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This paper examines the role that conceptual models of consumer behavior can play in a marketing audit. Research employing a model of consumer decision making (an expanded version of a normative model developed by Hauser and Urban), to assess the market position of a public transportation system, is reported. Use of this model to design and select strategy and to reassess market position after strategy implementation also is illustrated. The advantages and limitations of this approach to decision making are discussed.

A MARKETING AUDIT USING A CONCEPTUAL MODEL OF CONSUMER BEHAVIOR: APPLICATION AND EVALUATION

MANAGERS frequently employ conceptual models of consumer behavior when assessing the market for new products or when developing advertising programs. We believe that such models also can play an important role in marketing audits for established products and services (Kotler 1980, 650–657). These models provide a framework for collecting and integrating information about a firm's market position at a particular point in time. And they assist managers in designing, selecting, and evaluating strategies to modify that position.

This paper examines the contribution that models of consumer behavior can make when conducting a marketing audit for a mature product. We selected a model well suited to the objectives of a marketing audit, and one that is an expanded version of Hauser and Urban's (1977) formulation. First, the model's conceptual framework is summarized and its appro-

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Journal of Marketing
Vol. 45 (Summer 1981), 82–101.

priateness for a marketing audit discussed. Then the model is applied in an analysis of the market position of a transportation system. It also is used to develop and assess strategies for modifying that position. Finally, the application of the model is critically evaluated and its role as an ongoing research tool is discussed.

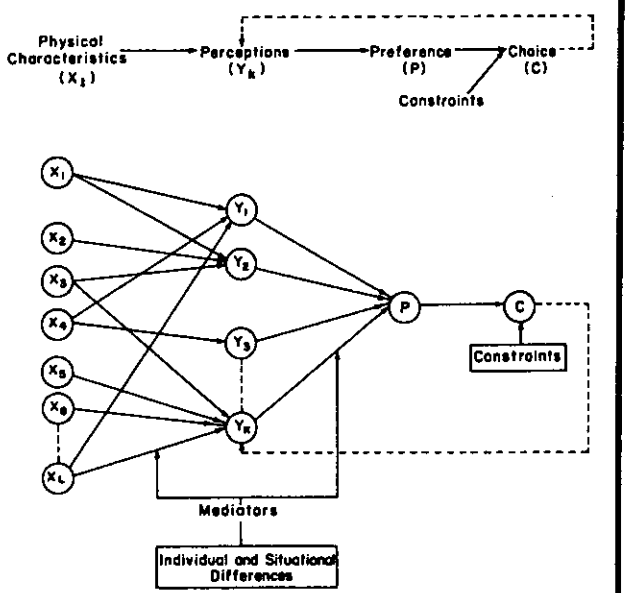
The Consumer Model

The consumer model is depicted in Figure 1. This model is similar to choice models proposed and applied by other marketing researchers (e.g., Green and Wind 1973, Pessemier 1977, Shocker and Srinivasan 1979). In this section the components of the model are briefly outlined. The reader is directed to the references for a more exhaustive elaboration of the underlying theory and tests of this theoretical position. The specific measures and analyses used to operationalize the conceptual model are described in the application section of this paper.

The model begins with physical characteristics or factors observable in the environment. The relationship between these characteristics and subjective evaluations or perceptions can be viewed in terms of Brunswik's lens model (1952). According to this perspective, physical cues in the environment (X_i in Figure 1), such as travel time, are abstracted to form the basis for consumers' perceptions (Y_k), say, about quickness.[1] A physical cue need not lead to a unique perception; it may contribute to several perceptions in different ways. Travel time may be negatively correlated with perceptions of quickness but positively correlated with perceptions of safety. Moreover, any single physical characteristic is likely to be an imperfect indicator of a particular perception. Multiple cues must be integrated, and mediating variables (individual and situational differences) must be considered in determining perceptions.

In the above discussion, the abstraction process is illustrated in terms of a physical attribute of an object, travel time. However, perceptions about a focal object also may be inferred from other environmental factors, such as its representation in advertisements or others' reactions to it (Fishbein 1967). Thus, the observation (either through media or directly) that admired others consume a product may contribute to perceptions of desirability and status for that product. The impact of factors beyond physical characteristics of the object on object perceptions may be difficult to quantify because

FIGURE 1
An Integrated Model of Consumer Choice



there are a large number of these cues and they vary at the individual level. Yet, the importance of these cues in forming perceptions, particularly for image laden products (e.g., soft drinks, analgesics, beer), cannot be denied. A first step in incorporating these factors in a marketing audit is to measure perceptions of factors beyond object attributes. To the extent that these factors are important determinants of preference, it may be necessary to conduct further research to understand the roots of these perceptions. Research testing the link between physical characteristics and perceptions is represented by Green and DeSarbo (1978), Hammond (1972), Hauser and Simmie (1981), Levin and Corry (1977), and Neslin (1978).

