Functional Analysis of Mode Choice

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This paper develops a relatively new paradigm for mode-choice behavior modeling. The paradigm emphasizes functional form by establishing functions that relate subjective evaluations of transportation system attributes to objective levels of these attributes and functions that relate observed mode choices and preferences to combinations of subjective impressions. These functions are derived from a theory of decision making and behavior that views the decision maker as an integrator of information. According to this theory, the overall evaluation of a given transportation system can be represented as an algebraic combination of the traveler's evaluations of the various attributes of the system. Two experiments were conducted to evaluate this paradigm. Questionnaires were distributed to respondents, who were asked to indicate their degree of preference for car or bus for each of a series of hypothetical mode-choice situations. These situations were generated by combining varying levels of time difference favoring car over bus, cost difference favoring bus over car, and number of riders in the car. Each judgment thus required a trade-off of cost, time, and interpersonal factors. Cluster analysis was used to separate respondents into distinct subgroups of homogeneous decision makers. These subgroups differed in terms of overall preference for car or bus and the relative weighting or trade-off of factors. Actual mode choice for work trips was then predicted on the basis of preference responses to the hypothetical mode-choice situations, estimates of cost and time factors for individual respondents, and transportation availability constraints. A high level of predictive validity was attained in each experiment. It is suggested that the present paradigm may be useful for analyzing traveler decision processes, for estimating latent demand for alternative transportation opportunities, and for predicting responses to altered or new transportation systems.

The purpose of this paper is to report an empirical evaluation of a new paradigm in behavioral transportation modeling. The paradigm is largely an outgrowth of a recent series of investigations into the processes of transportation mode choice that used the information integration (or functional measurement) theory of human judgment research (1). The general emphasis of the paradigm is on functional form—establishing functions that relate objective attributes to subjective impressions and functions that relate subjective impressions to observed choice behavior. While its general structure has previously been outlined in some detail (2), the paradigm has yet to be fully evaluated empirically. It is toward the end of achieving such an evaluation that this research is directed.

The first part of this paper reviews the paradigm in light of the current state of the art in disaggregate transportation modeling, and the second part reports the results of two investigations designed to relate abstract (hypothetical) mode preferences to actual mode choices for a sample of consumers. The paper concludes with a discussion of the advantages and limitations of the approach in predicting mode choice vis-à-vis existing capabilities.

STATE OF THE ART: RANDOM UTILITY MODELS

The literature on disaggregate modeling approaches to the study of mode-choice behavior is an extensive one. As a number of good reviews of this literature are available elsewhere (3), we shall provide only a rough sketch of the most salient directions evident in this literature in order to compare features of the proposed paradigm with those of the more traditional approaches.

The most prevalent modeling paradigm to date in the analysis of mode-choice behavior has been the stochastic (random utility) model (3). In this model, individuals are thought to hold independent utilities for each of N alternatives, and the probability that any alternative i will be chosen is the probability that the utility of alternative i is greater than the utility of any of the other N - 1 alternatives. These utilities are thought to comprise two independent elements: a vector of strict (nonstochastic) utilities reflecting observed characteristics of an alternative and an associated random component reflecting unobserved characteristics. The distribution function that best describes the random component is assumed on an a priori basis by a given investigator. Various model forms, such as the multinomial logit and probit models, are then generated by differing distributional assumptions.

The vector of strict utilities of an alternative may be characterized in terms of a set of salient attributes (dimensions) of the alternative and a transformation or composition rule by which the multidimensional vector is mapped into a unidimensional overall utility.

Until now there have existed few theoretical guidelines to assist the researcher in specifying either the components of the utility vector or the composition rule. Relevant attributes have commonly been assumed to be a set of objective measures of modes and users, such as observed mode travel time and user income (4), and the composition rule has traditionally been assumed to be linear-additive (5).

Given the arbitrary nature of these assumptions, stochastic choice models have been greatly weakened as theoretical tools for the analysis of individual traveler behavior. As a result, traditional models have served mainly as static, descriptive devices.

In recent years, a considerable amount of research has been directed toward providing a firmer behavioral basis upon which to construct models of traveler mode choice. Specifically, this research has been characterized by (a) attempts to identify relevant attributes in mode choices (6), (b) attempts to relate various attitudinal measures to mode choices (7), and (c) attempts to provide alternate conceptual frameworks for the analysis of traveler mode choice (8). While this research has served to introduce sets of methodologies and constructs that may be useful in the analysis of traveler behavior, it has fallen somewhat short of the goal of providing sets of firm behavioral postulates from which models of traveler choice behavior might be derived. Many basic questions relating to the characteristics and composition rules of individual utility functions remain unanswered.

