their trips within a five-day period. Parking arrangement for work trips in the trip diaries was very similar to the distribution of usual automobile users in the home interview. In addition, the 1969 Nationwide Personal Transportation Study (18) revealed that, on a national level, about 93 percent of work trips by automobile enjoyed free parking. For this reason, reported parking costs were accepted as objective costs in evaluating the quality of daily reports. As expected, there was quite a substantial difference between objective average parking cost based on zonal data and cost based on reports. Average daily parking cost based on zonal data was 80.96¢/day (standard deviation = 96.09). In contrast, average cost based on reports (including 73 percent of the users who reported zero cost) was only 41.86¢/day (standard deviation = 88.72).

Gasoline and Oil

One finds that people tended to overestimate gasoline cost as they did total daily cost. In fact, the widest discrepancy found between reported and objective measures was for fuel cost. Fuel cost is undoubtedly essential for the operation of the automobile and is a cost experienced by any driver or rider. Thus, one would have expected that people would have a fairly accurate estimate of its cost.

The largest discrepancy was found for those who claimed to estimate on a per-mile basis. The average objective cost of gasoline (for the BITS-2 sample) was 3.96¢/mile. The average cost reported by those using a per-mile method was almost three times larger: 10.80¢/mile. The average cost reported by those reporting on a daily basis, after adjustment for distance, was 7.05¢/mile, which was still almost twice as large.

The average gasoline cost encountered by consumers during the time of the interview was 58.9¢/gal. The interviews occurred after the drastic increase in gasoline cost following the 1973 oil embargo. Gasoline consumption was relatively high--13.6, 16.0, and 21.4 gal/mile for standard, compact, and subcompact cars, respectively. In other words, the cost of gasoline was not negligible. However, even at this price level the respondents did not seem to have accurate estimates of their cost.

Apparently, even if people were aware of gasoline cost at the pump, which seems reasonable, they could not separate fuel cost into work-trip versus nonwork-trip consumption. They grossly overestimated the work-trip fuel cost and tended to attribute too large a share of daily cost to fuel cost, in a rather random manner.

Cost Factors People Included in Their Automobile Cost Estimates

When costs were defined in terms of factors only--with no specific dollar value associated with each factor--the results of the BITS-2 questionnaire did not confirm the common wisdom held by analysts in defining perceived marginal cost in its entirety. It is true that respondents tended to ignore fixed costs. However, they also tended to exclude variable costs other than the costs of gasoline and oil. They excluded, in varying degrees, variable costs that are traditionally considered part of the perceived costs. The percentages of respondents who reported including any of seven defined factors in their previous cost estimates are given below:

Factor	Respondents (%)
Gasoline and oil	89.2
Maintenance	48.7
Parking	25.4
Insurance	24.6
Depreciation	18.0
Tolls	12.9
Other costs	1.3

Even more important than the question of which cost factors were more frequently mentioned is the one asking which factors were reported as a group by the respondent: Were they variable factors, fixed factors, or any other combination of factors? A respondent could have reported as many as seven factors, which leads theoretically to a possible 128 combinations. In fact, people reported 33 different combinations of cost factors. Reports varied from gasoline and oil only to the sum of all variable and fixed costs.

Table 3 gives the distribution, by number of respondents, for a selected sample of 11 combinations of cost factors. The sample includes the most frequent combinations appearing in the reports. Basically, it is a selection of five combinations, from the cost of only gasoline and oil (1) to the sum of

Table 3. Combination of reported cost factors.

Combination No.	Factors	Respondents No.	Respondents Percent
1	Gasoline and oil		
	Gasoline and oil only[a]	150	32.1
	Gasoline and oil + parking + tolls	121	4.5
	Gasoline and oil + parking	35	7.5
	Gasoline and oil + tolls	9	2.0
	Total	215	46.1
2	Gasoline and oil + maintenance		
	Gasoline and oil + maintenance[a]	69	14.8
	Gasoline and oil + maintenance + parking + tolls	10	21.6
	Gasoline and oil + maintenance + parking	15	3.2
	Gasoline and oil + maintenance + tolls	6	1.3
	Total	100	40.9
3	Gasoline and oil + maintenance + insurance[a]	25	5.4
4	Gasoline and oil + maintenance + depreciation[a]	29	6.2
5	Gasoline and oil + maintenance + insurance + depreciation[a]	32	6.7
6	All other 22 combinations	65	14.0
	Total	466	100.0

[a]Not including combinations that incorporate explicit reports on parking and/or tolls.

both fixed and variable costs (5). Because most people did not pay for either parking or tolls, even though they were probably aware of the existence of these costs, the table includes reference to this fact as well.

Table 3 clearly demonstrates that the notion commonly held by analysts that perceived cost is composed of the cost of gasoline and oil plus maintenance (2) is not held by the users. Only 21.5 percent of all respondents reported this combination of factors. In fact, about half of the respondents (46.1 percent) considered only gasoline and oil (in combination with parking and tolls when appropriate) to be the single travel cost associated with their automobile work trip.

The counter argument advocated by Keeler and Small (16), that perceived cost should include both variable and fixed cost, could not be supported by the data either. Only 6.7 percent of reported respondents included gasoline, oil, maintenance, insurance, and depreciation in their estimates. Other combinations of both variable and fixed cost also had small proportions of the same magnitude. All of the other 22 combinations of cost factors reported by respondents accounted for only 14 percent of all reports.

Total objective cost for the fleet of cars in this study was 10.5¢/mile. It is divided 37.8 percent for gasoline and oil, 39.4 percent for repair and maintenance, and 22.8 percent for parking and tolls. The combination of these data with the results on cost factors implies that almost half of the users (46.1 percent) underestimated about 40 percent of perceived costs imposed on them by analysts. Those are the cost of repair and maintenance. This is undoubtedly a substantial deviation, which supports the initial hypothesis that people probably do not use BART because they underestimate the cost of travel by automobile.

CONCLUSIONS

This paper has used two methods to evaluate perception of travel cost by the user. First, it examined the quality of point estimates reported by the users, and, second, it examined the specific items of the cost factors that the respondents included when estimating their cost. At first, the results obtained by each method seem ambiguous: The first method showed a tendency to overestimate, whereas the other showed a tendency to underestimate (with respect to objective measures). However, when the results are examined in their entirety, the paper leads to the conclusion that people perceive travel costs by automobile to be lower than what the analysts dictate when calibrating travel demand or estimating the value of time.

Indeed, when people are asked to quote a single figure, be it of cost, distance, or travel time, they consistently report a figure larger than the objective threshold. However, this overestimation should not be taken at its face value. Each report is, at best, an intelligent guess of one number. Not being experts in the field, respondents probably overguess in order to be on the safe side. To this one should add the tendency to report in whole numbers and in multiples of five, which aggravates the results even further. Moreover, analysis of correlation between reported and objective costs showed that people overestimated in a random manner. Finally, the highly inaccurate estimates of gasoline costs for the work trip give the best indication that the evaluation of perceived cost based on point estimates is not reliable.

It could be argued that reports on cost factors are more reliable than point estimates. A respondent might not have been able to separate bulk costs into a single daily work trip. However, reports on cost factors indicate the actual line items that influence respondents' decisions. Because they are easily comprehended, they are also highly reliable. Analysis of reported factors indicates that modelers might inflate perceived cost by as much as 65 percent. These findings raise serious questions about the validity of calibration procedures used in most studies of travel demand.

Another important finding, generally ignored by both modelers and planners, is that most people who usually drive to work do not pay for parking at the workplace. High parking fees are apparently not a deterrent for usual automobile users--i.e., for the majority of commuters. Again, using zonal parking data in the calibration of demand models highly inflates the cost as perceived by the user.

This paper challenges the inconsistency between claim and practice concerning use of perceptual values of travel cost in behavioral models. However, further research is necessary. It is quite striking to find how limited the knowledge is in this field. I found only two studies (4,6) devoted entirely to the study of correspondence between objective and subjective measures of travel impedance.

Unfortunately, this paper could not explain in detail how cost is perceived. Based on experience gained in this study, the following guidelines are suggested for obtaining better insight into the gestalt process:

1. Allow for an open-ended response concerning method of estimating automobile cost;
2. Compare perception of automobile cost with perception of other goods and services that are bought in bulk and consumed for different purposes--for example, residential telephone calls or electricity; and
3. Ask subjects about the cost of travel on a weekly or monthly basis.

Irrespective of specific results obtained in this study about the correspondence between objective and subjective measures of travel impedances, further investigation of this topic is essential for the accountability of behavioral models and the value of time.

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Application of the Situational Approach to Depict a Model of Personal Long-Distance Travel

WERNER BRÖG

A study undertaken to determine the amount of personal long-distance travel in the Federal Republic of Germany to explain present modal choice and to forecast the likely future development of modal choice is described. To achieve these goals, an individually oriented behavioral model was developed (the situational approach) that first identifies the individual's (perceived) decisionmaking situation as precisely as possible, then determines the maximum potential for change if external conditions are altered, and, finally, tries to forecast the likely responses to planned policies. It can be shown that in personal long-distance travel the potential number of persons who would change mode if travel duration and travel costs were altered is comparatively small. On the other hand, the question of trip generation is much more important. When trips are classified according to trip purpose, it can be shown that most vacation trips would be made even if external conditions were less favorable to travel, although the type of vacation trips made might be modified. For "other" personal travel, in which a comparable type of modification is frequently not possible, persons would often respond to restrictive measures by reducing trip frequency.

Although personal long-distance travel is quantitatively of considerable importance in the Federal Republic of Germany and major investments are required in order to improve highway networks, comparatively little is known about the number of such long-distance trips and the likely responses of long-distance travelers to planned policies. For these reasons, the Minister of Transport authorized a large-scale, comprehensive study of personal long-distance travel in 1979-1980 (1).