The relationship between individuals' perceptions and preferences depicted in Figure 1 is consistent with psychological models of utility and intention (Fishbein 1972, Rosenberg 1956). Preferences are viewed as the aggregation or combination of perceptions. The specific perceptions employed are ones that are salient to the individual in a given context. Although theoretically, different attributes may be salient for each individual in each situation, practically speaking individuals in similar situations often report similar attributes as salient.

The aggregation process may be represented by a variety of functional forms including linear, conjunctive, disjunctive, and lexicographic models. The

[1]By perception, we refer to a subjective dimension, such as quickness, as opposed to a subjective belief about a physical characteristic, such as perceived travel time.

appropriateness of these representations varies across individuals and contexts. (See Einhorn 1971, Shugan 1980, Wright 1972, 1975, for details.) For example, when an individual must form an evaluation of a multifaceted object under great time pressure and risk, he/she may employ a cognitively simple, conservative model such as the conjunctive model (Wright 1972, 1975). Although the aggregation process may take a variety of forms, linear models generally provide a good approximation of the process when the number of perceptions is small and the perceptions are monotonically related to preference (Dawes and Corrigan 1974). Such a linear approximation, which later can be modified, is useful in a marketing audit. Fishbein and Ajzen (1975, p. 224–228) summarize a number of tests of this theoretical linkage.

In turn, preferences are mediated by unforeseen environmental factors and constraints in determining choice (e.g., availability of an object, Wicker 1971). The choice experience is considered to feed back, producing new and/or altered perceptions. This view of the impact of choice on perceptions is consistent with psychological perspectives such as information processing (Norman 1976) and self-perception (Bem 1972) and with management science concepts of trial and repeat (Urban 1975). All situational and individual differences not directly represented in the model are considered to mediate the aggregation and abstraction processes (Fishbein 1972).

The model of consumer choice depicted in Figure 1 extends Hauser and Urban's (1977) formulation in two important ways. First, it highlights the distinction between physical characteristics and perceptions and maps their interrelationship. This conceptualization is useful strategically in that it indicates how physical attributes that are under managerial control affect consumers' perceptions that guide preference and choice. In addition, the model explicitly acknowledges the importance of perceptions based on environmental factors other than the products' physical characteristics. As a result, it affords the manager detailed diagnostic information on the market of interest, and it suggests a broad range of managerial strategies for affecting consumer choice. Choice may be influenced by varying physical characteristics of a product, perceptions of product characteristics and perceptions of environmental factors associated with the product, and the relative importance of perceptions in determining preference.

In contrast to the approach in Figure 1, models that consider consumer choice to be a function either of physical characteristics or perceptions, or a combination of the two, have limitations for a marketing audit. Models that base choice solely on physical characteristics may exclude a consideration of communication strategies as a means of influencing choice by modifying perceptions directly. Models that view choice solely as a function of perceptions provide little guidance as to which physical product characteristics should be emphasized in communications or considered for followup research on product design. Models that simultaneously employ both physical characteristics and perceptions as predictors of choice are subject to problems of interpretation. To the extent that perceptions are abstractions of physical characteristics, problems of multi-collinearity will make it impossible to unravel the determinants of choice. Further, physical product modification strategies to alter perceptions are obscured. Thus we believe the approach depicted in Figure 1, whereby physical characteristics determine perceptions, perceptions determine preferences, and preferences, in combination with constraints determine choice, provides managers with greater diagnostic information for a marketing audit. While we have chosen the expanded Hauser-Urban model to represent this approach, other similar models of consumer behavior also might be employed in marketing audits (see Shocker and Srinivasan 1979 for a critical review of eight such models including the Hauser-Urban model).

Model Implementation

Perspective of the Approach

In a marketing audit, the manager's goals are to understand the marketing system, to identify any short run actions that can increase profitability (or corresponding social goals), and to identify any long run actions that are worth further consideration and analysis. These goals suggest the manager begin by measuring the variables in Figure 1 and determining their interrelationships. To estimate the relationships in Figure 1 and to examine potential bases of segmentation, these variables must be assessed for a variety of competitive products using a large representative sample of consumers. A field survey provides a cost efficient method of collecting such data. Further, the nature of the task (i.e., trying to reach a broad cross section of the population with a lengthy survey employing many scaled questions) may make a mail survey preferable to a telephone survey or personal interview.

The use of a field survey represents a managerial tradeoff that puts a high premium on initial mea-

surement of important variables and their quantitative relationships. Use of a cross-sectional survey to study perceptions, preferences, and choice, identifies correlation but not causality. The feedback loop (dotted line in Figure 1) is not explicitly studied at this stage. Once the forward linkage is understood, the manager may wish to undertake further dynamic analyses to analyze the feedback loop. For example, a marketing audit might identify advertising strategies to improve a product's position in the market, which in turn affects choice. Such predictions are relevant for trial behavior. Repeat purchases depend upon how consumers perceive the product after they try it. Thus the manager may use a new advertising strategy based on the marketing audit and on his/her judgment that the product fulfills its claims. However, he/she must recognize that the audit cannot explicitly model repeat purchase behavior without additional data such as that collected with conjoint analysis, laboratory measures, or product tests.