An Alternate Paradigm

We shall advance an alternate paradigm to serve as a framework for analyzing travel behavior. Its most significant departure from other conceptualizations (8) is its emphasis on functional form—i.e., the relationships between decision attributes and observed choice behavior. Such functions permit better understanding of observed behavior within existing transportation systems and better prediction of likely responses to changes in such systems.

Louviere and others (2) outlined the general form of a paradigm from which a behavior-based theory of travel behavior might emerge. It consists of a series of relationships thought to reflect how measurable attributes of travel modes are translated into individual choice behavior. Specifically, they defined S_{ik} as the objective value of the ith attribute of mode k, S_k as a vector of such attributes (S_{1k}, S_{2k}, . . ., S_{ik}), x_{ikl} as the subjective (perceived) value of the ith attribute of mode k for trip purpose 1, and x_{kl} as a vector of perceived attributes of mode k for purpose 1 (x_{1kl}, x_{2kl}, . . ., x_{ikl}). Further, they defined R_{kl} as the unidimensional subjective value (utility) of mode k for trip purpose 1 and T_{kl} as the observed patronage of mode k for trip purpose 1. They then established the following recursive system.

$$x_{ikl} = F(S_{ik}) \quad (1)$$

$$R_{kl} = G(x_{kl}) \quad (2)$$

$$T_{kl} = H(R_{kl}) \quad (3)$$

$$T_{kl} = I(S_k) \quad (4)$$

In other words, Louviere and others established a formal framework for examining the following relationships:

1. Function relating subjective perceptions of mode attributes to objective magnitudes;
2. Function by which an i-dimensional vector of perceived attributes is transformed into a unidimensional subjective response space;
3. Function relating such overall subjective responses to observed travel behavior; and
4. Composite rule relating the original objective attribute values to observed choice behavior.

Much of the traditional research in mode-choice modeling might be characterized as attempts to directly examine the relationship expressed in Equation 4. We, however, argue that such a relationship becomes meaningful only when it is established in the context of a recursive system (such as outlined above). In addition, recent attitudinal research might also fit this framework. Studies that have attempted to derive measures of the perceived quality of modal attributes (6) involve Equation 1, while studies that deal with the relationship between attitudes toward modal attributes and mode choices (7) involve Equation 3.

The following section describes one approach for simultaneously establishing the functional forms expressed in Equations 1-4.

Functional Measurement

Functional measurement is a method of describing the judgment and decision processes underlying behavioral data. If our data are derived from observations of human choices and preferences, then the processes or functions describing these choices and preferences can be investigated within this framework. While other approaches such as conjoint measurement have been suggested for deriving such functions, functional measurement appears to provide the most flexible analytic tool because of its ability to diagnose alternative functional forms (combination rules). Reviews of functional measurement and its applications to modeling choice and decision rules are available (1, 8).

In this approach, each stimulus object is considered to be a combination of attributes. Algebraic rules or utility functions are used to describe the ways in which individuals trade off these combinations of attributes. The general form of the algebraic expression relating the overall evaluation or utility of a stimulus object (e.g., a transportation system) to the subjective values of its various attributes can be stated as $R_j = f(x_{1j}, x_{2j}, \ldots, x_{kj})$, where R_j is the overall evaluation of stimulus combination j and x_{ij} is the subjective value of attribute i on stimulus j.

In many applications, R_j is a rating of the desirability of stimulus j. The function f is estimated from goodness-of-fit tests of alternative model forms. The parameters x_{ij} are estimated from responses to various stimulus combinations and can then be related to objective stimulus attribute levels, S_{ij}. This relationship between x_{ij} and S_{ij} corresponds to Equation 1 above.

Equation 2 relating overall response to a combination of perceived attributes is typically obtained by an analysis of variance of responses in a factorial experiment where each dimension of a multiattribute stimulus is varied over several levels. The crucial design feature of such an experiment is that respondents make a single evaluation of a complex system rather than separately evaluate single attributes in unspecified contexts. Analysis of variance provides a goodness-of-fit test for alternative models. The reader is referred to Anderson (8) for a complete discussion of various model forms and how they are treated.

