fected by the new transportation facility in Providence may have increased their VKMT directly in response to increased speed shows that travel time may be the major impediment to travel. This result further supports the use of travel time as the measure of spatial separation in distribution models such as the gravity model and the intervening opportunities model.

Although the analyses performed in this study indicate that new highways result in more VKMT with no increase in VHT or the number of trips, the data were insufficient to measure the amount of change in the VKMT. In addition, the paucity of the data makes small changes difficult to detect. There may have been small changes in VHT and trips that escaped detection in this study. Therefore, the conclusion that VKMT increases by the same amount as average speed increases must be made with appropriate reservations.

Further research should address the question of how many extra VKMT are produced by new highways as well as the relationship to VHT, number of trips, average trip length, and average speed. Such a quantification would provide a major breakthrough in the field of highway planning. In addition, this analysis was limited to the comparison of residential trip productions; further research should investigate the effect of system supply changes on nonresidential trip generation (i.e., trip attractions).

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Destination Choice Behavior for Non-Grocery-Shopping Trips

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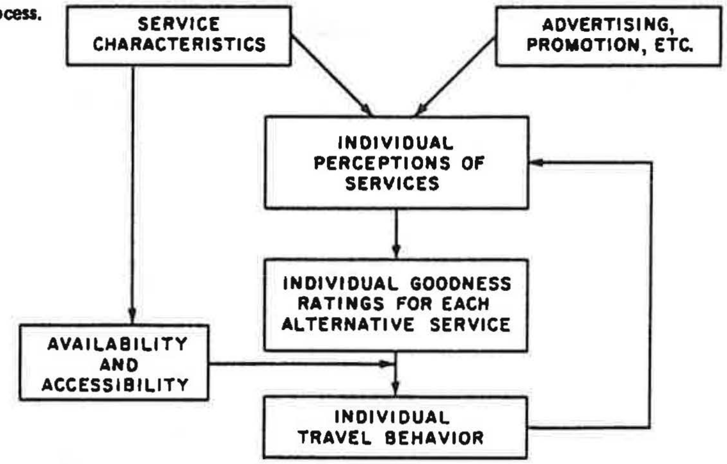
This paper combines attitude and market research and disaggregate behavioral demand modeling to produce a diagnostic and predictive model of destination choice for non-grocery-shopping trips. The analysis is based on perception and preference models to measure attractiveness and logit choice models to link attractiveness and accessibility to frequency of destination choice. Alternative analytic techniques were compared to identify the most effective technique for each step in the process. Factor analysis was found to be superior to nonmetric scaling to identify consumer perceptions of shopping location attractiveness because it is more understandable and predicts better. Statistical preference models (first preference logit, preference regression) provided consistent predictions and similar interpretations. For choice prediction, revealed preference (standard logit approach) and intermediate preference models provided complementary insight into the consumer behavior process. Use of both models leads to insights that would have remained hidden had either model been used alone. The results indicated that attractiveness of trip destination can be effectively measured with attitudinal models; that the five basic (measured) constructs of attractiveness are variety, quality, satisfaction, value, and parking; that of these quality is consistently the most important and prestige of store appears to be the most important aspect of quality; and that both attractiveness and accessibility are important determinants of destination choice. Any destination choice model should include both.

The focus of this study is on the trip maker's choice of destination for non-grocery-shopping trips. This research was undertaken in the belief that improved understanding of this destination choice process would provide insight into the general process of destination choice behavior. This research also develops effective analytic models that can be used for the analysis of destinations other than shopping areas.

Travel choice behavior can be represented by a simple

Figure 1. Consumer response process.



evaluation and selection process. Each individual evaluates each alternative that is known and available to him or her and chooses the alternative he or she values most highly. Because the value of an alternative to an individual cannot be precisely specified, the choice process is represented by a probabilistic choice model in terms of those aspects of value that can be identified. That is, based on a partial valuation of each alternative, the model predicts the probability that the individual will select each of the available alternatives. The individual probabilities can be aggregated across individuals to provide predictions of group behavior. The structure of the consumer response process used in this study extends the approach described above in two significant ways.

First, the characteristics of the alternatives are described by what the individual perceives rather than by engineering measures. This approach extends the range of attributes to include those that cannot be measured by direct engineering means; it accounts for differences of individual perceptions of identical alternatives; and it gives useful insight into how consumers actually perceive alternatives.