In the quantitative part of this project, it was found that, on a per capita basis, German residents made a total of almost four (3.94) long-distance trips/year to destinations at least 50 km away from their homes. Almost every fourth (0.88) trip was a vacation trip. This means that Germans make approximately 50 million vacation trips and approximately 175 million other personal trips per year. In five out of every six instances (83 percent), they travel by car. Every 10th trip (10 percent) is made by train, and every 33rd trip (3 percent) is made by plane. Every 25th trip (4 percent) is made by bus or by another mode. Thus, Germans make approximately 185 million long-distance trips by car, 23 million by train, about 7 million by plane, and about 9 million by bus. Germans spend an average of 23 days/year making these trips and cover an average of more than 2500 km.

A sociodemographic analysis of persons who travel and persons who do not travel is less enlightening than one might assume (2). Therefore, the study discussed in this paper tried to identify the actual reasons for long-distance travel; sociodemographic variables are only of limited use for this purpose.

MAIN FEATURES OF SITUATIONAL APPROACH

In the second (qualitative) part of this project, the (actual) reasons for making long-distance trips with the mode used were to be explained and the likely reactions to changed external conditions were to be forecast. The conceptual considerations were influenced by the fact that modal choice in personal long-distance travel is by no means a simple, one dimensionally explainable form of individual behavior. Rather, a large number of objective and subjective factors are of importance; the resulting subjective decisionmaking situation is, therefore, relatively complex.

Thus, a research concept was needed that could deal with this problem. Although efforts have been made to develop a more sensitive model concept and method of analysis for urban travel (3), an application of these more refined approaches to personal long-distance travel, where they would be so desperately needed, is only possible within limits since the individual can exercise more free will when making personal long-distance trips than in making work trips, for instance. The decisionmaking structure for personal long-distance travel is thus much more complex (4).

Therefore, an approach was chosen to study personal long-distance travel in which each travel situation could be dealt with individually. The actual travel options available to each decisionmaking unit (in this study, the traveler) were identified. The subjective decisionmaking situation was then used to forecast responsiveness to alternative planning situations. Although this so-called situational approach (5) was developed and tested to study urban travel (6), the approach is so flexible that it was relatively simple to apply it to a study of personal long-distance travel.

However, a prerequisite for the application of the situational approach was the use of special explorative techniques--the so-called interactive measurement methods (7). The many variables responsible for influencing individual behavior are processed by using a special qualitative procedure (individual situations are analyzed). These variables are then combined into various dimensions that define particular situations (8).

In this study, 10 such dimensions were selected. As the study was evaluated, these 10 dimensions were condensed to 7 (see Figure 1). Conditions as perceived by the traveler were always used as the basis. These dimensions made it possible to analyze each individual situation to see whether a change in personal long-distance travel behavior was possible if external conditions were altered.

Although the main emphasis of the study was on the possibility of changing modes, other responses were also carefully considered. For this purpose, the combined effect of all dimensions was determined for each individual traveler. This was important in order to establish situational groups. By using this situational group structure, one can explain the given modal choice for personal long-distance travel.

In order to describe situational groups, it is necessary to define a hierarchy of the dimensions. This hierarchy can be arbitrarily changed in the evaluation, since the effect of all dimensions in this paper is oriented to the priorities that the travelers set for themselves. This hierarchy is then used to examine each dimension and determine whether it suffices to explain the given travel behavior. If this is so, then the given traveler is eliminated from further inspection (although information concerning further effects of the dimensions is not lost in the study). Ultimately, this results in the identification of a group of travelers who would have been able to use another mode--the so-called "group with options". This group is especially important because it represents the actual potential for change. The group with options can be identified for status quo conditions as well as for when new policies would affect the structure of the situational group. In each of these instances, the size of the group with options represents the maximum potential for changed behavior (in this case, a change of modes).

The potential for change can be determined for different conditions that would result from planned measures (9). The basis for this is the so-called "explanatory tree", which explains modal choice in the personal long-distance trips actually recorded and shows how high the maximum share of persons is who could change mode given status quo conditions--i.e., with conditions as they now are. Figures 2 and 3 summarize the explanatory tree for car travelers according to travel purpose and alternative mode; the group with options is symbolized by the Roman numeral "VIII".

This shows that the objective and subjective options of the car travelers would have been rather limited. However, this need not necessarily apply to future long-distance trips, since certain constraints might be of only temporary importance. The so-called "sensitization" techniques better explain the general options that are available given status quo conditions. By using sensitization, the size of the threshold group for which constraints pertaining to the mode used can be eliminated in certain (specifically determined) conditions is identified for each dimension. Thus, the general potential for car travelers to change their travel modes is obviously generally greater than in the specific situation (see Figures 4 and 5).

This general potential for change is not yet related to a specific planned measure. In further steps of the study, however, one can determine the share of travelers who would generally react to changes in travel time or travel costs. However, identifying these rather theoretical maximums is not the main goal of this step of the study. Much more important is the fact that, by identifying the travelers who do not belong to the maximum potential, those persons are identified who would definitely not respond to measures that affect travel time and travel cost by changing mode.

The purpose of this study was to identify the impact that the following measures would have on personal long-distance travel:

1. The relative amount of time spent traveling with the different modes was to be changed by 20 and 40 percent.
2. The relative price for travel between train and plane was to be altered by 25 and 50 percent, and the relative price of travel between public modes and car was to be altered by 50, 100, and 200 percent.

Because the goal of the study was to determine

Figure 1. Criteria used to build situational groups.

DIMENSION	ALTERNATIVE MODE: CAR	TRAIN	PLANE
① Objective options	Always (exception: plane trips with long-distance destination and target persons, for which car travel seems to be totally unrealistic	Place of departure and destination are connected by train	Not for trips covering - less than 150 km - Less than 500 km If place of departure or destination is more than 50 km and target person did not perceive plane connection
② Constraints (use of mode impossible if)	Car not available, no driver's license (no option of driving along as passenger), too old, health reasons, baggage transportation, bad weather (ice)	Too old, health reasons, baggage transportation, package tour	Too old, health reasons, baggage transportation, weather (fog), package tour
③ Degree to which informed (not informed if)	Mode has never been used for this stretch and person is not fully informed or is inadequately informed about modes that might be used on this stretch		
④ Time	Examination of how important the quality of (door-to-door) connections is, especially with regard to the following criteria:		
(a) Importance		- Travel duration - Frequency of departures - Location of train station - Connections from train station - Transfer required - Punctuality	- Frequency of departures - Location of airport - Connections from airport - Transfer required - Punctuality
(b) Perception	If time is important, then a check must be made to see how accurately time is perceived (especially in light of the criteria referred to above)		
⑤ Costs	Examination of how important travel costs are, especially with regard to the following criteria:		
(a) Importance	- Gasoline price - Other costs	- Price per person - Cost of getting to/from train station	- Price per person - Cost of getting to/from airport
	← - Cost for food (longer trips) - Costs for overnighting (for trips lasting more than one day) →		
(b) Perception	If cost is important, then a check must be made to see how accurately cost is perceived (especially in light of the criteria referred to above)		
⑥ Comfort/service	Examination of how important comfort and service are, especially with regard to the following criteria:		
(a) Importance	← - Dependability - Size - Baggage space - Hygienic facilities - Food services - Cleanliness →	- Cleanliness of station	
(b) Perception	If comfort and service are important, then a check must be made to see how accurately comfort and service are perceived (especially in light of the criteria referred to above)		
⑦ Subjective disposition	Examination of other subjective attitudes toward the modes in light of all given responses, including those that are not rational		

market shares, it was initially irrelevant if these relative changes were caused by the fact that the one mode became cheaper or faster or the other mode became more expensive or slower.

DETERMINING POTENTIAL FOR MODAL CHANGE

With the help of the situational analysis, four different potentials for modal change could be identified:

1. The general potential for change irrespective of the implementation of any specific measures,
2. The general potential for change when restrictions in one dimension were done away with (e.g., it was assumed that perceived travel time for the mode used and its alternative would be the same),
3. The general potential for change as the result of a specific measure pertaining to one dimension (e.g., travel time for the alternative mode was reduced by 20 percent and then by 40 percent), and
4. The current potential for change given status quo conditions (i.e., the group with options).

Figures 6 and 7 summarize the different potentials for modal change among persons traveling by car when the relative amount of time spent traveling by different modes is altered. (Group C is subdivided according to the different measures to be studied.) If one looks at "other" personal long-distance trips, one sees that 87 percent of these trips are made by car and 8 percent are made by train (potential A). If the perceived travel costs are hypothetically made equal for train and car, only a maximum of 14 percent of the car travelers would be willing and/or able to respond (potential B). This potential shrinks when the travel time by train is reduced by 40 percent, then by 20 percent, and finally by 5 percent (potential C1) or 4 percent (potential C2). With status quo conditions, the maximum potential was already 2 percent of all persons traveling by car (potential D).

The maximum potential for change is similar when the relative price for different modes is changed. This clearly indicates that the most important way of responding to changed external conditions that affect personal long-distance travel is not by changing mode (see Figures 8 and 9).

Figure 2. Explanatory tree for vacation trips made by car.