Application of the Model in a Marketing Audit

In this section, the application of the expanded Hauser-Urban model is illustrated through its use in a marketing audit of a transportation service. This research extends previous work, summarized in Hauser, Tybout, and Koppelman (1981) in several ways. Most importantly, it provides a detailed, rigorous evaluation of the model's strategy predictions, includes tests of the necessary conditions underlying the conceptual model, and incorporates concept descriptions in the analysis. Finally, it employs a different data base than earlier research using the model. As a result the generalizability of the model can be examined, though across a limited set of applications.

For purposes of this application, a specific set of measurement instruments and statistical techniques have been chosen. While other techniques could be employed, we feel our selection is well suited to the needs of the manager who has just begun to analyze his/her marketing environment. The audit reported is viewed as the initial step in an ongoing relationship between the researcher and manager.

Managerial Problem

The product line that was analyzed using the consumer response model was transportation services available within the city of Evanston, Illinois. The research was funded by the City Manager's Office and the U.S. Department of Transportation.

Evanston is a northern suburb of Chicago and has a population of approximately 80,000. The Evanston public transportation includes a rapid transit system serving Evanston and connecting with the Chicago transit system, access to a commuter railroad, extensive local bus service, and bus service to neighboring suburbs. In addition, many consumers choose to drive or walk to get around Evanston and to commute to work or school. The specific managerial purpose of the model's application was to conduct a marketing audit to:

- assess consumers' perceptions, preference, and choice of each mode of transportation and understand their interrelationship;
- identify potential strategies for modifying service in a manner consistent with both consumer needs and city goals of reducing congestion, pollution, and energy consumption;
- forecast the initial effect of strategy changes on consumer behavior so that the impact can be weighted against costs and city goals; and
- evaluate the model's role and effectiveness in decision making.

Measurement

The set of measurements for the marketing audit are described in Table 1. A short mail survey of

TABLE 1
Summary of Data Collection

Needed Information	Methodology
(1) Market shares Usage situations	Short Mail Survey (455)* [November 1975]
(2) Attribute identification Physical characteristic identification Qualitative issues	Focus groups and Archival Literature [August 1977]
(3) Quantification of: Perceived physical characteristics Perceptual dimensions Feelings Preference Choice constraints Behavior	Three 16-page Mail Surveys: (i) General Travel (950) (ii) Downtown Travel (1900) (iii) Work Travel (1900) [January 1977]

*Numbers in parentheses indicate sample sizes for the mail surveys.

445 households was done to determine the modes used and their physical characteristics for various types of trips (e.g., shopping, work). This usage audit identified the competing modes of travel considered, and it suggested that consumers have different usage patterns for work trips, downtown-oriented trips, and general purpose trips. The differences were sufficient to warrant separate surveys for each type of trip.

Next, focus group interviews and a literature review of previous studies were conducted to develop an exhaustive list of attributes consumers use to evaluate the modes. On the basis of pretest results, this list of attributes was reduced to a manageable set of distinct attributes (21–25 per mode) that were significantly related to mode preference and choice.

Finally, the three 16-page surveys were mailed to a total of 4750 households, as indicated in Table 1. In this paper, to facilitate exposition subsequent discussions focus only on the general travel destinations questionnaire. (General travel destinations account for 52% of the trips within Evanston.) For details on downtown destinations, see Hauser, Tybout, and Koppelman (1981), and for details on work destinations see Koppelman and Lyon (1981).

Transportation service fulfills many purposes. Ideally, each consumer would describe the service he/she perceives for each usage situation. Unfortunately, the length of such a survey would be prohibitive. Instead, a random sampling of usage situations can be achieved by having consumers report characteristics, express perceptions, feelings and preferences, and report constraints and choice for their most recent trip. This method was employed in our survey and, to the extent that behavior patterns observed matched reported behavior frequency, it appears that a representative sample of usage situations was obtained.

Specifically, each component of the consumer model was measured in the following way where each respondent provided all this information with reference to his/her most recent trip.

Physical Characteristics. Respondents gave estimates of travel time, broken down by access, wait, and on-vehicle time; distance to the nearest bus stop; and mode cost. They also provided data that was used to compute auto availability (i.e., they reported the number of autos and drivers in their household). The tradeoff of using self-reported physical characteristics was necessary for cost considerations. In transportation, detailed measurement of actual physical characteristics is expensive and did not appear justified to the manager for the first stage of a marketing audit.

However, a class of graduate students conducted a separate study comparing individuals' estimates of travel time and costs to actual levels of these variables (i.e., they clocked bus travel time for a subsample of trips, origin-destination links, that respondents actually reported). In general, they found respondents provided accurate estimates of these variables. This suggests that respondents' self-reports may be reasonable approximations of these variables in this case.

Perceptions. Two types of perceptions were measured: those directly related to physical attributes of modes and those related to more abstract modal cues and other cues in the environment (i.e., advertising, opinions of others). For convenience, the former will be referred to as mode perceptions and the latter as mode feelings.