Second, the substantive aspects of the destinations—their attractiveness—are modeled separately from the spatial aspects of these alternatives—their accessibility. This approach follows the research direction suggested earlier by Hanson (1).

The resulting model structure consists of three integrated components that describe individual perceptions of shopping locations, individual evaluations of shopping location attractiveness based on relative preferences for perceived characteristics, and choice of shopping location based on attractiveness ratings and accessibility measures. This model is based on a consumer behavior model formulated by Hauser and Urban (2) and independently by Shocker and Srinivasan (3) and modified for transportation by Hauser and Koppelman (4).

OBJECTIVES OF THE RESEARCH AND APPROACH

The research had two objectives. The first was to increase understanding of the process by which individual consumers select locations for non-grocery-shopping trips. The second was to develop and critically evaluate alternative empirical models of the consumer choice process.

These objectives were achieved by developing and interpreting alternative models of perception and preference and integrating them with a choice model. The alternative models provide different perspectives on the consumer process and contribute to an overall understanding of that process. Comparing models provides a basis for selecting those that will be most useful in particular situations. The primary criteria are their ability to provide useful insights into consumer behavior and to predict accurately consumer preferences and choice behavior.

The model structures examined include three models of perceptions and three models of consumer preference combined with the multinomial logit choice model. The models of perception include fundamental attributes, factor analysis, and nonmetric scaling. Fundamental attributes represent perceptions in terms of an extensive list of attributes. Factor analysis and nonmetric scaling identify the underlying cognitive dimensions consumers use to evaluate products or services.

The preference models considered are preference regression, first preference logit, and revealed preference logit. Preference regression and first preference logit select relative importance weights for attributes in order to best explain rank-order preferences or first preferences, respectively. Revealed preference models select relative importance weights for both the attractiveness attributes and the accessibility characteristics by analysis of observed choices. These importances identify those dimensions that most affect the consumer choice process and thus help managers identify which characteristics to stress in the formulation of strategy or policy.

The details of the research are described in the remainder of this paper. The second section reviews the theory and models used; the third describes the empirical setting and experimental design; the fourth and fifth evaluate the different models with respect to interpretability and predictive accuracy, respectively; and the conclusion presents a summary of results and indicates directions for further research.

THEORY AND MODELS OF SHOPPING LOCATION CHOICE BEHAVIOR

The process by which consumers evaluate and choose among a set of alternatives can be described in different ways. In this study, we represent the consumer response process by the sequence of distinct but interrelated stages described in Figure 1. This simplified representation of perception, attractiveness, accessibility, and choice is a part of a more complex market process that describes interaction among individuals, information diffusion, changes in behavior based on experience, differences between market segments, etc. (2, 3, 4). Nonetheless, this representation provides a useful framework for the analysis of destination choice behavior and provides a critical link in any behavioral model of the transportation consumer.

Methodologies based on combining perception, preference, and choice have proved extremely productive in other contexts (2, 3). It is reasonable, therefore, to posit that these methodologies will enjoy similar success in transportation. They do not replace the disaggregate behavioral demand models now in common use but augment them, enhance their predictive abilities, and make them more responsive to the planning needs of today's managers.

Modeling Consumer Perceptions

Consideration of consumer perceptions rather than direct (engineering) measures of alternatives makes it possible to include attributes or characteristics for which direct measures do not exist and to account for differences between consumers' subjective evaluation of alternatives and objective reality. The usefulness of incorporating nonengineering measures in travel choice behavior has been demonstrated in studies by Spear (5), Nicolaidis (6), and Dobson and Kehoe (7). Differences in perceptions among individuals or differences between perceived and engineering measures or both have been identified by Burnett (8) and Dobson and Tischer (9).

We shall examine three alternative perceptual models in this study. The simplest and most obvious method of representing consumer perceptions is by individual ratings for an exhaustive list of attributes. These attribute scales, called fundamental attributes, provide a complete description of consumer perceptions and are conceptually easy to use because no further data collection or analysis is required. Use of the complete list assumes that the individual simultaneously evaluates a long list of attributes in formulating preferences among alternatives. Alternatively, one can assume that underlying cognitive dimensions exist and that consumer ratings of attributes include a common component attributable to these cognitive dimensions, an attribute-specific component, and some measurement error. The common components or cognitive dimensions can be found by factor analysis of the attribute ratings across alternatives and consumers (2). The advantage of factor analysis over fundamental attributes is that it identifies a simpler perceptual structure that can provide clearer insight into how consumers perceive alternatives.