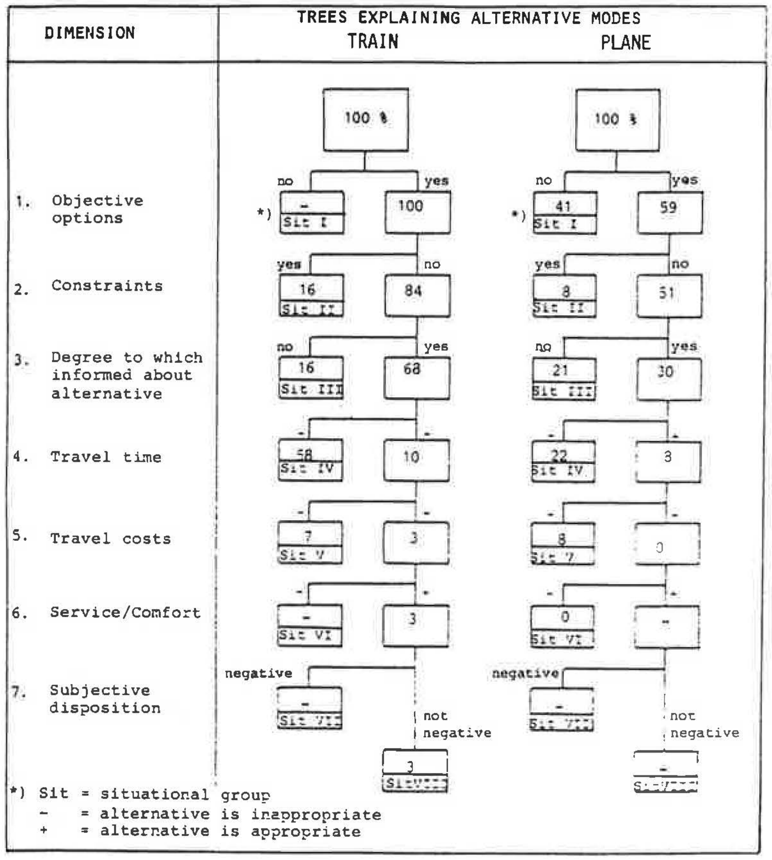
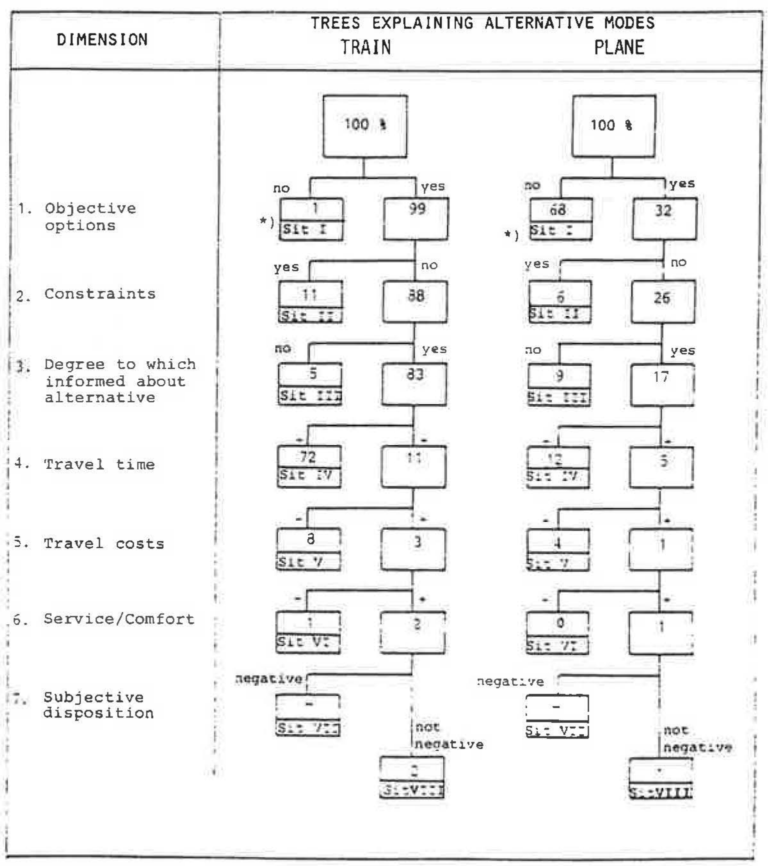


Figure 3. Explanatory tree for other personal trips made by car.



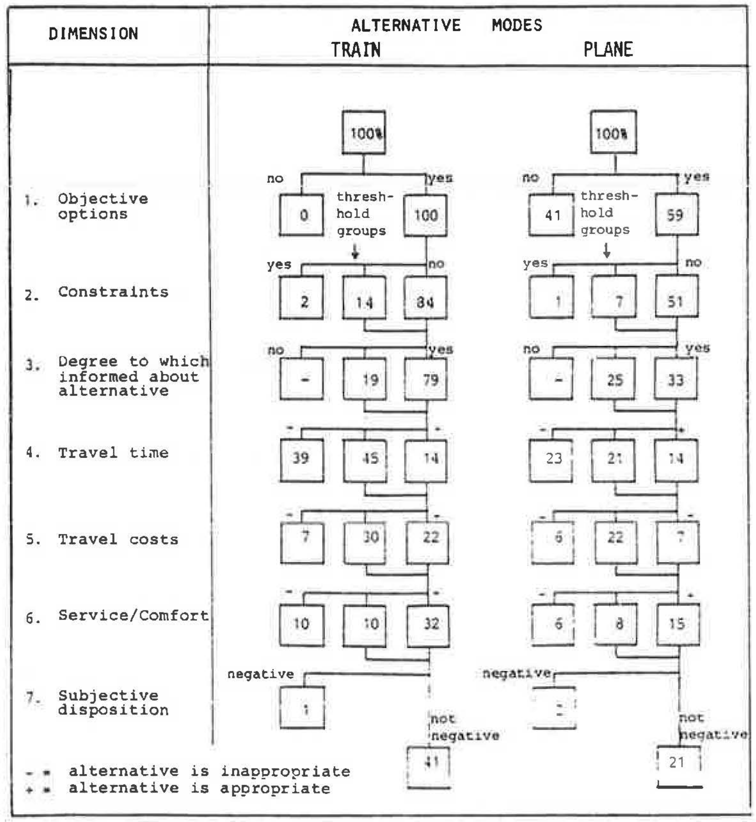


Figure 4. Use of sensitization technique for vacation trips made by car.

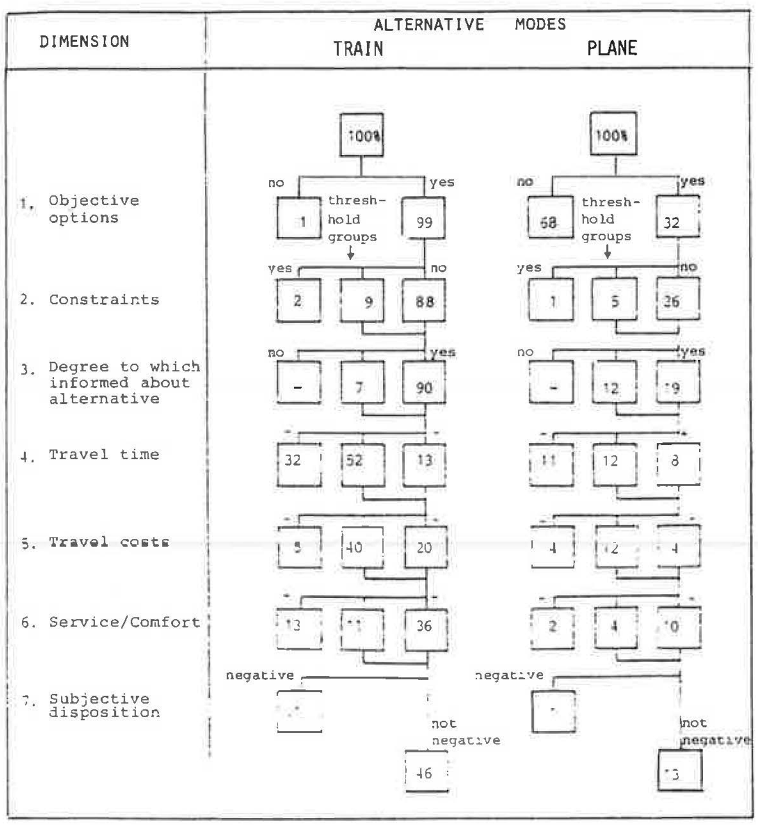


Figure 5. Use of sensitization technique for other personal trips made by car.

Figure 6. Potential for change to train among car travelers: time scenario.

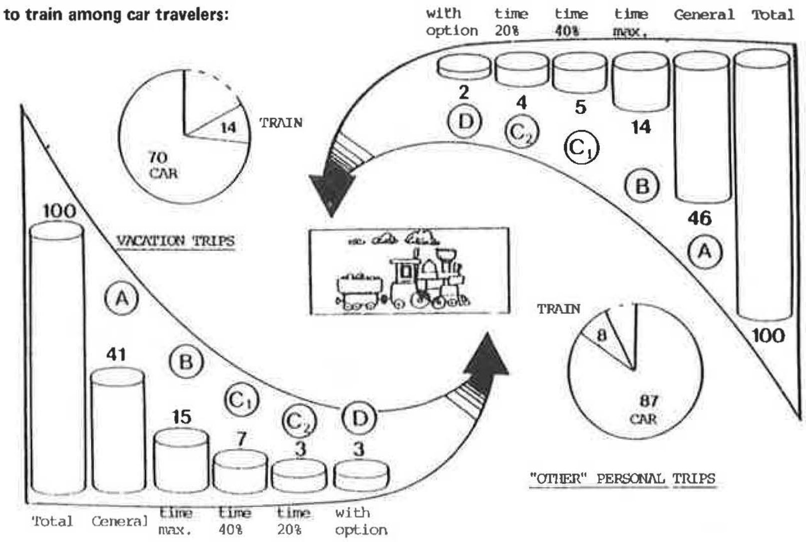


Figure 7. Potential for change to plane among car travelers: time scenario.