The functional measurement technique has been applied to the study of mode-choice decisions in a number of instances. For example, studies by Levin (1) employed functional measurement in the analysis of student mode preferences and generally uncovered decision rules that were nonlinear in form. These findings were significant in that they cast doubt upon the assumption of linearity in utility functions common in applications of existing mode-split models such as the multinomial logit. Although these studies were primarily concerned with diagnosing combination rules used in simulated mode-choice situations rather than with describing actual mode choices, some pilot work has tried to relate laboratory-derived models to actual mode choices. The results of these pilot studies suggested that habitual car drivers and bus riders have different trade-offs (combination rules) in evaluating car and bus attributes. Such results are encouraging, because they help to empirically define the relationships expressed in Equations 3 and 4 of our recursive system—that is, the relationships between subjective responses in a laboratory simulation setting and actual mode-choice behavior.

The experiments described below follow this latter trend and employ the functional measurement approach to further explore the relationships given in Equations 1-4. In addition, they expand the simple car-bus mode choice to include shared rides as well as solo car driving. The purpose of the experiments was to uncover the form of the algebraic utility or decision model underlying mode-choice trade-offs and to relate this model to actual mode-choice proportions. Also of interest were (a) whether variations in utility functions across groups of consumers can be related to socioeconomic, demographic, and situation characteristics, and (b) whether actual mode choices for work trips can be predicted on the basis of responses to hypothetical mode-choice situations.

EXPERIMENT 1

Responses to a questionnaire were obtained from a sample of 99 employees of the University of Iowa. The questionnaire included sections designed to assess the worker's personal background, work schedule, distance from work, present mode split and satisfaction level, estimates of transportation costs, and estimates of the

importance of a variety of factors related to transportation. The most important section of the questionnaire was a series of mode-choice responses to various trade-off situations. The specifics of this key series are described below. Finally, in an effort to gain information about constraints that may have influenced actual mode choices, the following open-ended question was inserted at the end of the questionnaire: "What are the most compelling reasons why you personally choose the method of travel you use to get to and from work?"

Specifics of Mode-Choice Questions

Respondents were presented with descriptions of 27 hypothetical trade-off situations described by these factors: (a) time difference (0, 15, or 45 min/d longer for bus than for car), (b) cost difference (0, 25, or 75¢/d more for car than for bus), and (c) number of riders in the car with the driver (0, 1, or 3). This latter factor thus includes both ride sharing and solo driving as mode-choice alternatives. Each given situation was described by one level of each of two factors, (a) and (b), (a) and (c), or (b) and (c). One complete factorial design was formed for each pair of factors; three 3-×-3 factorial designs were formed overall.

In the instructions, respondents were told to assume that both a car and a bus were available to them in each hypothetical situation and that, assuming these availabilities, they were to respond on the basis of the information presented.

The purpose of this instruction was to elicit a car-bus propensity abstract from an availability constraint. For each hypothetical situation, the respondent was asked to rate the relative likelihood of taking the bus or car. A 20-point rating scale was used, where 0 represented "certain to take car" and 20 represented "certain to take bus." Respondents were to use numbers between 0 and 20 to represent varying degrees of preference for car or bus. This car-bus preference scale was used previously (1) and provides information about degree of preference as well as binary mode choice.

Results

Description of the results will be divided into three phases. In phase 1, analyses of responses to the hypothetical mode-choice situations will be presented. Phase 2 will explore the relationships between decision processes identified in phase 1 and group differences in socioeconomic, behavioral, and situational characteristics. In phase 3, responses in the experimental task will be related to actual mode choices.

Phase 1

Because each respondent completed only one replication of the experiment, decision models could not be tested at the level of the individual respondent. However, by grouping respondents who exhibited similar arrays of responses into segments, inferences about individual decision-making processes could be made at a minimum risk of fallacy.

In order to derive homogeneous decision-making segments, the raw responses of each of the 99 respondents in the experimental task were subjected to a cluster analysis. This appeared to provide the most reasonable grouping tool for this purpose by virtue of its ability to differentiate respondents based on both pattern and magnitude of response. Q-mode factor analysis, a possible alternative, would differentiate purely on pattern. For example, an individual who would take the car under all trade-off situations could, quite conceivably, be grouped with one who would ride the bus under all situations. Because we were interested in relating the groups to actual mode ridership, this would clearly not be a desirable result.