Finally, one can identify cognitive dimensions by analysis of perceived similarities between products or services. Nonmetric scaling positions alternatives in n-dimensional space so that the distance between pairs of alternatives corresponds as closely as possible to the reported similarity between them (10, 11). The advantage of nonmetric scaling over factor analysis is that it does not assume the ratings scales are metric, because scales are determined independently of the attributes and can uncover dimensions not represented in the attributes. However, nonmetric scaling requires additional, hard-to-collect data on similarity judgments; also, the scaling procedures are difficult and expensive to use. Furthermore, the assumptions built into these algorithms are very restrictive behavioral postulates and could, therefore, restrict the model. For example, a commonly used algorithm called INDSCAL assumes that all consumers have perceptions that are homogeneous subject to a scale transformation. Finally, the number of dimensions that can be identified is severely constrained by the number of stimuli (10, 12).

Modeling Consumer Preferences by Attractiveness

We describe the consumer response process as one of perception, preference, and choice. The purpose of separating the preference and choice steps is to avoid confounding performance or attractiveness characteristics, which influence both preference and choice, with other characteristics such as availability, awareness, and accessibility, which primarily influence choice. In this study, this two-step process is tested by comparing importance weights and predictive ability of models, including an intermediate preference step, with revealed preference models that exclude the intermediate preference step.

The analysis of consumer preferences is directed toward finding a function that maps consumer perceptions into a preference rating, or attractiveness index. The preference models considered in this study determine the relative importance of the fundamental attributes or cognitive dimensions by estimating a linear compensatory model of the form

$$P_{ij} = \sum_k w_k d_{ijk} \tag{1}$$

This model states that consumer i's preference or attractiveness index for product j, P_{ij}, is the weighted sum of his or her perceptions, d_{ijk}, of alternative j for attribute or dimension k where the estimated importance weights are average insights for the population. Three models are evaluated.

Preference regression statistically estimates the importance weights by using rank-order preference as the dependent variable and the consumers' perceptions as independent variables. Ordinary least squares is used to estimate importance weights, despite the implicit metric assumption, because it has been shown that these results are similar to those that would be obtained by more expensive monotonic regression (13). Preference regression uses full rank-order information in the estimation of importance weights.

Preference logit assumes that the true preference, P^T_{ij}, is composed of an observable part, P_{ij}, as in Equation 1, plus an error term, e_{ij}:

$$P^T_{ij} = P_{ij} + e_{ij} \tag{2}$$

Assuming an independent Weibull-distributed error term makes it possible to derive a functional form for the probability L_{ij} that consumer i ranks j as his or her first preference (14). This probability is given by

$$L_{ij} = \exp(P_{ij}) \Big/ \sum_l \exp(P_{il}) \tag{3}$$

where the sum is over all alternatives, l. The importance weights are estimated by maximum likelihood techniques (14). The appeal of the logit model is that it explicitly models stochastic behavior (15) and that it makes no metric assumptions about preference rankings. Although it uses only first-preference information, it can be extended to use rank-preference information (16) with similar results.

Revealed preference assumes that the underlying preference weights must be obtained by analysis of choice behavior. It assumes that each individual selects an alternative that has the greatest utility to him or her. The importance weights, w_k, are estimated jointly with the importance of nonpreference characteristics such as the time, effort, or cost of obtaining a selected alternative (see Equation 6, below).

The advantage of the revealed preference model is that it does not rely on reported preference data but on observed choice behavior. However, the estimates of cognitive importance weights may be biased if the nonpreference choice elements are not carefully specified.

Modeling Consumer Choice Behavior

The consumer response process is designed to explain and predict individual choice based on a model of perceptions and preferences. The choice model postulates that individual consumers associate a value v_{ij} with each available alternative and select the alternative that has the greatest value. Our estimate of the individual value $\hat{v}_{ij}$ is a linear combination of the preference index, P_{ij}, and situational variables, Z_{ijm}, influencing choice behavior.

$$\hat{v}_{ij} = \beta_0 P_{ij} + \sum_m \beta_m Z_{ijm} \tag{4}$$

The true value is equal to the estimated value plus a random component that represents unobserved influence and specification errors. Using the same distribution assumption as for preference logit, we obtain the multinomial logit choice model, which describes the probability of individual i's choosing alternative j on a single occasion by

$$C_{ij} = \exp(\hat{v}_{ij}) \Big/ \sum_l \exp(\hat{v}_{il}) \tag{5}$$

When the preference index has not been estimated, the value function is formulated in terms of the fundamental attributes or cognitive dimensions,

$$V_{ij} = \beta_0 \sum_k w_k d_{ijk} + \sum_m \beta_m Z_{ijm} \tag{6}$$

and the revealed preference importance weights, w_k, are estimated simultaneously with the other parameters of the choice model.