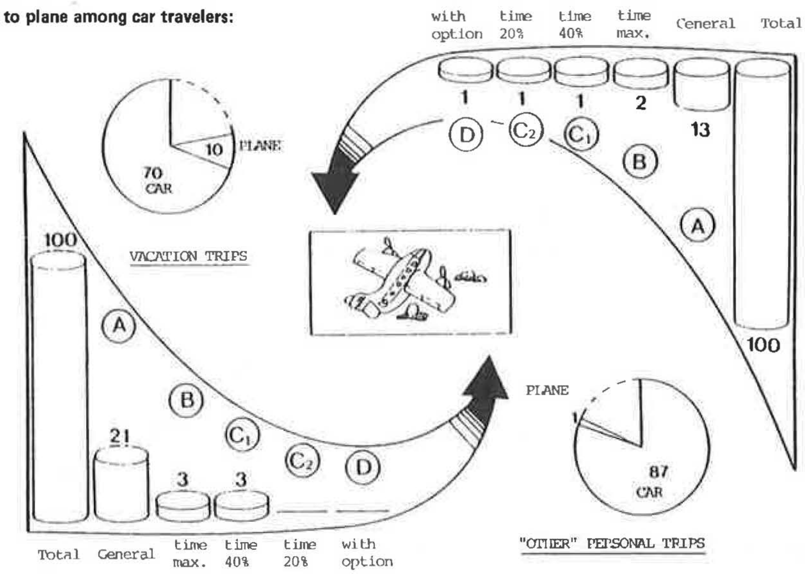


Figure 8. Potential for change to train among car travelers: cost scenario.

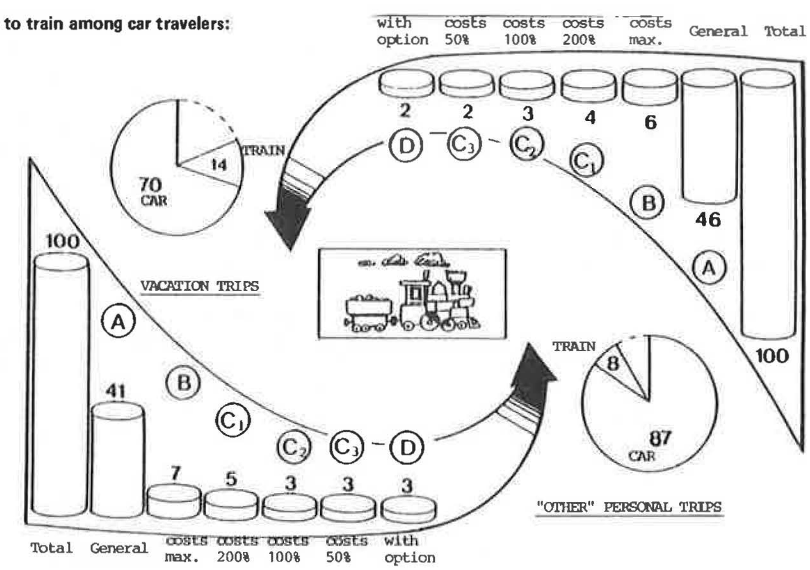


Figure 9. Potential for change to plane among car travelers: cost scenario.

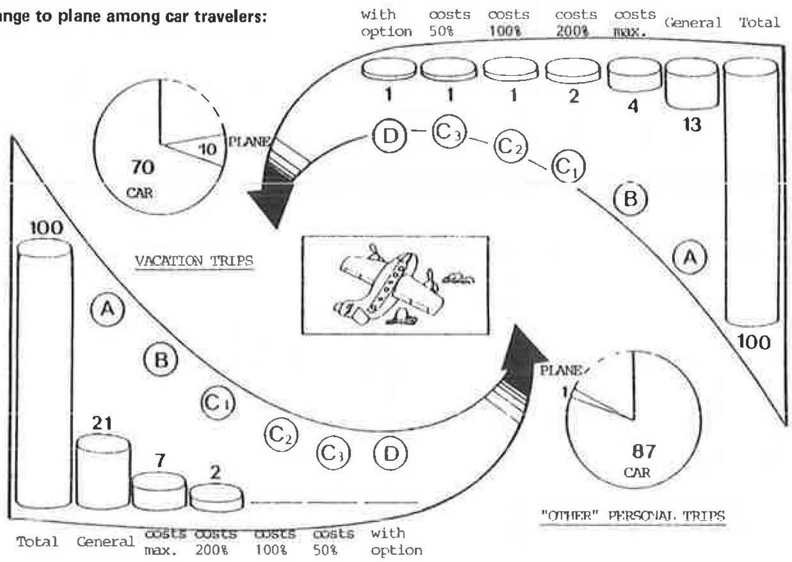


Table 1. Possible share of users for car, train, and plane.

Item	Maximum Possible Share of Users: Car, Total Personal Long-Distance Travel	Car, Vacation Trips	Car, Other Personal Trips	Train, Total Personal Long-Distance Travel	Train, Vacation Trips	Train, Other Personal Trips	Plane, Total Personal Long-Distance Travel	Plane, Vacation Trips	Plane, Other Personal Trips
Time									
With options[a]	101	101	101	122	117	123	124	107	237
Improved 20 percent	101	101	101	135	117	141	124	107	237
Improved 40 percent	101	101	101	148	134	152	141	127	237
Cost									
With options[a]	101	101	101	122	117	123	124	107	237
Improved 25 percent[b]	101	101	101	122	117	123	124	107	237
Improved 50 percent[c]	101	102	101	122	117	123	124	107	237
Improved 100 percent[d]	X	X	X	128	117	132	124	107	237
Improved 200 percent[e]	X	X	X	136	128	138	155	117	287
Base or present share (% = 100)	83.2	69.8	87.1	9.5	13.6	8.2	2.9	10.3	0.8

[a] No further measures.
[b] If costs are improved by 25 percent for car versus both alternatives, train versus plane, and plane versus train.
[c] If costs are relatively improved toward both alternatives by 50 percent.
[d] If costs are relatively improved toward car by 100 percent and toward train or plane by 50 percent.
[e] If costs are relatively improved toward car by 200 percent and toward train or plane by 50 percent.

Initially, this analysis disregards the number of persons who use different modes for their personal long-distance trips. However, when the relative number of travelers using the different modes is considered, the maximum share per mode for each planned measure can be given. However, these figures should be used to identify the relative number of persons using the modes and not to exactly forecast the market share, since it is more or less impossible to do this. Thus, it is appropriate to compute these values as indexes. This was done in Table 1.

All in all, the proportion of travelers using different modes defines a realistic upper limit that shows the extent to which a reorientation of the long-distance travelers to other modes can take place in specific situations. However, one should not forget that this upper limit will not be reached in normal situations.

LIKELY RESPONSES TO CHANGED EXTERNAL CONDITIONS

Likely responses to measures were then estimated by analyzing the responsiveness of the travelers (using interactive measurement methods) to changes in external conditions. The responsiveness pertained to all possible ways of reacting--whether the trip was unchanged, modified, temporarily delayed, or not made at all or whether the mode was changed. A change of mode could only be made by that group of persons with options, since the idea of the situational group was used. (Potential increases in demand caused by a changed supply that induces persons who previously did not travel to travel were not accounted for in this project.)

Before the likelihood that different types of responses will occur is discussed, the validity of the study results must once again be checked. The main goal of the study was to determine the demand potential for a modal change. Therefore, measurement instruments were used that would ensure that modal change could be estimated as accurately as possible. Among other things, this means that the persons identified as travelers who would change mode would, in fact, change to another mode. Thus, the values in this paper refer to the lower limit of

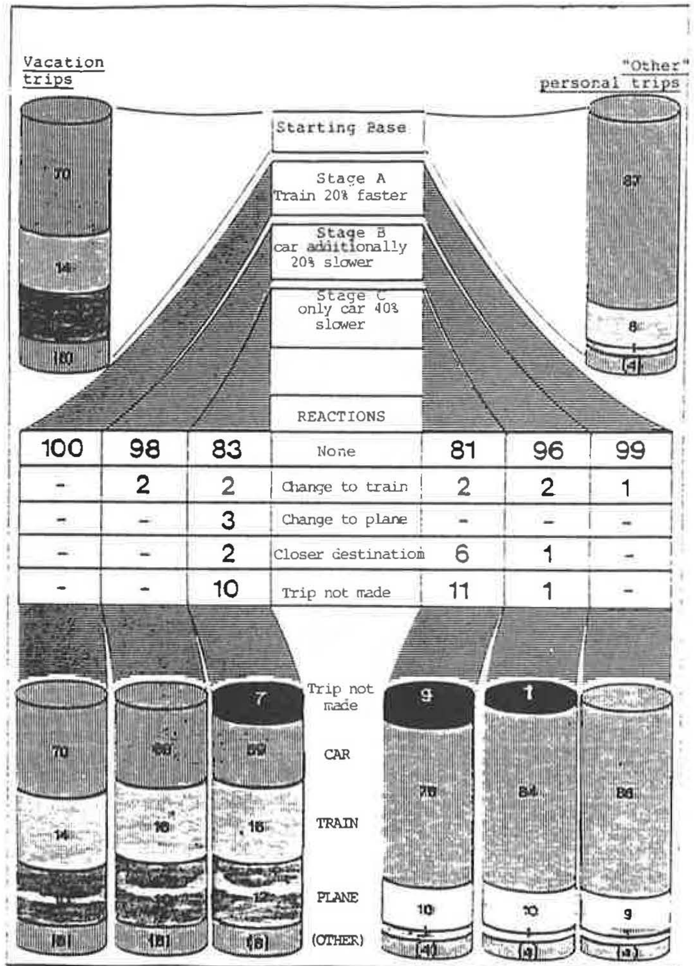


Figure 10. Responsiveness of car travelers: time scenario.

Table 2. Time scenario for vacation and other personal trips: relative changes in modal choice.