The results of the analysis suggested that the data set comprised three salient clusters of respondents, one with 30 members, one with 51 members, and one with 18 members. The next stage of analysis was to identify each group in terms of differences in their revealed decision-making processes.

To permit this identification, separate analyses of variance were performed for the responses of each group. Three two-way repeated measures analyses, corresponding to the three 3-×-3 designs contained in the experiment, were conducted for each segment. An examination of the grand mean across all cells for each analysis for each group provided a clear interpretation of the groupings.

Group 1 (30 members) had a grand mean of 6.3; group 2 (51 members) had a grand mean of 10.5; group 3 (18 members) had a grand mean of 15.3. Recalling that responses were recorded on a 20-point rating scale, we see clearly that group 1 was a car-biased group and group 3 was a bus-biased group. Group 2 was in the middle and, for reasons that will be made clear later, was defined as an unbiased group.

Plots of mean values for each cell of the cost difference-time difference subdesign for each group are shown in Figure 1. Several things should be kept in mind when examining the three panels. Parallel or nearly parallel lines show that the two factors being plotted combine in an additive fashion to determine car-bus preference ratings for that group. The slopes and separations of the lines reflect the relative degrees of importance or weights of the two factors.

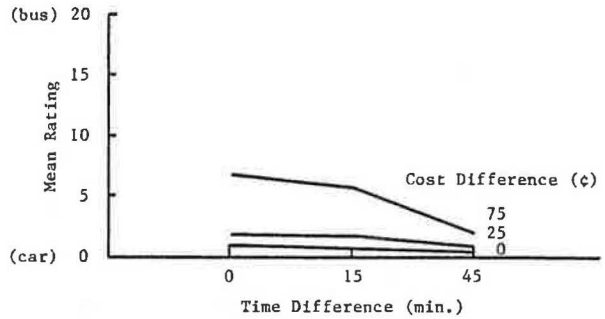
The comparative spacing of the lines in a given panel and the shape of each line (straight, negatively accelerated, or positively accelerated) provide information about the psychophysical functions, that is, the relationships between objective attribute values and their subjective counterparts (Equation 1). If the lines in a given panel converge at a particular level of the variable plotted on the abscissa, this shows differential weighting (nonadditivity), with that particular level having greater weight than other levels of that variable.

For all three groups, preference for the car increased (approached the low end of the scale) as time savings for car over bus increased and preference for the car decreased as cost savings for bus over car increased.

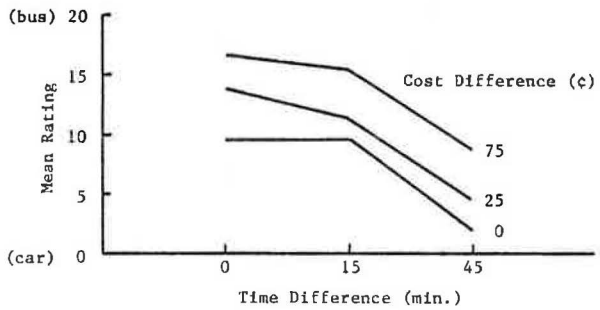
For the car-biased group (Figure 1a) the nonparallelism suggests a nonadditive combination rule for time differences and cost differences in determining car-bus preferences. This was confirmed by a significant interaction in the analysis of variance. Convergence of the lines at a time difference of 45 min indicates that cost difference had less effect at high time differences than at low time differences. This finding replicates and extends the generality of the Levin study (1) and supports the interpretation that car-bus preferences are based on a weighted averaging (a common form of Equation 2) of cost and time factors, where respondents place greatest weight on those pieces of information that support their initial biases. Car-biased individuals thus tended to ignore the cost differences favoring the bus when time savings favoring the car were great.

For the unbiased group (Figure 1b), the curves are nearly parallel, which suggests that weight biases were not present in this group. The sizable spacings and

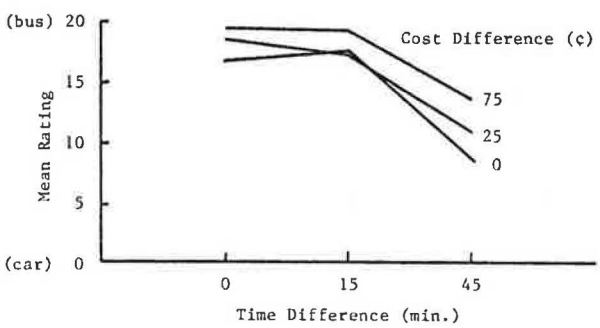
Figure 1. Time difference and cost difference interaction plots for three bias groups.