EMPIRICAL SETTING

The empirical focus of this study is on non-grocery-shopping trips. Historically, researchers in both transportation (18) and marketing (19, 20) have emphasized the importance of accessibility or distance from the consumer's residence to the shopping center. Some studies have included measures of shopping location size, usually retail floor space or number of retail employees (21). Although size of shopping locations, which also represents the range of opportunities available to the shopper, is a relevant measure of attractiveness, it is unlikely to capture all the aspects of attractiveness that influence shopping location choice behavior. In order to understand the construct of shopping location attractiveness from the perspective of consumers, we must determine the cognitive dimensions of shopping location attractiveness, their relative importances in forming preferences, and their importance relative to accessibility in influencing choice behavior.

The models estimated in this study are based on data collected at shopping locations in the North Shore suburbs of Chicago. The process of sampling individuals at their chosen destination requires the use of choice-based estimation procedures to obtain consistent estimators of parameters (17). The data collected describe attitudes toward and use of seven shopping locations. The data used in this analysis include rank-order preference for each shopping location, similarity judgments for all pairs of shopping locations, direct ratings of each shopping location for 16 attributes, and frequency of trips to each location. The 16 attributes (see the list below) chosen to describe the general characteristics of shopping locations and the questionnaire were developed through extensive literature review, preliminary surveys, and analysis of developmental questionnaires (22). The 16 attributes are

1. Layout of store,
2. Ease of returning or servicing merchandise,
3. Prestige of store,
4. Variety or range of merchandise,
5. Quality of merchandise,
6. Availability of credit,
7. Reasonable price,
8. Availability of sale items (specials),
9. Free parking,
10. Stores located in a compact area,
11. Store atmosphere (heating, cooling, noise, crowds, etc.),
12. Ability to park where you want,
13. Shopping center atmosphere (pedestrian-only area, flowers and shrubs, covered walkways, etc.),
14. Courteous and helpful sales assistants,
15. Availability of a specific store, and
16. Number and variety of stores.

The analysis is based on a random sample of 500 consumers who reported familiarity with all seven shopping locations. All models were then tested for ability to predict on a saved-data sample of an additional 500 consumers. Predictions were quite good for all preference and choice models on factor analysis and fundamental attributes. Furthermore, all relative model comparisons were supported by the saved-data analysis (23).

The data collected did not include information on the costs (time, out-of-pocket cost, physical effort, etc.) of traveling to each of the shopping locations. Only the residential location of the shopper was obtained. For this reason accessibility is represented by the distance between each shopping location and the shopper's residence.

MANAGERIAL INTERPRETABILITY

The primary goal of this study was to understand and explain consumer response in the selection of destinations for non-grocery-shopping trips. Thus initial analysis of and comparison between models was based on managerial interpretability. The model interpretations, which provide basic insight into the behavioral process, serve as a first test of model usefulness and validity.

Perception Models

A plot of the average ratings of each shopping location for the 16 fundamental attributes (Figure 2) reveals a number of insights into the existing pattern of perceptions. However, the complexity of the figure and excessive amount of data in it make it difficult to focus on critical areas.

The alternative perceptual models, factor analysis and nonmetric scaling, produce simpler perceptual representations. Although the methods of analysis differ, each of these perceptual models identifies cognitive dimensions by structure matrixes that relate them to the 16 fundamental attributes. These structure matrixes are used to identify the cognitive perceptual dimensions.

Figure 2. Map of fundamental attributes ratings for seven shopping locations.