Mode	Vacation Trips: Starting Base (%)	Relative Change (%) Stage A	Stage B	Stage C	Other Personal Trips: Starting Base (%)	Relative Change (%) Stage A	Stage B	Stage C
Car	69.8	±0	-2	-14	87.1	-1	-3	-13
Train	13.6	±0	+10	+10	8.2	+11	+24	+24
Plane	10.3	±0	±0	+18	0.8	±0	±0	±0
Reduction in total travel	-	-	±0	-7	-	-	-1	-9
Other	6.3				3.9			
Total	100.0				100.0			

modal change. The upper limit has been shown in Table 1. On the other hand, other possible ways of responding (modifying the trip, not making the trip, etc.) were studied by using different types of survey instruments that made it possible to define an upper limit of possible responses. This upper limit will never quite be reached, since it can be assumed that trip frequency will be reduced, especially when persons respond by not making some of their "other" personal long-distance trips. These changes in external conditions deal with time and cost, both of which were studied by using two different scenarios.

The time scenario assumed that the total travel time for the alternative train was reduced by 20 percent and then assumed that the time needed to travel by car was simultaneously increased by 20 percent. This was then compared with a situation in which car travel time was increased by 40 percent while the time it took to travel by train remained the same.

The cost scenario assumed that the price of traveling by car went up by 50, 100, and 200 percent while the relative price of traveling by train and plane remained the same (simultaneous fare increases for plane trips were disregarded here).

LIKELY RESPONSES TO TIME SCENARIO

The likely responses to the three stages of the time scenario are summarized in Figure 10. The potential increase in demand for trains when travel time is simply reduced is rather moderate. When car travel time increases, persons tend to respond by reducing trip frequency or traveling to a nearer destination (Figure 10).

The time scenario showed that restrictive mea-

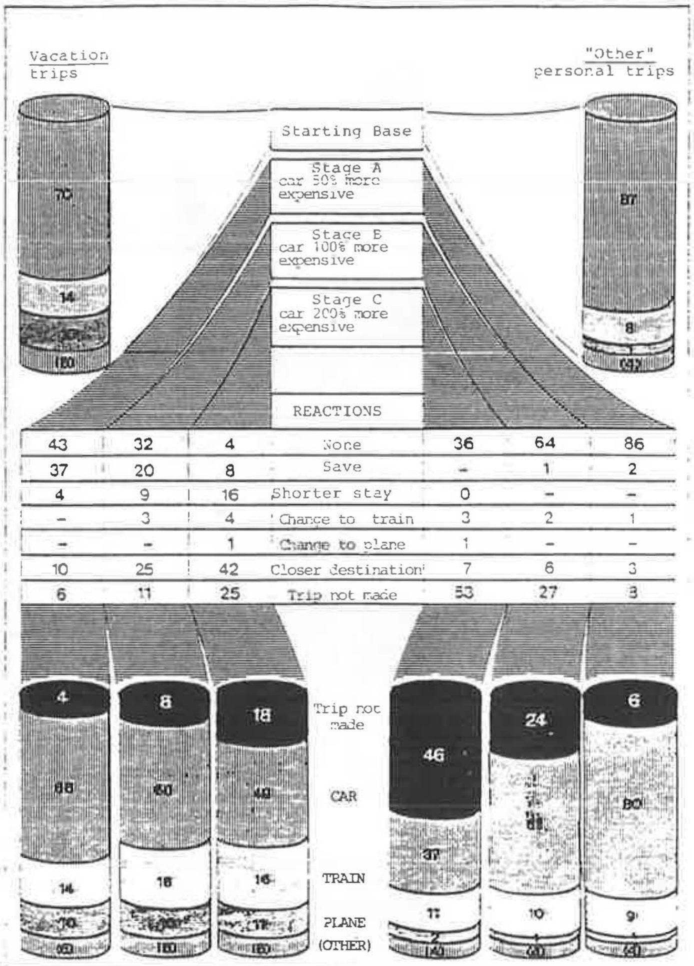


Figure 11. Responsiveness of car travelers: cost scenario.

Table 3. Cost scenario for vacation and other personal trips: relative changes in modal choice.

	Vacation Trips				Other Personal Trips			
		Relative Change (%)				Relative Change (%)		
Mode	Starting Base (%)	Stage A	Stage B	Stage C	Starting Base (%)	Stage A	Stage B	Stage C
Car	69.8	-6	-14	-30	87.1	-8	-30	-56
Train	13.6	±0	+13	+18	8.2	+4	+27	+29
Plane	10.3	±0	±0	±6	0.8	±0	±0	+75
Reduction in total travel	-	-4	-8	-18	-	-7	-24	-46
Other	6.3				3.9			
Total	100.0				100.0			

sures pertaining to car travel are much more effective than reducing train travel time. Table 2 gives the relative changes in modal choice that could be expected.

LIKELY RESPONSES TO COST SCENARIO

In studying car travelers' responses to the price of personal long-distance travel, only such expenses as gasoline and oil were taken into consideration. The more drastic price increases would have a considerable impact on personal long-distance travel (see Figure 11).

The travelers would go to almost any extent in order to be able to make their vacation trips, even if these have to be somewhat altered. The vacation trips that are eliminated tend to be the second and third yearly vacation trips that have become so popular in Germany in recent years. On the other hand, it is difficult to similarly modify "other" personal long-distance trips, since the destination of these trips is so frequently fixed--e.g., trips to visit a weekend house or relatives who live in a different city. Thus, the number of these trips can easily be reduced, but it is difficult to "modify" them. This resulted in the relative changes depicted in Table 3.

DISCUSSION OF PLANNING SITUATIONS

The situations depicted above did not deal with the economic and social changes that would simultaneously have occurred had external conditions changed in the manner described. Therefore, the term "scenario", which refers to a specific interview technique, must be used with reservation. On the other hand, it is obvious that, if the relative price for gasoline triples, it will have an economic impact greater than the behavioral changes discussed in this paper. Therefore, the results presented here only help to explain the mechanisms of personal long-distance travel and make it possible to forecast the individual behavioral changes that would result under certain conditions.

However, the findings of this paper clearly show that the existence and actualization of personal long-distance travel are the result of highly complex decisionmaking processes within private households. Although travel time and travel costs involved in using different modes are important, it is the subjective perception of these factors that influences decisionmaking. In concrete decisionmaking situations, other factors besides travel time and travel costs are important determinants of behavior. Changes in travel time and travel costs have only a limited effect on modal choice. Thus, the problem of trip generation plays a much larger role than modal choice. When it becomes more difficult to make personal long-distance trips, a change of mode is not the most likely response; it is more frequent for persons taking vacation trips to travel to a nearer destination and for persons making other personal long-distance trips to reduce the frequency with which they make these trips.

Because there is a great need for data (a problem discussed at the beginning of this paper), the main goals of this study were to make explanatory data for the analysis of long-distance travel available and to develop a model that can more realistically depict behavioral changes. The quality of further forecasts dealing with personal long-distance travel in Germany will depend, to a large degree, on the extent to which these new data can be included in the synthetic models that are already operating.

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Traveler Responses to Reconstruction of Parkway East (I-376) in Pittsburgh

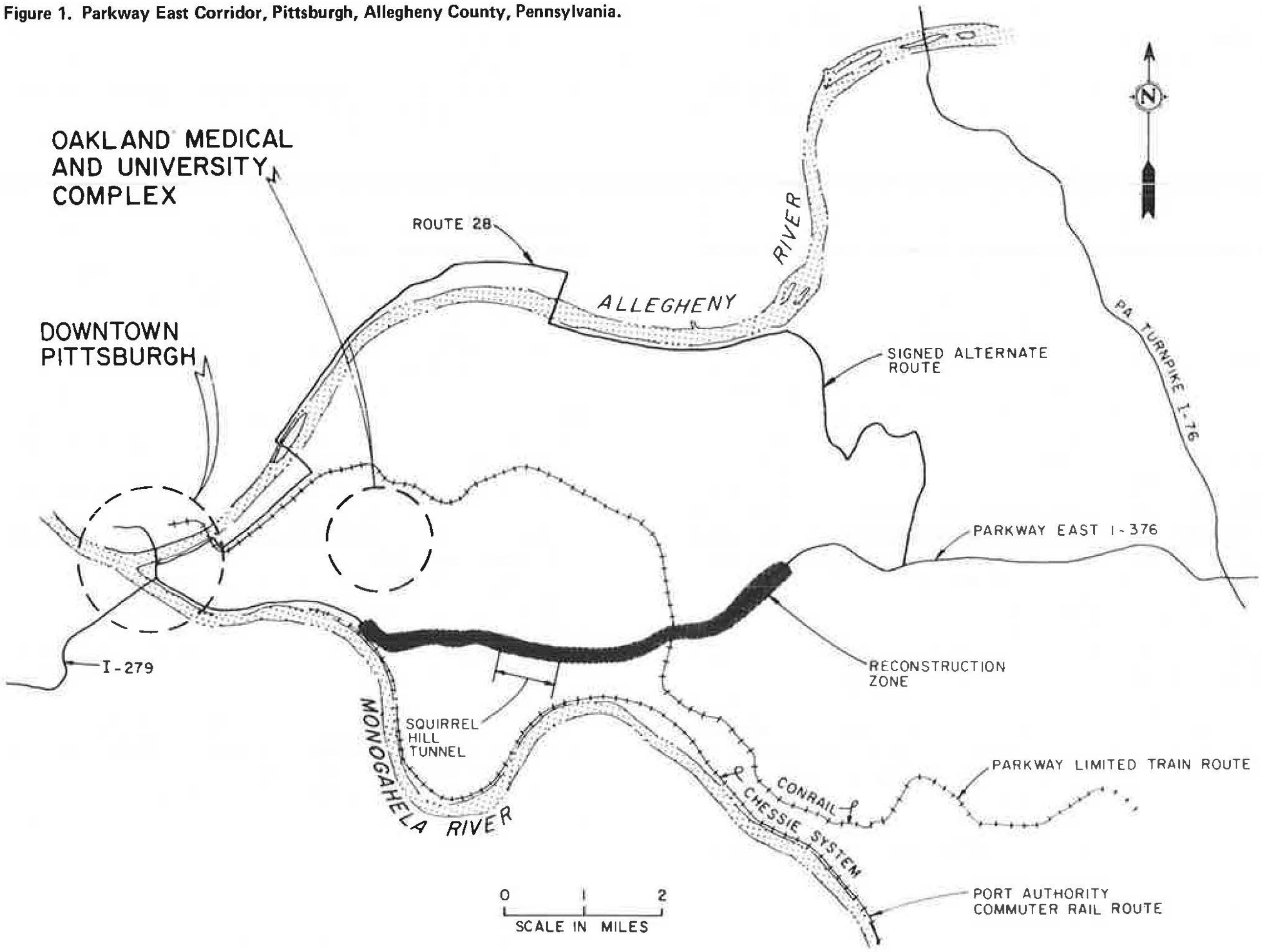
CHRIS T. HENDRICKSON, ROGER E. CARRIER, THOMAS J. DUBYAK, AND ROBERT B. ANDERSON