(a) Car-Biased Group



(b) Unbiased Group



(c) Bus-Biased Group

Table 1. Group means and standard deviations on questionnaire items.

	Car-Biased Group		Unbiased Group		Bus-Biased Group	
Item	Mean	SD	Mean	SD	Mean	SD
Age, years	37.4	10.5	36.3	13.9	39.1	13.1
Sex, 0 = female, 1 = male	0.47	0.5	0.49	0.5	0.61	0.5
Income, 7 categories	5.3	1.7	4.6	1.9	4.8	1.5
Years employed at University of Iowa	8.5	8.3	5.5	13.7	8.9	6.5
Home-to-work distance	3.8	3.4	7.8	9.6	2.5	3.2
Home-to-bus-stop distance	0.96	2.9	4.40	9.4	0.93	3.3
Variability of work shift, 0 = no, 1 = yes	0.57	0.5	0.45	0.5	0.28	0.4
Importance ratings (20-point scale)						
Travel time	15.3	1.3	13.0	3.6	11.5	3.5
Cost	7.9	4.2	11.8	2.7	12.0	2.7
Amenities	7.9	5.5	4.6	3.9	1.1	0.5
Convenience	13.6	3.1	9.7	4.6	6.7	5.4
Privacy	12.6	2.9	12.6	3.3	11.1	5.4
Energy conservation	9.1	3.5	11.2	3.8	12.6	4.5
Satisfaction with current mode	17.5	4.3	14.9	4.7	17.4	3.2

slopes of the curves suggest that the manipulated factors had large and systematic effects on the car-bus preferences of the unbiased group. Thus, the approximately neutral mean response of this group reflects a balancing or trade-off of factors rather than a lack of responsiveness to the variations.

Finally, the plot for the bus-biased group (Figure 1c) reveals a small (but statistically significant) interaction between cost differences and time differences that is of opposite form to that observed for the car-biased group. Cost differences tended to have less effect at low time differences than at high time differences.

The figure also shows how responses to multiattribute systems can be used to define the functions relating subjective perceptions of mode attributes to objective magnitudes (Equation 1). Car-bus preferences change little as time difference increases from 0 to 15 min, but preference for the car increases greatly as time difference increases from 15 to 45 min. The psychophysical function for time difference is thus positively accelerated for each group.

The three groups identified by the cluster analysis differed in terms of the relative weighting of factors manipulated in the experiment. The car-biased and bus-biased groups differed considerably; the unbiased group showed some of the same effects as each of the other two groups, namely, a large time difference effect as the bus-biased group and a significant rider effect as the car-biased group. Only the bus-biased group was uninfluenced by the number of riders. The other two groups showed a decreased preference for the car as the number of riders increased.

At first thought, it might seem counterintuitive that respondents who preferred the money-saving mode (bus) would be heavily influenced by time factors and that respondents who preferred the time-saving mode (car) would be heavily influenced by cost factors. However, what this means is that degree of preference for the bus by respondents in the bus-biased group was influenced by the amount of extra time involved in taking the bus, and degree of preference for the car by respondents in the car-biased group was influenced by the amount of added cost involved in driving a car. Viewed in terms of these trade-off processes, the results make sense.

The next phase of data analysis examines the relationship between group differences found in phase 1 and differences in other factors measured in the experimental questionnaire.

Phase 2

Table 1 summarizes results for various parts of the questionnaire when respondents were divided into the groups identified in phase 1. In terms of the socioeconomic variables, the key differences among groups were in terms of income, home to work distance, and work shift variability.

As might be expected, the car-biased group tended to have a higher income and greater variability in working hours. The most pronounced difference was in terms of home to work distance, where the unbiased group lived considerably farther from place of employment than either of the other two groups.