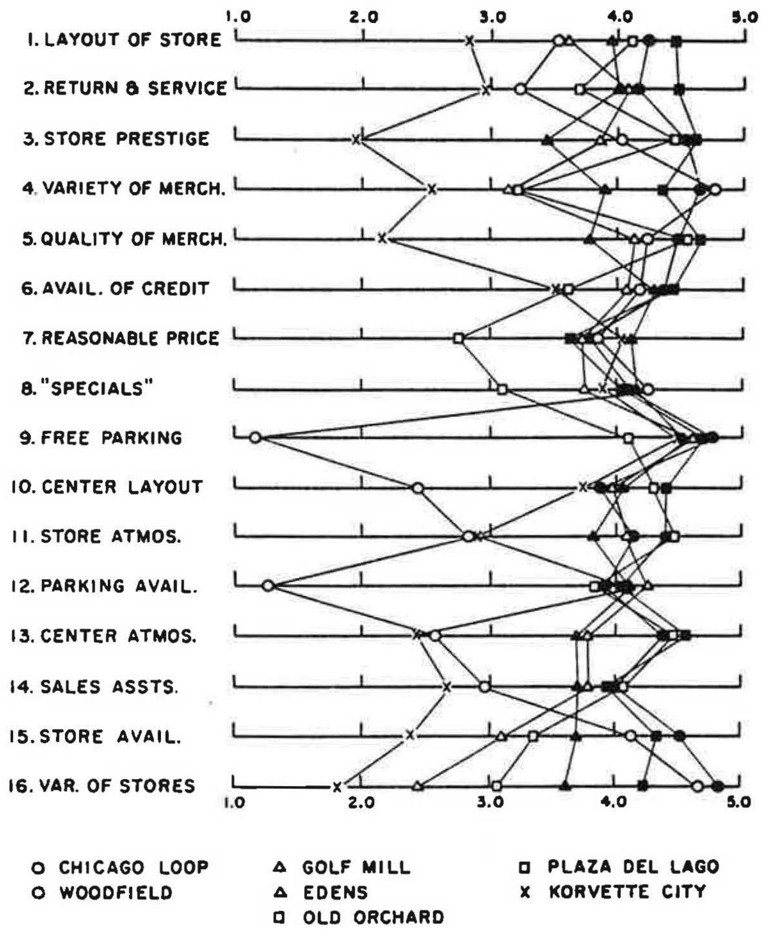


Table 1. Structure matrixes for perceptual models.

Attribute Number	Factor Analysis, Factor Loadings: Variety	Quality and Satisfaction	Value	Parking	Nonmetric Scaling Directional Cosines: Variety	Quality Versus Value	Parking and Satisfaction
1	0.27	0.58	0.16	0.20	0.22	0.50	0.84
2	0.10	0.53	0.34	0.26	0.32	0.12	0.94
3	0.34	0.82	-0.00	-0.06	0.30	0.80	0.52
4	0.67	0.33	0.31	-0.19	0.93	0.36	0.08
5	0.31	0.81	0.04	-0.07	0.30	0.81	-0.51
6	0.16	0.34	0.49	0.05	0.88	-0.09	-0.47
7	0.07	-0.06	0.60	0.11	0.49	-0.85	0.19
8	0.22	0.07	0.74	0.01	0.79	-0.59	0.17
9	-0.15	0.07	0.04	0.81	-0.29	-0.55	0.78
10	0.03	0.31	0.07	0.56	-0.45	0.04	0.89
11	0.08	0.66	0.03	0.40	-0.20	0.45	0.87
12	0.15	0.11	0.11	0.84	-0.46	-0.48	0.75
13	0.24	0.69	0.04	0.40	-0.10	0.48	0.87
14	0.17	0.56	0.15	0.32	-0.05	0.41	0.91
15	0.62	0.32	0.20	0.03	0.87	0.43	-0.24
16	0.83	0.29	0.16	-0.17	0.92	0.39	-0.05

Based on statistical rules and intuitive interpretations, the best results were obtained by using a three-dimensional perception space for nonmetric scaling and a four-dimensional space for factor analysis. The perceptual structures for each model are presented in Table 1.

Both models identify combinations of five basic constructs of variety, quality, satisfaction, value, and parking. These constructs are consistent with earlier studies by Singson (24), Monroe and Guiltinan (25), and Jolson and Spath (26). However, the grouping of these constructs is different between models. Factor analysis groups quality with satisfaction, while nonmetric scaling groups quality versus value and groups parking with satisfaction. The reverse directionality of quality and value in the nonmetric scaling solution undermines interpretability because it is impossible to identify a clear direction of goodness along this scale. The appropriateness of these alternative models will be examined in terms of their predictive abilities.