Input for determining mode perceptions was obtained by having respondents evaluate each of the three frequently used modes (car, bus, walk) on 21–25 attribute statements using a 5-point strongly agree to strongly disagree Likert scale.[2] These attribute ratings were first standardized across scales and stimuli by individuals to minimize halo effects, and then factor analyzed across individuals and stimuli to uncover the fundamental perceptual dimensions. Factor analysis was selected on the basis of evidence for its theoretical and empirical superiority over discriminant analysis and similarity scaling (see Hauser and Koppelman 1979). A three-dimensional solution was selected on the basis of scree rules, eigenvalue rules, and managerial interpretation.[3] Factor loadings appear in Table 2.

The perceptual dimensions were labeled Quickness and Convenience, Ease of Travel, and Psychological Comfort. Quickness and Convenience reflects the ability of a mode of travel to provide on-time service that gets consumers to their destinations quickly with no long wait, service that is available when needed, and service that allows the consumer to come and go as he/she wishes.

[2]Perceptions and preference for bike were also obtained for this data set because bike is a potential mode for trips around Evanston. Space constraints prohibited collecting feelings data for this mode, and the usage audit did not identify bike as a significant mode. Therefore, bike perceptions and preference data are included in Figure 2 but are not discussed further.

[3]The scree test plots incremental variance explained by each factor vs. order in which that factor is extracted. Factors are retained up to the point where incremental contribution levels off (see Urban and Hauser 1980, p. 202). The three factor solution for the perception data explains 33% of the variance. The three factor solution for the feelings data explains 23% of the variation. While these solutions may seem low, further analyses, which were performed on four- and five-factor solutions, indicated that little or no information was lost in the preference and choice models when the more parsimonious three factor solutions were used.

TABLE 2*
Perceptual Analysis: Tables of Factor Loadings Relating Attribute and Perceptual Dimension

Attribute	Quickness and Convenience	Ease of Travel	Psychological Comfort
Use to be on time	.50	.34	−.03
No trip scheduling necessary	.36	.09	−.02
Relaxing	.36	.15	.41
Correct temperature	.06	.41	.15
No worry of assault	.02	.33	.36
Can come and go as I wish	.70	.10	.10
Errands take little time	.52	.51	−.12
No worry about injury	−.11	.19	.50
Know how to get around	.46	.13	.13
Little effort involved	.31	.49	.16
Available when needed	.64	−.01	.12
Not made uncomfortable	.17	−.01	.57
No problems in bad weather	−.04	.52	.12
Pleasant drivers	.09	.15	.32
Get to destination quickly	.56	.50	−.01
Protected from smoking	.39	−.09	.24
Safe at night	−.02	.54	.32
Not annoyed by others	.09	.03	.60
No long waits	.70	−.01	.09
Easily carry packages	.16	.63	.05
Easy travel with small children	.09	.52	.01
Not tiring	.24	.57	.22
Easy getting in and out	.28	.13	.20
Easy walk access	.22	.12	.22

a) Attribute measures

Attribute	Bus Feelings	Walk Feelings	Car Feelings
Different from bus riders	−.31	.06	−.10
Enjoy travel by car	−.06	−.15	.52
Enjoy travel by bus	.69	.01	.24
Enjoy travel by foot	−.02	.73	−.05
Depressing to travel by car	−.01	.03	−.78
Depressing to travel by bus	−.53	−.01	−.48
Depressing to travel by foot	−.08	−.56	−.29
Peers surprised if ride bus regularly	−.62	−.02	.07
Ought to travel by car	−.15	−.26	.44
Ought to travel by bus	.56	.01	−.02
Ought to travel by foot	.10	.58	−.26
Peers surprised if drove car regularly	.28	.04	−.14
If weather bad, fewer car trips	.06	−.05	.11
If weather bad, fewer bus trips	−.30	−.22	−.06
If weather bad, fewer walk trips	.05	−.21	.07
If gasoline price doubled, more car trips	−.13	−.02	.06
If gasoline price doubled, more walk trips	−.04	.43	−.09
If gasoline price doubled, more car pool trips	.03	.08	.04
If gasoline price doubled, fewer car trips alone	−.03	−.03	.17
Peers surprised if walked a lot	−.03	−.60	.22
If bus fares lower, more trips by bus	.11	−.04	.03
If bus fares lower, fewer trips by bus	.13	.06	.01
If bus ran more often, more bus trips	.24	−.01	−.06
Would travel by car regardless of cost	−.30	−.20	.27
Would travel by bus even if long walk	.52	.09	−.06
If parking cost doubled would walk	.07	.43	−.13
Willing to car pool some trips	−.04	.03	−.04

b) Feelings measures

*Scale ratings have been standardized by individuals to remove scale bias and reduce halo effects.