Ratings of importance of various factors differed among groups. As would be expected, amenities, convenience, and privacy were rated more important by car-biased respondents than by bus-biased respondents, while conserving energy was rated more important by bus-biased respondents. The high rating of privacy by the car-biased group is consistent with the large effect of number of riders observed for that group in

phase 1. Travel time was rated more important by car-biased respondents, and cost was rated more important by bus-biased respondents. While this seems to be the opposite result of phase 1, these ratings were made in the abstract and did not actually involve trade-offs of specified levels of competing factors.

While car-biased respondents may presently choose car over bus because of time savings, this does not necessarily mean that they would be unresponsive to changes in cost factors. The functional measurement procedure used in phase 1 revealed trade-off relationships that operate in car-bus preferences and would seem to provide more information about decision processes underlying mode choice than would simple importance ratings. In particular, the nonlinear functions obtained in the trade-off analyses show that cost and time factors increase in importance when they reach extreme values.

Ratings for the unbiased group were generally intermediate to the other two groups. However, this group had lower ratings of satisfaction than did the others. This is consistent with responses to the open-ended question at the end of the questionnaire. Respondents in the unbiased group were most apt to indicate that they took their present mode only because it was the only one available. Results for this group suggest that it is composed of many respondents who are captives of their present mode but who would consider switching modes if transportation alternatives were offered.

A regression analysis was then conducted to quantitatively relate the grouping assignments to the following socioeconomic measures, demographic characteristics, and transportation constraints obtained in the questionnaire: home to work distance, home to bus stop distance, work time (day versus night), type of work shift (fixed versus variable), variability of work schedule, business and personal needs (ratings) for car, convenience of parking at work place (rating), work place (code), age, sex, and income.

The ability of a linear combination of these variables to predict group membership was measured by two statistics: the overall proportion of variance (R^2) of grouping explained by the linear combination and the proportion of cases correctly assigned to each bias group. The resulting overall regression was significant beyond the 0.01 level, but it explained only 27 percent (corresponding to $R = 0.52$) of the variance in grouping. This corresponded to 67 percent of cases being correctly assigned to bias groups in a discriminant analysis. While this result is disappointing from the point of view of identifying bias groups on an a priori basis, it was not unexpected, since the effect of socioeconomic variables on attitudes is most likely one that operates over time. One might, then, expect the cross-sectional correlation to be low.

Phase 3

The next phase of analysis was the crucial one of relating responses in the experimental task to actual mode-choice behavior. Ideally, this would be done by taking a model of mode choice derived from hypothetical trade-offs for individuals and substituting in measures of the individuals' real-world transportation environment. Each of these one-point predictions would then be correlated with frequency of patronage of car and bus. In the present case, individual models were not available and a simplified alternative model was tested for the frequency of a given mode choice:

$$F_i = f \tag{5}$$

where f equals bias, home-to-work distance, most expensive mode, and bus availability.

Bias was measured by the individual's mean response over all cells in the experimental design. The second factor, home-to-work distance, was a surrogate for the time difference factor manipulated in the experiment. The third factor, most expensive mode, was a binary surrogate for the cost difference factor, because many respondents could not articulate their estimates of costs of various travel modes, but some respondents indicated that it was actually cheaper to drive a car than to take the bus. The last factor, bus availability, was inserted as a binary variable to reflect constraints on actual mode choice.

It might be helpful at this point to briefly discuss the substantive meaning of the model being tested. It is hypothesized that, in an experimental situation, individuals carry with them and reflect in their responses the factors and attitudes relevant to them in their transportation decisions. These affect their overall bias in the experimental task and their weighting of factors manipulated in the experiment. However, real-world constraints may be removed in the controlled experimental task to simplify analysis of the decision processes, such as by specifying that both car and bus are available in the present case. Thus, the present model for predicting actual mode choice incorporates a measure of response, surrogates for the variables manipulated, and a classification of real-world constraints into the experimental task.

The dependent variable, mode patronage, was measured in terms of the proportion of work trips by bus during the month prior to receipt of the questionnaire. As the questionnaire was administered during the summer, a number of respondents indicated that they either walked or rode a bike. However, in all but one of these cases, respondents added information about their non-summer mode. This information was used to reassign nonmotor vehicle trips. The one exception was dropped from further analysis, as was one other respondent who indicated proportion of trips on the inner-campus bus system rather than home-to-work trips. Hence, the final sample size used for this analysis was 97.