These models are used to develop perceptual maps of shopping locations based on the underlying cognitive dimensions. These maps are shown in Figure 3. It is immediately apparent that the maps are simpler for managers to interpret, but one can hypothesize that this simplicity comes at a cost of reduced detail. We must compare the predictive ability of these perceptual models with that obtained from the fundamental attributes.

Figure 3. Perceptual maps for models of consumer perceptions.

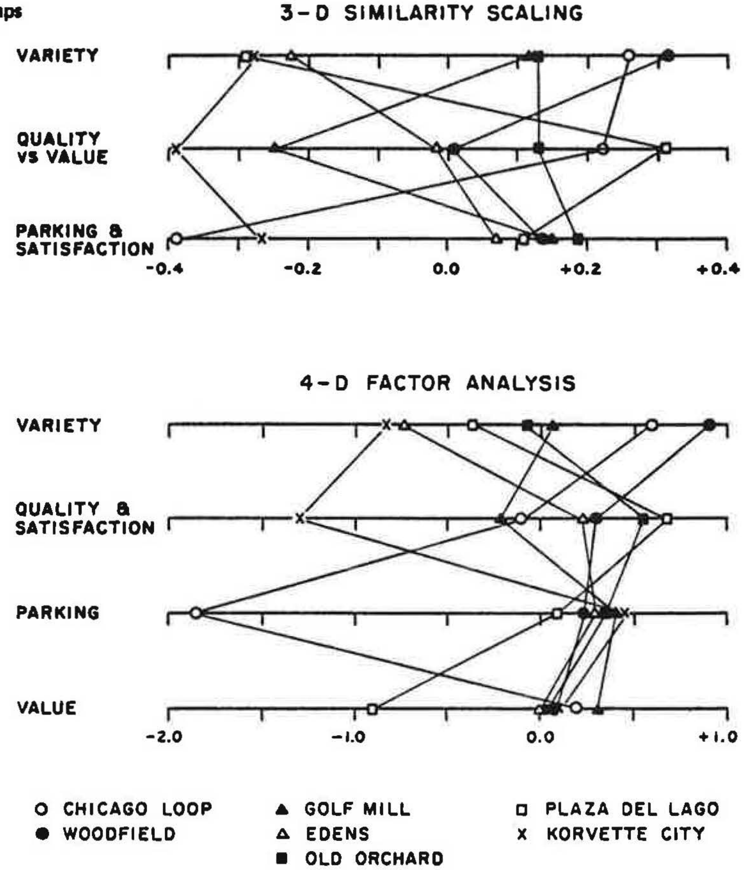


Table 2. Normalized importance weights for reduced models.

	Factor Analysis				Nonmetric Scaling		
Consumer Model	Variety	Quality and Satisfaction	Value	Parking	Variety	Quality Versus Value	Parking and Satisfaction
Preference regression	0.39	0.57	0.03*	0.01*	0.26	0.43	0.31
First preference logit	0.30	0.41	0.23	0.06*	0.26	0.49	0.26
Revealed preference	0.05	0.48	0.29	0.19	0.22	0.76	0.03*

*Not significant at the 5% level.

Preference Models

The normalized importance weights for the various models on the two reduced perception structures are shown in Table 2. The most important dimension for each perception structure includes quality as a component. The importance weights estimated by preference regression and preference logit are similar for each of the perception structures. This robustness of direct preference models is important because it suggests that the choice of perception model is more crucial to the identification of strategically important policies than is the choice of preference model. The similarity of the importance weights between preference regression and preference logit for each perception model is partially retained in the revealed preference model. Quality-related dimensions remain the most important. However, the revealed preference weights differ for the other dimensions. For factor analysis, parking gains in importance at the expense of variety. In nonmetric scaling, quality versus value gains at the expense of parking. These shifts are strategically important as they produce insight into the strength of feeling about the aspects of shopping destinations.

For example, suppose (as will be shown later) that factor analysis is the preferred model for this data set. The increase in parking importance can be explained because it is partially confounded with accessibility. The decrease in variety importance can be explained in this data set by the characteristics of the destinations available to the residents of the North Shore suburbs of Chicago. That is, the two destinations highest in variety are least accessible. Thus, in the revealed preference choice model, variety and accessibility are highly correlated and the relative weights may not be stable. These correlations are reduced in the two-step choice mode.

Other hypotheses for the differences observed can be developed but not tested with the available data (23). The difference in results illustrates the importance of using both a revealed preference choice model and a two-step preference choice model. This use of convergent models is a powerful tool that can lead to insights not obtainable by either model alone. Note that in this case interpretations based on either model alone might miss the interactions between variety and accessibility.