Reconstruction of urban expressways will be required in many metropolitan areas in the next few decades. A summary is presented of traveler responses to a reconstruction project on the Parkway East (I-376) in Pittsburgh, Pennsylvania, which normally serves more than 100 000 daily vehicle trips. Volume counts, vehicle occupancy counts, travel time measurements, and traveler surveys were made before and during the reconstruction. The major responses observed were in route choice and departure times. Large modal diversion did not occur despite ridesharing promotions and train, bus, and park-and-ride lot service improvements. However, a slight measured shift to shared-ride modes may have resulted in significant local benefits for Parkway East travelers during peak periods. Generally, the roadway system in the parkway corridor accommodated a major change in traffic patterns without substantially increased levels of congestion.

Maintaining traffic and minimizing adverse traffic impacts during reconstruction on roadways have long been a concern to highway departments. This concern is especially critical during the reconstruction of urban freeways that serve large volumes of traffic and may require several construction seasons. Major reconstruction projects of this type will become increasingly frequent in the next decade due to the deterioration of many urban roadways. Planning traffic control measures for these projects requires an understanding of traveler responses to major reconstructions.

This paper reviews the type and range of traveler responses that have occurred during reconstruction of a 10.5-km (6.5-mile) section of the Parkway East (I-376) in Pittsburgh, Pennsylvania. This highway connects the Pennsylvania Turnpike (I-76) to I-279 via downtown Pittsburgh. It is the most heavily traveled highway in the region (see Figure 1): Approximately 84 000 vehicles pass through its Squir-

Figure 1. Parkway East Corridor, Pittsburgh, Allegheny County, Pennsylvania.



rel Hill Tunnel each weekday. During the two-year reconstruction project, parkway traffic was limited to one lane in each direction and on-ramps at four interchanges were closed. The $58 million reconstruction included a 20-cm (8-in) concrete pavement overlay, rehabilitation of 21 bridges, new lighting and ventilation in the Squirrel Hill Tunnel, new signing and high-mast lighting, and a concrete median barrier.

In response to the parkway restrictions, travelers could change mode of travel, switch to off-peak hours, use alternative routes, change destinations for nonwork trips, or even reduce the number of trips made. The extent to which each of these responses occurred is considered here. In addition, changes in travel times and volumes on the Parkway East and on alternative routes are discussed.

Observations of traveler responses were made from surveys completed by travelers in the parkway corridor, traffic counts, vehicle occupancy and classification counts, and transit patronage records. Changes in travel times were determined from both survey responses and floating car travel time measurements.

This information was gathered in order to evaluate the effectiveness of a series of innovative strategies to reduce the adverse impacts of the parkway reconstruction. These strategies included a new commuter rail line (that would use existing tracks), a special vanpool promotion program, new park-and-ride lots, several new bus routes, restriction of two on-ramps to high-occupancy vehicles, and various traffic system improvements such as parking restrictions and signal synchronization. These strategies were developed by District 11 of the Pennsylvania Department of Transportation (PennDOT) as an experimental portion of the general plan for maintenance and protection of traffic associated with the Parkway East project. Although evaluation of these strategies is beyond the scope of this paper, the use of various strategies is considered in relation to overall traveler responses. Evaluation of these strategies is the objective of an ongoing joint research project conducted by GAI Consultants, Inc., and Carnegie-Mellon University and sponsored by PennDOT and the Federal Highway Administration.

POTENTIAL EFFECTS OF RECONSTRUCTION PROJECT

The potential for severe traffic disruption due to the reconstruction of the Parkway East certainly existed. During the early stages of planning for the project, the decision was made to ensure that one lane of traffic in each direction was available throughout the reconstruction period. With two lanes open for traffic, the project required two full construction seasons and traffic restrictions were scheduled from March to November in both 1981 and 1982. During these periods, on-ramps throughout the length of the affected roadway would be closed.

The most prominent bottleneck along the length of the Parkway East is the Squirrel Hill Tunnel, which includes two 1.3-km (0.8-mile) long tunnel bores with two lanes each. There were lengthy queues during peak periods at these tunnels even prior to reconstruction. During reconstruction, all traffic was routed through one tunnel bore without lane separation. Thus, the number of lanes was cut in half, and the lack of tunnel traffic separation meant that the effective capacity was reduced by more than 50 percent.

Traffic on the Parkway East dropped dramatically after the traffic restrictions were introduced (see Table 1). At the Squirrel Hill Tunnel, average daily volume dropped more than 50 percent, from an average of 84 000 vehicles to 37 000. There was a drop in traffic volumes even before 24-h traffic restrictions were imposed in March 1981 as the public was alerted to the impending restriction and the availability of alternatives. The late February volume counts already represented a decline of 9000 vehicles/day at the tunnel (Table 1).

Alternative routes in the Parkway East corridor are limited. The parkway serves as the major route to and through the central business district (CBD) from the eastern portion of the Pittsburgh metropolitan region; it is the only access-controlled, multilane expressway from this direction (Figure 1). The designated alternative to the parkway during the reconstruction involved travel via arterial streets to PA-28, located roughly 4 miles north of the Parkway East. PA-28 is a high-speed, access-controlled expressway outside of Pittsburgh but becomes an arterial street within 2 miles of the CBD. Thus, only arterial streets were generally available as alternative routes to the parkway. Many of these roads were congested even before traffic restrictions were imposed on the parkway.

This lack of alternative roadways was a motivation for introducing strategies that would concentrate on movement of people rather than just vehicles through the parkway corridor. Diverting trips to transit, carpools, or vanpools would permit equal numbers of person trips while reducing the number of vehicle trips in the corridor.

In this regard, the regional transit agency (the Port Authority of Allegheny County) operates about 80 bus routes and a commuter rail line in the corridor. During the reconstruction project, another commuter rail line, six new bus routes, and a number of park-and-ride lots were introduced by PennDOT. With traffic restrictions on the parkway and newly available capacity in the transit system, a significant diversion of trips to transit was expected.

EVIDENCE OF MODAL DIVERSION

Although attention to transit and other people-moving strategies is understandable in the parkway corridor, the response of travelers indicates that very little modal diversion occurred. Relatively few travelers switched to carpools, vanpools, or transit.

One direct indication of the lack of modal change is vehicle counts across screenlines in the parkway corridor. Observations of vehicle volumes crossing two screenlines are summarized in Table 1. Screenline 3 passes roughly through the center of the reconstruction project and includes the Squirrel Hill Tunnel (see Figure 2). Total traffic volume past screenline 3 was within 1 percent of that measured in 1978 even after traffic restrictions were imposed. For screenline 2, which was 2 miles closer to the CBD than screenline 3, a 5 percent decrease in traffic was observed. Given the amount of measurement error in the volume counts, it would be difficult to conclude that volumes either increased or decreased in the corridor, but it is certain that little overall change in volumes occurred.

Observations of average vehicle occupancy in the corridor during the morning peak period also suggest that little modal diversion to high-occupancy vehicles occurred. On screenline 2 and on the parkway near downtown, no significant change in vehicle occupancy was observed. Farther from the CBD, screenline 3 had a slight increase in average vehicle occupancy. As with vehicle volumes, however, it is unclear whether average vehicle occupancy increased or decreased on balance, but it is apparent that little overall change took place.

Surveys of travelers in the corridor also suggest that little modal change occurred. These survey respondents were identified by mail-back cards handed to travelers on transit services, alternative routes, and the Parkway East. A panel was formed from the respondents that was representative of travelers affected by the Parkway East travel restrictions (1). This panel was contacted periodically during the course of the project. The following data are taken from the July 1981 traveler panel surveys. The responses are weighted to reflect vehicle occupancies and the differential sampling rate for transit users:

Mode	Before Reconstruction (%)	During Reconstruction (%)
Drive alone	37	34
Shared ride		
Carpool with family	9	9
Carpool with others	19	20
Vanpool	3	5
Total	31	34
Transit	31	31
Other	1	1

As the table indicates, shared rides increased slightly, primarily due to an increase in vanpooling. Transit modal share remained approximately constant.

A special survey asked for the former mode of travel of new members of vanpools. Interestingly, the results suggest that new vanpool members were largely attracted from carpools and transit services (data from a survey of 249 new vanpool riders with a 72 percent response rate):

Mode	Percentage
Drive alone	21.7
Carpool	26.7
Port Authority Transit	43.3
Commuter train	2.8
Other vanpool	5.5

Thus, vanpools do not seem to have directly resulted in an appreciable reduction in the amount of vehicle travel despite increases in ridership.

Whereas increases in shared-ride modes did not represent a significant shift of overall travel in the corridor, promotion of shared rides, particularly vanpools, was relatively inexpensive and may have resulted in significant benefits during peak hours of travel on the Parkway East. The effectiveness of ridesharing and other strategies in reducing peak-period congestion is being studied and will be reported on later.