Specifically, the following regression of the factors defined in Equation 5 was used to predict bus patronage:

$$\text{Prop}_B = [a(\text{mean}) + b(\text{HWD}) + c(\text{min})]\,(\text{avail}) + e \tag{6}$$

where

Prop_B = proportion of bus trips,
mean = mean response to experimental task (20-point scale),
HWD = home to work distance,
min = $\begin{cases} 1 \text{ if car rated cheaper than bus or} \\ 0 \text{ if otherwise, and} \end{cases}$
avail = $\begin{cases} 0 \text{ if no bus available or} \\ 1 \text{ if otherwise.} \end{cases}$

The availability factor was entered as a multiplier in the regression equation because, if it were at a 0 level, then frequency of bus patronage would be 0.

The prediction was good and explained over 78 percent (based on $R = 0.885$) of the variance in the proportion of bus trips for different respondents. An examination of residuals revealed some tendency for overprediction of low values and underprediction of high values, but overall the model appears to provide a reasonable description of the data, especially in light of the crudity of measurement of some of the predictor variables.

The single factor, bias (mean response on experi-

mental task), accounted for over 70 percent of the variance in the number of bus trips. It is quite likely that, had actual travel time and cost difference measures been available, the overall predictive ability of the model would have been even higher.

In order for the predictive ability of the present model to be compared to more traditional models such as the logit, respondents were divided into two groups, car riders and bus riders, according to the most frequently used mode. The present model was then applied in a discriminant analysis to determine its classificatory ability. The result was that 94 percent of the cases were correctly classified. This result is comparable to those obtained in the more successful applications of logit-type analyses that have been reported (4).

For a further comparison with traditional methods, a linear combination of importance ratings of various factors measured in the questionnaire was used in place of the bias measure in Equation 7 to predict bus patronage. The following importance ratings were used: travel time, cost, amenities, convenience, privacy, and energy conservation. The resulting regression model was highly significant, but the predictive ability of 59 percent was clearly less than that obtained with the bias measure from the experimental task.

EXPERIMENT 2

In an effort to provide further substantiation of the results obtained in the first experiment, a second questionnaire was designed and distributed to a random sample of 150 residents of Iowa City.

Questions

The form was similar to the first, with two major modifications: (a) the experiment included the factors travel time difference, cost difference, and number of riders in a 3-×-3-×-3 factorial design where each evaluation made by the respondent was based on all three factors (as compared to two factors for each evaluation in experiment 1); and (b) direct estimates were obtained for each respondent of actual car-bus travel time and cost differences, as well as number of auto riders.

Results

Of the original 150 questionnaires distributed, 72 were returned. As the focus of the investigation was on car-bus modal split for work trips, nonworkers and individuals living a few blocks from their work places who indicated walking as the primary mode were deleted from the analysis. This reduced the total sample size to 48.

Following the steps employed in the analysis of the first experiment, raw responses by each of the 48 individuals to the hypothetical mode-choice situations were first cluster analyzed. As in the first experiment, three salient clusters of respondents were identified: a car-biased group (N = 14), a bus-biased group (N = 17), and an unbiased group (N = 17). Responses within each of these groups were then subjected to analysis of variance.

Despite the small sample sizes, results bore a general resemblance to those obtained in the first experiment. For example, plots of the cost difference times time difference interaction revealed a noticeable convergence of responses toward the lower end of the scale (indicating car preference) for the car-biased group at a time difference of 45 min. This, again, suggests a nonadditive combination rule for time and cost differences for this group. The major dissimilarity between the two sets of results was an absence of response concentrations at extreme ends of the scale for the car- and bus-biased groups. This would appear to be related to the nature of the new design—the rider factor was considered simultaneously with time and cost differences. Hence, the observed effects of time and cost reflect the averaging of a third factor that has a moderating influence.

Actual mode-choice behavior was related to experimental response in a fashion similar to that of the first experiment. In the new analysis, however, estimates of time and cost differences as provided by respondents were available. The model tested, therefore, was

$$\text{Prop}_B = [a(\text{mean}) + b(\text{cos dif}) + c(\text{tim dif}) + d(\text{riders})] \times (\text{avail}) + \epsilon \qquad (7)$$

where

mean = mean response to experimental task (20-point scale),
cos dif = estimate of actual car-bus cost difference,
tim dif = estimate of actual car-bus time difference,
riders = number of riders who share (or would share) a work trip, and
avail = $\begin{cases} 0 \text{ if no bus available or} \\ 1 \text{ if otherwise.} \end{cases}$

The level of prediction of the proportion of bus trips was similar to that reported for the first experiment. The resulting R^2 was 0.77 (based on R = 0.88), which corresponded to 95 percent of respondents being correctly classified into predominantly bus or predominantly car groups in a discriminant analysis.