Ease of Travel includes correct temperature, no problems in bad weather, little effort needed, not tiring, easily carry packages, or travel with children, as well as safe at night. Psychological Comfort includes attributes such as relaxing, no worry of assault or injury, and not made uncomfortable or annoyed by others.

Respondents also provided data for determining mode feelings. They responded to statements (6–9 per mode) regarding their liking, obligation to use, commitment to use, and perception of significant others' responses to their use of each mode on a 5-point Likert scale from strongly agree to strongly disagree. These ratings were standardized and factor analyzed in the same manner as mode perceptions. This factor analysis produced three dimensions, each representing a mode bias for one of the three frequently used modes—auto, bus, and walk. The factor loadings on the underlying dimensions appear in Table 2 (see footnote 3).

Preference and Choice. Respondents rank ordered the modes in terms of preference for trips like their most recent trip. They also indicated the mode actually chosen.

Consumer and Situational Difference. Participants responded to a battery of demographic questions (e.g., age, income, education) and described characteristics of their most recent general travel destination trip.

In addition to evaluating the three existing modes, participants were presented with two concept statements for hypothetical modes, personal-

ized premium service (PPS), and a public oriented dial-a-ride system and budget taxi plan (BTP), a shared-ride system operated by a private taxi company. These were included to assess the potential market position of new transportation alternatives and to assist management in estimating the impact of potential strategies. After reading the descriptions, consumers were asked to provide data on their perceptions and preference for these modes. The concept statements used appear in Table 3.

Sample

38% of the households returned the general travel questionnaire. Comparison of these respondents with respondents in hand-delivered pretests (where the response rate was approximately 80%) revealed no systematic nonresponse bias. Further evidence for the representativeness of the sample was obtained by comparing the demographic characteristics (age, sex, marital status, education, occupation, income, etc.) of the respondents in 1970 census data for the community as a whole. Overall, the sample conformed to the community profile, although there was a slight upward bias in income and education, and a downward bias in age. The differences in income and education are probably attributable to shifts in the population on these dimensions since the census. The difference in age distribution may be attributable to older persons having greater difficulty completing the questionnaire. Segmentation on age can test and, if necessary, allow for some correction of this bias. (As shown later, these tests suggested no variation in structure or parameters across age groups.) Nonetheless, the manager is cautioned to consider that there are 62% nonreturns.

Analysis

Analysis entailed first examining the abstraction, aggregation, and choice process for the total sample. Then, the effect of various subgroups as bases of segmentation on these processes was assessed. If no basis for segmentation is identified, the total sample analyses are used for managerial diagnostics. If not, the subgroup analyses are used. For ease of exposition only the analyses on the total sample are reported in detail.

For the remainder of this subsection the technical analysis is briefly described. The outputs leading to managerial diagnostics are discussed in the next subsection.

Abstraction (Physical Characteristics → Perceptions). To gain insight into the abstraction process, mode performance on physical characteristics and perceptual dimensions was determined, and the

TABLE 3
Description of Concept Modes

Personalized Premium Service

The City of Evanston introduces a new public transportation service for you and your family. A new fleet of air conditioned minibuses takes you where you wish to go in Evanston when you want to travel.

Suppose you want to travel from your home to a destination within Evanston. Rather than waiting on the corner for the next bus, you can simply call a special number and request service. You are asked where you are calling from and where you wish to go. Then the dispatcher immediately locates the nearest minibus and informs you of the approximate time that the vehicle will arrive. (Usually within the next 20 minutes.)

You wait in the comfort of your home for the minibus to arrive at your door. Once on the bus you are taken to the destination you request. The bus may stop along the way to pick up or drop off 1 or 2 other passengers but the total trip will not take you more than a few minutes out of your way.

Some of the features of this new service are:

1. Package racks in every vehicle.
2. Direct line, no-charge phones at convenient locations throughout Evanston.
3. Special entrances on selected vehicles for people who have difficulty getting on and off regular buses.

PERSONALIZED PREMIUM SERVICE is designed to serve you. The one-way fare is 75¢ for one person, but only 25¢ for each additional friend or family member making the same trip. Service is available 8:30 A.M. to 6:00 P.M. weekdays and Saturdays, and 10:00 A.M. to 6:00 P.M. Sundays.

Budget Taxi Plan

The Red and White Taxi Company has an established reputation for providing prompt, courteous taxi service in Evanston. Conventional taxi service is available by calling Red and White. A taxi usually picks you up within a few minutes of your call.

Now the Red and White Cab Company introduces a new form of taxi service in addition to the existing service to provide you with personalized transportation services at reduced prices.

This new service, called the Budget Taxi Plan, provides similar service at a lower price. Under the budget plan you will still request service by phone and you will still be picked up at your door. The only change is that if you request the budget plan, the driver may pick up or drop off other passengers on the way to your destination.

Taxi fares usually range between 75¢ and $2.50 for trips between the downtown area and other parts of the city. Under the BUDGET TAXI PLAN you pay a fixed fare ranging from 50¢ to $1.50, depending on the length of the trip. These fares generally result in savings of one-third to one-half the regular taxi fare. This service will be available from 8 A.M. to 10 P.M., seven days a week.