ROUTE CHANGES

With little change in the average weekday volumes observed past screenlines and substantial decreases in volumes on the parkway, it is no surprise that a substantial diversion in routes occurred in the corridor. For occupants of the 37 000 vehicles that formerly used the on-ramps in the construction section on the Parkway East, there was little choice:

New routes had to be adopted if the trips were to be made at all. Other travelers changed routes to avoid the congestion on the parkway.

Although substantial route diversion did occur, it was concentrated on the arterial streets close to the parkway. Figure 3 summarizes the changes in average daily volumes measured on screenline 3 between 1978 and April 1981. Whereas the parkway had a decrease of 47 000 vehicles/day, the six counting stations within 2 miles of the parkway showed an in-

Table 1. Changes in roadway volumes and vehicle occupancies during reconstruction of Parkway East.

Item	Measurement Data			Change (%)	
	1978	February 1981	April 1981	1978-April 1981	February-April 1981
Avg daily vehicle volume (000s)					
Screenline 2[a]					
Parkway	68	NA	51	-25	
Twelve locations including parkway	268	NA	255	-5	
Screenline 3[b]					
Parkway	84	75	37	-56	-51
Seventeen locations including parkway	285	NA	281	-1	
Avg morning peak vehicle occupancy (persons/vehicle)[c]					
Screenline 2[a]					
Parkway	NA	1.43	1.39		-3
Twelve locations including parkway	NA	1.42	1.40		-1
Screenline 3[b]					
Parkway	NA	1.40	1.49		+6
Seventeen locations including parkway	NA	1.40	1.43		+2

Note: Measurements made by GAI Consultants, Inc., for 1981 and Southwestern Pennsylvania Regional Planning Commission for 1978. Occupancy counts are an average for all inbound vehicles during a 15-min interval of the morning peak period.

[a]Screenline 2 is located 3 miles east of the CBD.
[b]Screenline 3 is located 5 miles east of the CBD.
[c]Average screenline occupancies are calculated as total persons crossing the screenline divided by total vehicles crossing the screenline, excluding transit vehicles.

Figure 2. Pittsburgh experiment: alternative routes and modes.

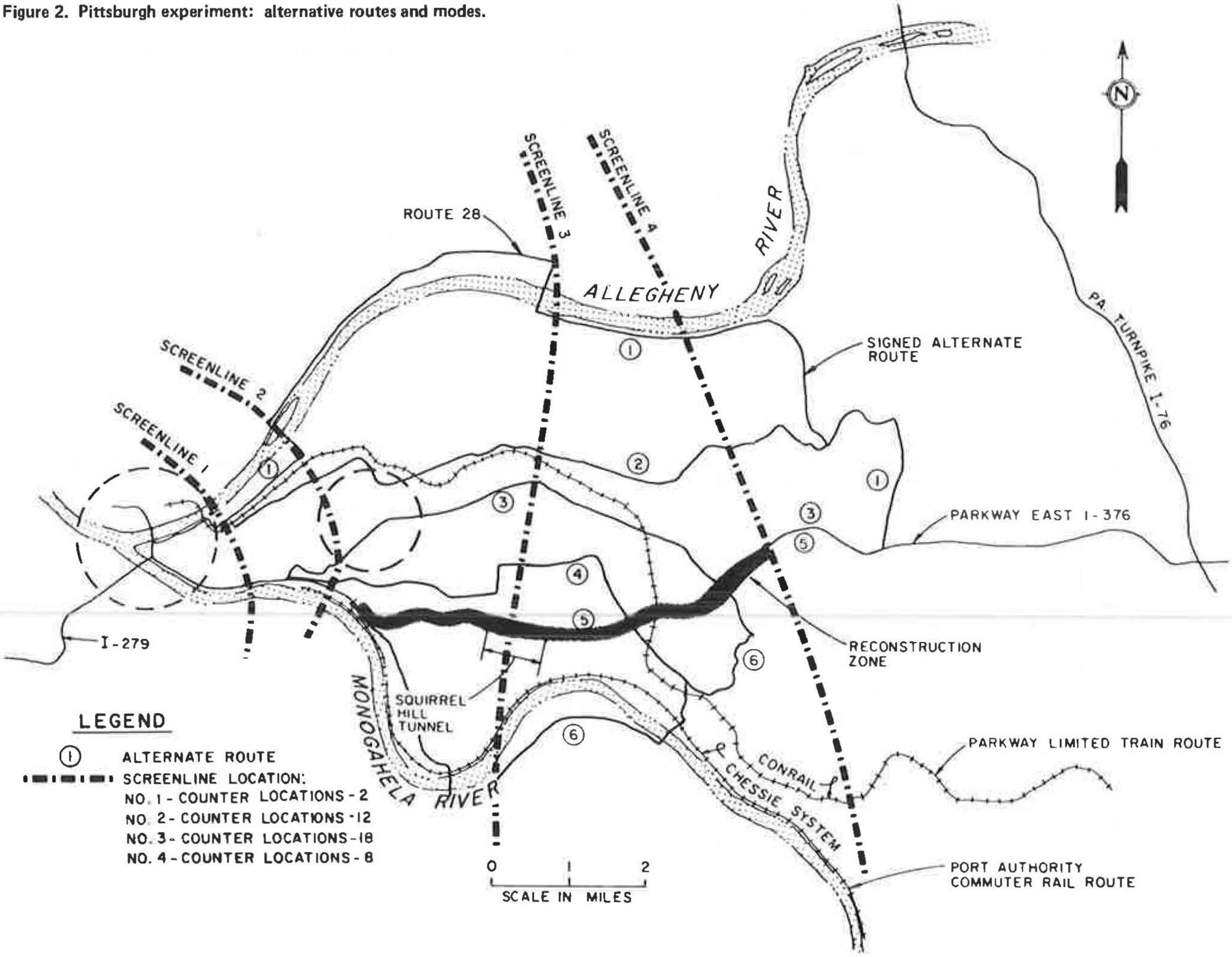


Figure 3. Changes in average daily traffic volumes between 1978 and April 1981 on screenline 3.

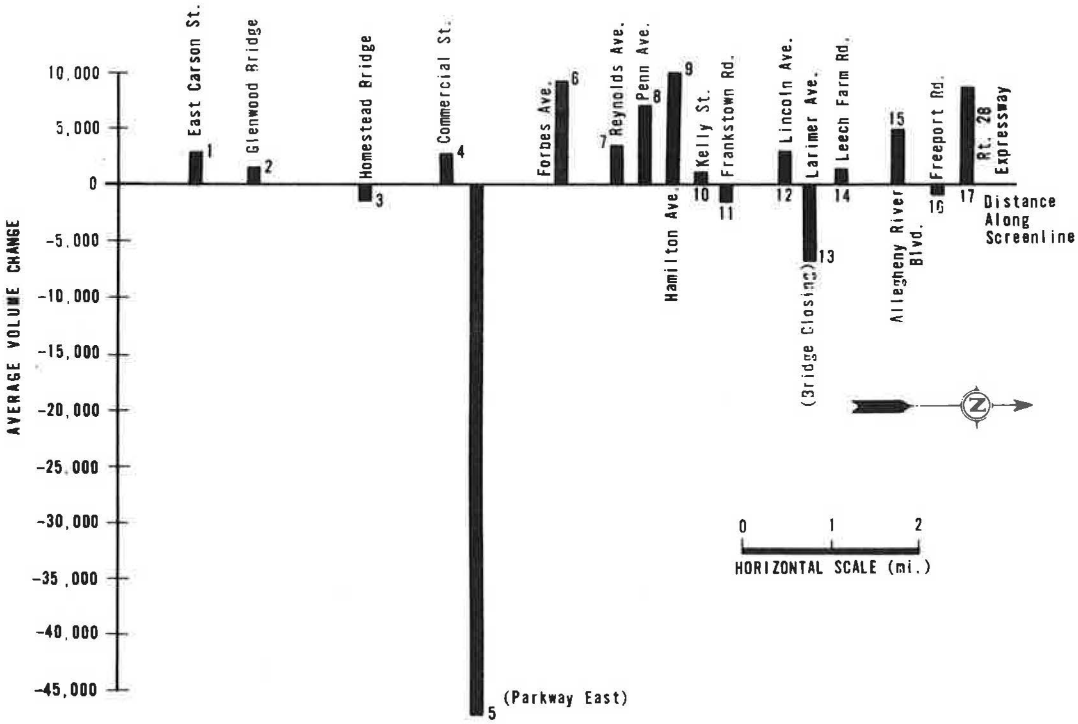
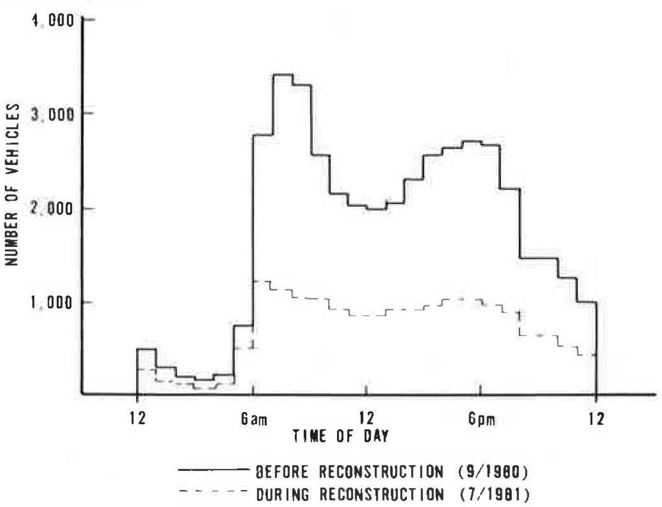


Figure 4. Average weekday traffic volume westbound at Squirrel Hill Tunnel on Parkway East.



crease of 29 000 vehicles. In comparison, traffic on the PA-28 section of the designated parkway alternative increased by only 7000 vehicles/day.