DISCUSSION

This paper has advanced and empirically assessed an alternate paradigm in the modeling of transportation mode choice. The approach departs from most traditional modeling paradigms in terms of its emphasis on deriving functional forms that best describe the processes by which individuals arrive at transportation-related judgments.

Results of the reported studies produced two findings with respect to the utility of behavioral models of mode choice. First, they showed that mode-choice models derived in earlier laboratory studies with student populations can be generalized to nonstudent populations. In fact, cluster analysis of behavioral data led to a more meaningful system of classifying respondents than would a priori population subdivisions. Second, they showed that the rating responses to hypothetical mode-choice trade-off situations are related to actual mode choices. Specifically, a model that combined responses to an experimental task with situational constraints yielded high explanatory ability in the prediction of actual mode choices. The levels of prediction obtained with the simple regression models compared favorably with reported successful applications of traditional stochastic mode-choice models.

A series of equations was outlined for developing a behavior-based theory of travel behavior. The experimental task of the present study directly examined Equations 1 and 2, which deal with subjective evaluations of mode attributes and the transformation and integration of subjective evaluations into an overall subjective response. Equations 3 and 4, which deal with the relationships linking objective and subjective attribute values to actual choice behavior, were examined, at least in a preliminary manner, in the current at-

tempt to predict actual mode choice.

The establishment of stronger links to actual choice behavior awaits further study in which trade-off factors manipulated in hypothetical mode-choice situations can be measured accurately for each individual in the sample and decision models can be calibrated for individual consumers.

Once clear links are established between rating responses in abstract settings and actual mode-choice behavior, the stage will be set for the most useful application of the behavior-modeling approach. The derivation of decision-making models through carefully designed experimental tasks can be used to predict future responses to changes in transportation systems. Existing stochastic demand models seem theoretically weak for such purposes. Behavioral models can be used to directly estimate latent demand for alternative transportation opportunities. In the present study, for example, the mode-choice model without the availability constraint might be thought of as measuring such demand.

The relative degree of success of this study in predicting mode choice directly from attitudinal data is noteworthy. The functional measurement approach appears to be a means of side-stepping traditional issues related to the identification and measurement of all the relevant variables in mode-choice decision making. By combining experimental design and demographic analysis, a variety of variables affecting mode choice can be studied directly; other factors can also be shown to exert their influences through individual differences in response bias and the weighting of information.

The general paradigm proposed in this paper is one that seeks to advance our understanding of human travel behavior through a concerted program of laboratory experimentation and real-world verification. If laboratory behavior in simulated transportation environments can be shown to be predictive of that observed outside the laboratory, then such simulation would provide a powerful tool in the testing and development of theories of travel behavior.

This research provided some initial support for such a link. Nevertheless, the research program remains at an embryonic stage, and many basic questions related to the utility of behavioral models in the prediction of travel behavior remain unanswered. We hope the results of this research will encourage additional efforts in this direction.

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Publication of this paper sponsored by Committee on Passenger Travel Demand Forecasting and Committee on Traveler Behavior and Values.

Incentives and Disincentives of Ride Sharing

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This research examines consumer motivation concerning ride sharing, particularly carpooling, according to a market segmentation approach. A sequential design permitted (a) developing hypotheses about ride-sharing motivation based on qualitative data from intensive discussions in decision analysis panels, (b) testing those hypotheses by means of quantitative data obtained by survey, (c) developing program strategies on the basis of the results and pretesting those strategies with an additional series of decision analysis panels. The major market segmentation involved dividing the sample by commuting mode and pattern and by occupation type, although additional independent variables were also utilized. This paper concentrates on the carpooling attitudes and perceptions of carpoolers versus solo drivers. Illustrative findings are also presented by occupation group, commute pattern, and sex to illustrate the power of the finer market segmentation. The factors discussed include, first, attitudes toward costs or interpersonal aspects of carpooling (including match methods), time variables, carpool routes, parking management and convenience issues and, second, demographic characteristics of the two types of commuters. A special analysis focuses on the attitudes of those solo drivers who stated that