TABLE 4
Correlation Matrix

	Physical System Characteristics			Perceptions			Feelings			Constraints	
	TT	BLOCK	COST	Q/C	ET	PC	BF	WF	CF	APD	P
Travel Time (TT)											
Blocks to Bus Stop	•										
Cost	.08	•									
Quickness/Convenience	•	−.14	.10								
Ease of Travel	−.14	•	−.41	•							
Psychological Comfort	•	.21	.20	•	•						
Bus Feelings	•	•	.16	.37	.48	.47					
Walk Feelings	•	—	.28	.52	.48	.14	—				
Car Feelings	•	—	•	.28	.23	.31	—	—			
Auto per Driver (APD)	•	—	•	.12	•	•	—	—	•		
Preference	•	•	−.40	.40	.32	•	•	.36	.38	•	
Choice	•	•	−.50	.36	.35	•	.23	.19	.25	.21	.68

*Starred correlations are *not* significant at the .05 level.
—Indicates that the correlation is not defined.

relationship between these variables was examined.

The physical characteristics measured were travel time by each mode, number of blocks to the nearest bus stop, and cost of each mode. The perceptual dimensions were measured by the factor scores of quickness and convenience, ease of use, psychological comfort, and the three mode feelings.

The correlations between physical characteristics and perceptions were examined to help understand the abstraction process (see Table 4). Perceptions of mode quickness and convenience are negatively correlated with distance to the nearest bus stop and positively correlated with mode cost. In contrast, perceptions of ease of travel are negatively correlated with mode travel time and mode cost. Finally, perceptions of psychological comfort are positively correlated with distance to the nearest bus stop and mode cost.

These correlations are suggestive of the bases for perceptions. They are not, however, exhaustive or causal. Physical characteristics excluded in this research because they did not provide variation at the individual level in the natural environment (i.e., ability to control temperature) also may contribute to perceptions. Further, the relationships described between physical characteristics and perceptions may or may not be causal, i.e., it may be that mode cost is used directly to infer ease of travel, or it may be that cost and ease of travel are both a function of some other variable(s), say, accessibility to mode and physical barriers between mode user and others. In the marketing audit, the purpose of the correlation matrix is to give the manager insight into what relationships should be considered. For example, the correlations in Table 4 between the physical characteristics and the perceptions are significant, but small (.10 to .21). This can be the result of nonmeasured characteristics affecting perceptions, nonlinear relationships, heterogeneity, or error. Once perceptions important in determining preference and choice are known, followup studies with conjoint analysis, decision calculus, experiments, or econometrics can be conducted to quantify precisely the impact of major modifications in the physical characteristics of the transportation system.[4] To identify these significant perceptions we examine the aggregation process.

Aggregation (Perceptions → Preference). Operationalization of the aggregation component of the conceptual model involves modeling the relationship between perceptions and preference. Then, perceptions for two hypothetical modes are measured. This analysis enables managers to determine the relative importance of perceptions in forming preferences, thereby allowing evaluation of strategies altering preferences for existing alternatives by changing perceptions of them, and strategies involving the introduction of new alternatives.

A decompositional approach to understanding the aggregation process was employed. Multinomial logit (McFadden 1973, 1980) was used to derive

[4]We only examined the abstraction process for mode perceptions, not mode feelings, because many physical characteristics of the modes themselves should be related to the former but not the latter (an assumption that is borne out by the nonsignificant correlations between mode feelings and the physical characteristics other than cost). Mode feelings are considered to be abstractions of a wide range of environmental cues beyond physical characteristics of the object, and it was not feasible to include measures of these in our questionnaire. However, under other circumstances, it is in theory possible to measure these effects.

preference functions in which a consumer's first preference was the dependent variable, and factor scores for the perceptual dimensions (mode perceptions and mode feelings) were the explanatory variables.[5] The model is shown below.

$$\text{Prob}[i \text{ prefers } j] = e^{p_{ij}} \Big/ \sum_m e^{p_{im}} \qquad (1)$$

$$p_{ij} = \sum_{k=1}^{3} w_k y_{ijk} + v_j y'_{ij}$$

where p_{ij} = consumer i's preference for mode j (not directly observed)

y_{ijk} = consumer i's evaluation of mode j on perceptual dimension k (factor score)

y'_{ij} = consumer i's feeling with respect to mode j (factor score)

w_k = importance weight for the k^{th} dimension (to be estimated)

v_j = importance weight for the feeling with respect to mode j (to be estimated).

The unknown parameters (w_k,v_j's) are estimated with maximum-likelihood computer programs where the analysis is run across individuals because there are inadequate degrees of freedom at the individual level.[6] Alternative specific constants (McFadden 1973, 1980) are included to obtain consistent estimates for the importance weights.

Across-individual analysis identifies representative importance weights that are useful for visualizing population behavior.[7] These are tested for potential segmentation as discussed later and, in some cases, followup research can collect additional data on product profiles for individual level conjoint analyses (see footnote 5).