DEPARTURE TIME AND TRAVEL PEAKING CHANGES

In addition to route changes, travelers also reported earlier departure times for work. The data given in the following table are from July 1981 and February 1982 surveys of Parkway East travelers. The responses are weighted to reflect vehicle occupancy:

Departure Time from Home	Before Reconstruction (%)	During Reconstruction (%)
Before 6:00 a.m.	5	10
6:00-6:30 a.m.	8	9
6:30-7:00 a.m.	41	41
7:00-7:30 a.m.	41	35
7:30-8:00 a.m.	2	2
After 8:00 a.m.	2	3

Average departure time was earlier by 20 min during the reconstruction. Although some of this shift is attributable to seasonal effects, travelers also shifted departure times to ensure arrival on time or to avoid congestion.

On the parkway itself, the effect of the traffic restrictions was to nearly eliminate peak traffic periods altogether. Figure 4 summarizes hourly traffic counts in the westbound direction (toward the CBD) on the Parkway East for average weekdays before and during the reconstruction. The traffic volumes shown in Figure 4 occurred at the Squirrel Hill Tunnel. As can be seen in Figure 4, the pattern of traffic before reconstruction has an early morning peak for travel toward the CBD. During the reconstruction, traffic volumes are nearly constant on the Parkway East throughout the day. What little peaking exists during reconstruction begins earlier than the peak before the reconstruction. Volumes in the eastbound direction had a similar shift from the peak evening commuting hours.

OTHER TRAVEL RESPONSES

The preceding sections described changes in mode, route, and time of travel. The travelers in the parkway corridor might also have responded by changing the destination of trips and by traveling less frequently. Observations of the travel volumes past screenlines in the corridor (as summarized in Table 1) indicate that little net change in the overall

Table 2. Inbound (westbound) travel times in Parkway East corridor.

Period	Travel Time (min) PA-28	PA-380	Penn Avenue	Allies Boulevard	Parkway	PA-837	Weighted Avg[a]	Weighted Change (%)
Morning peak								
After[b]	38	36	42	30	37	35	36	
Before[c]	43	36	30	28	28	40	31	
Change	-5	0	+12	+2	+9	-5	+5	16
Off-peak								
After[b]	36	33	32	24	16	32	27	
Before[c]	37	32	36	25	20	35	26	
Change	-1	+1	-4	-1	-4	-3	+1	4
Evening peak								
After[b]	28	29	44	25	21	29	28	
Before[c]	38	35	34	28	17	32	25	
Change	-10	-6	+10	-3	+4	-3	+3	12

Note: Each travel time represents the average of five separate vehicle runs.

[a]Calculated as the travel time on each route weighted by the February or April 1981 volume counts at the intersection of screenline 3 and each route.

[b]Measurements taken in April 1981.

[c]Measurements taken in February 1981.

Table 3. Outbound (eastbound) travel times in Parkway East corridor.

Period	Travel Time (min) PA-28	PA-380	Penn Avenue	Allies Boulevard	Parkway	PA-837	Weighted Avg[a]	Weighted Change (%)
Morning peak								
After[b]	31	25	28	23	21	29	26	
Before[c]	34	27	30	19	13	21	19	
Change	-3	-2	-2	+4	+8	+8	+6	37
Off-peak								
After[b]	39	33	39	17	33	33	32	
Before[c]	34	30	34	22	12	31	21	
Change	+5	+3	+5	-5	+21	+2	+11	52
Evening peak								
After[b]	45	34	36	33	33	32	36	
Before[c]	39	31	37	26	13	38	23	
Change	+6	+3	-1	+7	+20	-6	+13	57

Note: Each travel time represents the average of five separate vehicle runs.

[a]Calculated as the travel time on each route weighted by the February or April 1981 volume counts at the intersection of screenline 3 and each route.

[b]Measurements taken in April 1981.

[c]Measurements taken in February 1981.

number of trips occurred in the corridor, although these observations might be the combination of decreased tripmaking for one purpose and increased tripmaking for other purposes.

Survey responses provide another indication of the extent of traveler responses along these two dimensions. In July 1981, travelers were surveyed who were identified as making nonwork trips in the corridor prior to the traffic restrictions. Of these 700 travelers, 83 percent reported the use of new routes and 69 percent indicated that they often avoided travel on the Parkway East during the construction project. In addition, approximately one-third of the travelers reported that they occasionally shopped in different places and made fewer trips than they normally did as a response to the parkway reconstruction and associated traffic restrictions. Since only one-third of these travelers indicated that they made fewer trips, and since only nonwork trips may have changed, the net effect of such changes was likely to be relatively small.

Downtown merchants corroborated this conclusion with respect to downtown shopping. According to an article in the Pittsburgh Post Gazette on April 1, 1981, merchants could not identify any reduction in sales after imposition of traffic restrictions.

TRAVEL TIME AND DISTANCE CHANGES IN PARKWAY EAST CORRIDOR

Floating-car travel time measurements were made immediately before and then two months after the imposition of 24-h traffic restrictions on the parkway. These travel time measurements were made between points at the eastern end of the Parkway East and in the Pittsburgh CBD for both directions during three time periods and on the six separate routes illustrated in Figure 2. Before reconstruction, in all but one case the travel time on the Parkway East was somewhat less than the travel time on alternative routes. After traffic restrictions were imposed, times for other routes were within a few minutes of the travel time on the Parkway East.

Table 2 summarizes the average travel times for westbound travel (toward the CBD) on the six routes. As noted above, the parkway provides the fastest travel times for the trips taken, even after the imposition of traffic restrictions. Surprisingly, some routes showed a decrease in travel time between February and April 1981. Because there was diversion of traffic from the parkway to other routes, travel times on these other routes would normally be expected to increase. With the traffic restrictions, inbound travel times on the parkway during peak periods showed significant increases of 9 min in the morning peak and 4 min in the evening peak. However, a decrease in the average travel time during off-peak periods was observed even on the parkway.

This mixture of travel time changes can be ascribed to a number of factors. Most prominent are the traffic system improvements installed by PennDOT, a process of searching by travelers immediately prior to the imposition of traffic restrictions, and the effects of measurement variation. PennDOT system improvements, such as parking restrictions, signalization, pavement patching, and traffic policemen, undoubtedly contributed to a reduction in travel times on alternative routes.

The impact of traveler searches is more ambiguous, but they may well have influenced the travel time measurements. The travel time measurements for the before case in Table 2 were taken in February 1981. During this month, the traffic volume on the parkway had already dropped (Table 1). Travelers diverted from the parkway may already have been searching for new routes, and their unfamiliarity with the alternative routes may have caused a temporary increase in travel times during February. Measurements taken after traffic restrictions were removed may give some indication of the magnitude of this effect. Such measurements will be presented in future reports.

Changes in the weighted average of travel times give an indication of the overall effect on travel times in the Parkway East corridor. As Table 2 indicates, the average inbound morning peak travel times increased by 5 min, off-peak travel times by 1 min, and evening peak travel times by 3 min. Thus, although travel time was reduced on individual routes, the overall effect was that of increased travel times in each period. In comparison with the overall travel times before the traffic restrictions, the weighted average travel times increased from 4 to 16 percent; the largest increase was for inbound travelers in the morning peak and the smallest was for off-peak travelers.

Changes in travel times outbound were similar to those inbound, although the magnitudes of the changes were somewhat larger (see Table 3). Again, some routes showed a decrease in the measured travel times. The weighted average travel times showed increases of 7 min in the morning peak, 11 min in the off-peak, and 13 min in the evening peak. The magnitude of these changes may be somewhat overestimated because of the abnormally low traffic volumes on the parkway in the week prior to traffic restrictions, when these measurements were taken. As noted earlier, a process of searching among alternative routes began even before the traffic restrictions were imposed.

Surveys of commuters in the corridor also suggest that the changes in travel times and trip distances are relatively small. In a mail-back survey of 1350 commuters, approximately two-thirds of the respondents reported increased travel times with an average change of slightly less than 7 min. In the same survey, one-third of the respondents reported increased travel distance to work with an average increase of 1.3 km (0.8 mile).

CONCLUSIONS AND IMPLICATIONS

Despite a large reduction in the effective capacity of the Parkway East and a large diversion of traffic in the corridor, the overall traveler impacts and responses to the reconstruction were small. Changes in route choice and somewhat earlier departure times for work were the primary responses.

The changes in trip characteristics were also relatively small, with a reported increase of roughly 7 min in travel time and 1.3 km (0.8 mile) in travel distance for work trips. These travel time increases were not significant enough to induce more extensive changes in route, departure time, or modal choice. As with the recent Eden Expressway reconstruction in Chicago, predictions of chaos resulting from the traffic restrictions on the Parkway East were quite exaggerated (2).

Of course, the lack of serious impact may be due to some special characteristics of the Parkway East corridor, to effective preconstruction traffic planning, and to the local benefits of ridesharing promotions, including transit and vanpooling. There was a measurable increase in vanpooling in the corridor. PennDOT made special efforts to increase the capacity of streets that were alternative routes. It may also be the case that an unusually large amount of excess capacity existed in the corridor's arterial streets, although this was not evident prior to the project. Further research will attempt to isolate the effects of these considerations.

The major conclusions of this study are twofold:

1. Large modal diversions did not result from temporary traffic restrictions. Decisions on route choice and departure time appear to be more flexible and were the primary mechanisms of traveler response.
2. The roadway system accommodated a major change in traffic patterns without substantially increased levels of congestion.

Several interesting questions remain for research:

1. To what extent are traffic systems improvements on alternative routes and ridesharing promotions warranted in order to reduce traffic congestion? More broadly, what is the cost-effectiveness of alternative, congestion-reducing strategies? If particular strategies are inexpensive, they may be cost effective even if they have small overall impact.
2. Could greater traffic restrictions on an expressway be accommodated without unacceptable congestion elsewhere? This issue is particularly important since maintenance of traffic on the Parkway East (I-376) involved considerable expense, including a longer construction period.

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