Preference models estimated by using fundamental attributes consistently identify prestige of store, which is closely related to quality, as the most important

Table 3. Prediction tests.

Consumer Model	Preference: First Preference Recovery	Preference: Rank Preference Recovery	Choice: Percent Correctly Predicted	Choice: Information
Base models				
Equally likely	14.3	14.3	14.3	0.0
Market share	26.7	-	18.5	24.7
Distance only	-	-	31.9	32.6
Best fundamental attributes model	55.6	37.9	32.7	39.2
Theoretically best model	-	-	38.7	100.0
Factor analysis				
Preference regression	50.6	32.9	32.7	36.4
First preference logit	55.0	37.0	32.9	37.3
Revealed preference	-	-	32.6	38.5
Nonmetric scaling				
Preference regression	36.6	25.1	31.8	33.5
First preference logit	34.8	24.4	31.8	33.7
Revealed preference	-	-	32.2	34.1

attribute. However, there is a high degree of instability in the estimated values for other importance weights due to multicolinearity. Thus, while there is consistency in preference estimation with reduced perceptual dimensions, there is a high degree of instability in the estimation of preference weights for fundamental attributes (23).

PREDICTIVE ABILITY

This section tests the ability of each model to predict preference and choice on the estimation data sample. Separate predictions on a saved-data sample of 500 observations support the results reported here (23).

Prediction Formation

Individual predictions are made by applying the alternative model structures to each individual's ratings on the fundamental attributes and distance for each shopping location. The prediction process consists of the following sequence of steps.

1. Perception measures are obtained by applying the perception models to the fundamental attribute ratings or individual similarity measures to obtain perception scores for the cognitive dimensions.
2. Perception scores formulated are combined with the estimated or measured importance weights to obtain individual preference (attractiveness) measures for each shopping location.
3. Preference measures are rank ordered to obtain individual preference ranks used in the analysis of preference prediction.
4. Preference and accessibility measures are used in the choice models to predict overall ratings and choice probabilities for each shopping location. These predictions are used in the analysis of choice prediction.

Preference predictions are made with each of the perceptual and preference models, and choice predictions are made with each of the linked choice models. These predictions are compared to a variety of base models that serve as bounds on prediction and help indicate the power of each set of models. The lower bounds include random (equally likely) preference choice in proportion to market share with distance as the only variable. Perfect prediction of choice frequency serves as the upper bound.

For a detailed discussion of these bounds see Hauser (27). Prediction with the best fundamental attributes models identifies the loss in predictive ability, which may result from reduction in cognitive data through faster analysis or nonmetric scaling.

Preference Prediction Results

Preference prediction results for each perceptual and preference model are reported in Table 3. Factor analysis dominates nonmetric scaling with respect to first preference recovery and rank preference recovery. Furthermore, factor analysis does as well as fundamental attributes, indicating that there is no loss in predictive ability due to the simplification of perception structure. Preference logit is slightly superior to preference regression, but the most important differences among models is in the choice of perception model.

Choice Prediction Results

Choice prediction results are presented in Table 3 in terms of percentage of correct predictions and percentage of information explained (27). The model comparisons are the same as for the preference predictions, but the differences are not as great. Revealed preference does better on choice but not significantly better than the two-step preference and choice models.

The overall predictions are quite good. The best model (factor analysis with preference logit) correctly predicts 32.9 percent of the choice occasions as opposed to the 38.7 percent that is theoretically possible in this population.

The goal was to predict frequency of choice for each individual. Since situational variables were not included, the model cannot predict for each choice occasion. Furthermore, the maximum information is quite respectable compared to previous results with similar models. The factor analysis models do well compared to the equally likely and market share proportional models and are almost as good as the fundamental attributes model.

Of the perceptual models tested, factor analysis is the superior predictive model for both preference and choice. It does as well as the fundamental attributes but provides important simplification of the perceptual process. Thus for this data set it appears that factor analysis is most representative of the consumers' cognitive process. It is interesting to note that these results have since been replicated on another data set (28).

The differences among the preference models are less dramatic. This further supports the observation that the preference models are relatively robust and that the selection of preference model is less crucial than the selection of perceptual model. The predictive similarity of revealed preference and two-step preference and choice models supports the conjecture that the use of these models in parallel is an important managerial tool.