The estimated preference models appear in Table 5. The relative weights in these models have been normalized so that they sum to 100%. The goodness of fit statistics that are reported are the percent of first preferences correctly predicted, the percent of total uncertainty explained (Hauser 1978b), and a chi-squared statistic based on the likelihood ratio.

TABLE 5
Preference Analysis

Variable Name	Relative Importance Weights Model 1	Model 2†	Model 3
Quickness and convenience	.48	.22 [.53]	.26 [.53]
Ease of travel	.31	.12 [.28]	.15 [.31]
Psychological comfort	.21	.08 [.19]	.08 [.16]
Bus feelings		−.20*	
Walk feelings		.24	.32
Car feelings		.14	.19
Percent correctly predicted	79.2	80.2	80.2
Information	56.7	61.5	61.3
χ^2-Statistic	290.0	314.7	313.6

χ^2 (model 2 vs. model 1) = 24.7 d.f. = 3 $p < .05$
χ^2 (model 3 vs. model 2) = 1.1 d.f. = 1 $p > .05$

*Starred coefficients are *not* significant at the .05 level.
†The numbers in brackets represent the importance of the evaluative dimensions normalized to add to 1.0.

Model 1 uses only mode perceptions. It does well, explaining 57% of the uncertainty and predicting 80% of the first preferences correctly. This is significantly better (.05 level) than naive models that base predictions on chance (0% uncertainty explained, 25% correct prediction), or market shares (39% uncertainty explained, 58% correct prediction).

Model 2 adds mode feelings to the set of explanatory variables. This new model explains significantly greater (.05 level) uncertainty than Model 1. This finding has two implications. It suggests that factors beyond traditional mode attributes may influence perceptions and thereby encourages inclusion of such factors (the status and image of various modes, etc.) in efforts to model consumer choice.[8] The weight of these variables on the prefer-

[5]Compositional approaches are possible (Fishbein 1972), but these would have required an additional survey once perceptual dimensions were identified. A variety of statistical models other than the one chosen, including monotonic regression (Johnson 1975), preference regression (Urban 1975), LINMAP (Srinivasan and Shocker 1973) and PREFMAP (Carroll and Chang 1967, also summarized in Urban and Hauser 1980, p. 245) are consistent with the decomposition approach. Logit analysis was selected on the bases of previous comparative studies (Hauser and Koppelman 1979; Hauser and Urban 1979; Jain, Acito, Malhotra and Mahajan 1979).

[6]For each individual we observe an indicator variable, δ_{ij}, which equals 1 if and only if individual i prefers mode j. Because we predict probabilities while observing events, this is a maximum likelihood problem. See McFadden 1973, 1980.

[7]Logit coefficients are parameters characterizing the distribution of consumer preferences. They do not represent an assumption of complete homogeneity in preferences. See discussion in McFadden 1973, p. 105; 1980.

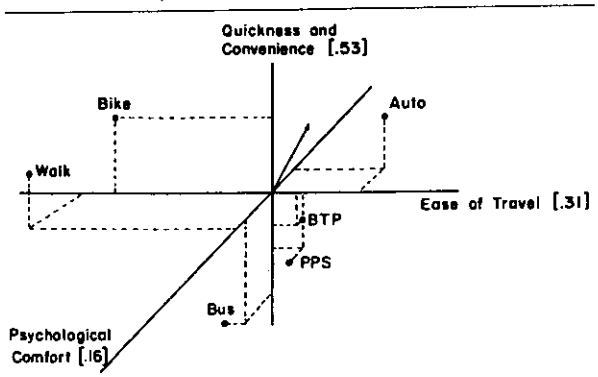
[8]Our analyses suggest that feelings are important in a model of consumer behavior. However, our analyses deal only with the forward causality from feelings to preference. This approximation is appropriate for a marketing audit if we assume that the net effect of feedback or joint causality does not substantially alter the coefficients of the forward linkage. The theoretical model in Figure 1 plus the magnitude of the coefficients in Table 4 suggests future research with data collected over time to further investigate this approximation.

ence model also serves as an index of their importance relative to perception of product attributes. And, these variables expand the set of strategies available to managers for influencing preference. Strategies designed to alter individuals' feelings about modes through the images they project (i.e., advertising) could have a significant impact. While marketers have long acknowledged the impact of image, its operationalization for inclusion in decision support models of consumer behavior is less common, and its incorporation enhances managerial action (for an alternative operationalization, see Srinivasan 1979).

Finally, because bus feelings are insignificant in Model 2 they are dropped to produce Model 3, which is not statistically different from Model 2 but still superior to Model 1. As indicated by the numbers in brackets in Table 5, the introduction of the feelings dimension into the model does not have a substantial impact on the relative importance of the evaluative dimensions. This suggests that the collinearity between mode perceptions and feelings (see Table 4) does not have a detrimental effect on the estimation of the relative importance weights. Because Model 3 is more complete and statistically superior to Model 1, it is used in further analyses.