CONCLUSIONS

The focus of this research is on the behavioral modeling of destination choice. The models developed use state-of-the-art techniques in marketing and transportation to provide strategic, policy-sensitive models for the explanation and prediction of destination choice behavior for non-grocery-shopping trips. The products of this research are a behavioral model of destination choice and an identification of the most accurate and useful techniques to analyze destination choice behavior.

Behavioral Model of Destination Choice

The interpretations and insight about consumer behavior come from the combined analysis. This process of convergent analysis provides insights that might not be obtained from a single model structure. In summarizing these results we look for consistent results when the models converge and "best model" results when they diverge. The primary results are that

1. Attractiveness can be measured with combined perceptual and preference models, and this measure predicts well and provides useful insight into consumer behavior;
2. Five basic constructs best measured by the factor analysis perceptual model describe shopping destination attractiveness: variety, quality, satisfaction, value, and parking;
3. Quality is consistently the most important construct of shopping destination attractiveness, and prestige of store appears to be the most important aspect of quality; and
4. Both attractiveness and accessibility are important determinants of travel behavior, and any destination choice model should contain good measures of both.

Comparison of Model Structures

A number of alternative techniques are tested to select the best models for the analysis of destination choice. The results suggest that factor analysis is the best perceptual model for identifying a concise set of dimensions to describe the consumers' cognitive process and that the statistical preference models (first preference logit and preference regression) are reasonably robust in providing consistent predictions and similar interpretations.

Based on these results but subject to confirmation in other empirical studies, we recommend that statistical analyses of consumer destination choice be based on factor analysis to identify perception, preference regression or first-preference logit or both to identify importance weights, and convergent analysis with revealed preference and two-step preference and choice models to analyze choice behavior.

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Trip Distribution in Subregional Analysis

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The paper describes the formulation and calibration of the access and land development trip distribution gravity model (ALDGRAV) for use in highway planning at a subregional level. The model is being used as an element of the thoroughfare analysis process (TAP), which, in turn, is one module of the thoroughfare planning system (TPS). TPS has been developed by the North Central Texas Council of Governments, in close cooperation with the local governments, to answer present planning needs, in particular to provide tools for orderly, inexpensive, and fast response evaluation of small- and medium-scale strategies. TAP provides the analysis capabilities of the system. The paper introduces the hierarchy of objectives, design requirements, and the resulting design decisions of TPS, TAP, and the ALDGRAV trip distribution model. A detailed description of the latter is given.

The North Central Texas Council of Governments (NCTCOG), together with the participating local governments, has developed the thoroughfare planning system (TPS). The system is designed to answer many of the recent needs in the field that have arisen primarily from shifting stress from large-scale, capital-intensive projects to subregional projects. Major objectives of TPS include providing tools for the planning of the principal and minor arterial network that supports the freeway system in the region and tools for evaluating projects such as the annual capital improvement programs of individual communities, on a local scale, and providing support, cost effectively, for the analysis of small- and medium-scale projects within the framework of the regional thoroughfare plan.

TPS is described in detail elsewhere (1). Its major elements include: (a) an approved regional thoroughfare plan complete with design standards, (b) a base inventory of the thoroughfare system with procedures for continuous updates, (c) a thoroughfare information system (TIS) that facilitates the storage and easy access of both inventory data and analysis results, (d) a thoroughfare analysis process (TAP) to evaluate the impact of alternative strategies, and (e) a methodology for evaluating transportation system management (TSM) strategies.

THOROUGHFARE ANALYSIS PROCESS

TAP is the travel simulation component of the TPS and has the following specific design requirements. It must be able to analyze a wide range of potential strategies, such as the effect of land-use changes (e.g., a new shopping center), the effect of major TSM strategies, and small- and medium-scale capital projects, and it should develop and maintain the regional long-range plan and analyze small-scale problems quickly and inexpensively. The structure of TAP is described in Figure 1. Its logic closely follows that of the conventional urban transportation planning system. Major innovations in the system include windowing and streamlined processing.

Windowing means that by using computerized procedures subfiles for analysis are built from base data files that describe the zones and networks of the region in much detail. Typically, these subfiles include detailed presentation for the area of interest; the level of detail decreases gradually with distance from the area of interest. Different subfiles are built for practically every analysis.

In streamlined processing, through both the selection of models and the use of computerized procedures, it is possible to go through the whole analysis process for one alternative in one or two computer jobs. At the same