The information in perception and preference analysis is summarized visually by the perceptual map in Figure 2. Existing transportation alternatives (bus, auto, walk and bike) and the two concept modes (PPS and BTP—see Table 2) are represented by points corresponding to consumers' average perceptions of each mode on the three perceptual dimensions. The preference information is included with an ideal vector (heavy arrow, Figure 2). The direction of the arrow is determined by the bracketed values in Model 3 of Table 5. Notice that the concept modes represent transportation alternatives closer to the ideal vector than the current bus system.

FIGURE 2
Perception, Preference, and Concept Diagnostic Information (Numbers in brackets are the importance weights of the dimensions.)



Behavior (Preference, Situational Constraints → Choice). The ultimate concern of the manager is the impact of preference on choice. In the present research, 80% of consumers chose their most preferred mode. Thus, while preference was a good indicator of choice, situational constraints mediated the behavior of a significant minority (20%).[9] Behavior models mapping the relationship between preference, situational constraints (e.g., mode availability, budgetary constraints), and choice were developed to provide insight into the behavior process.

The impact of situational constraints is considered in terms of conditional probability. Due to measurement errors and model errors, the preference index ($\hat{p}_{ij} = \Sigma_k w_k y_{ijk} + v_j y'_{ij}$) is not a perfect predictor of choice. Thus $\hat{p}_{ij}$ is modeled as a compaction function (Hauser 1978a) in the sense that the probability that a consumer chooses stimuli j is monotonic in the predicted preference if there are not situational constraints. Using the β-logit model (Hauser and Urban 1977), which is consistent with the axioms of a compaction function, the following equation is obtained:

$$\text{Prob(i choose j | no constraints)} = e^{\beta \hat{p}_{ij}} \Big/ \sum_m e^{\beta \hat{p}_{im}} \quad (2)$$

Note that for $\beta = 1$ equation (2) reduces to equation (1). This function gives the probability of choice conditional on there being no constraints. The observed probability of choice is the unconditioned probability. Thus by the laws of conditional probability:

$$\begin{aligned}\text{Prob(i choose j)} &= \text{Prob(i choose j | no constraints)} \cdot \text{Prob(no constraints)} \\ &\quad + \text{Prob(i choose j | constraints)} \\ &\quad \cdot [1\text{-Prob(no constraints)}] \end{aligned} \quad (3)$$

Because in empirical situations surrogates for constraints rather than actual constraints are observed, the probability that a constraint does not hold is modeled as a transformation of the surrogate variable. Thus,

[9] In general, variation across situations would help explain instances where a nonpreferred mode is chosen. However, for our data collection procedure, preference and choice are both measured for the most recent trip.

Prob(no constraint for stimulus j)

$$\sim e^{\alpha_1 c_{ij1}} e^{\alpha_2 c_{ij2}} \ldots e^{\alpha_n c_{ijn}} \quad (4)$$

where the α_n's are constants to be estimated, the c_{ijn} represent the constraint variables for stimulus j, and $\sim$ is used to mean proportional. If we let c_{ijn} be equal to zero for all stimuli except stimuli j, then the probability L_{ij}, that i chooses j is simply [10]

$$L_{ij} = e^{\beta \hat{p}_{ij} + \Sigma_n \alpha_n c_{ijn}} \Big/ \sum_m e^{\beta \hat{p}_{im} + \Sigma_n \alpha_n c_{imn}} \quad (5)$$

which can be estimated with standard logit packages. Note that this is a two-stage model because the relative importances (w_k, v_j's) of the perceptions and feelings are constrained by the preference model ($\hat{p}_{ij} = \Sigma_k w_k y_{ijk} + v_j y'_{ij}$)—they are not re-estimated. This is necessary because collinearity among the situational constraints and perceptual variables can potentially blur the preference relationships. See Hauser, Tybout, and Koppelman (1981) for a discussion and empirical evidence of this effect.

Two potential situational constraints were examined: auto availability as measured by the ratio of autos to drivers for the household, and budgetary constraints, as measured by the perceived expensiveness of alternative modes.[11] Only autos per driver (APD) was a significant situational constraint in any of the models. The insignificance of cost in this analysis may be attributable to the low cost of all modes considered in this analysis (25¢ bus fare, walk and bike free, and auto costs low for short trips within Evanston).

The choice models appear in Table 6. In Model 1, choice is predicted from the preference index alone, whereas in Model 2 autos per driver is included as a predictor variable. Model 2 does quite well and is superior to Model 1. It predicts 87% of the consumers' choices and explains 68% of uncertainty. Model 2 is significantly better (.05 level) than models based on chance or on market share. On this basis Model 2 is selected for use in diagnosing market position and developing strategies to modify that position.

Segmentation. The preceding analysis assumes that the parameters are the same for all consumers. To complete the model analysis, this assumption of homogeneity is tested. If no basis for segmentation is found (as was the case in our analyses), the manager has increased faith in the unsegmented models. If significant differences are found among segments, then the manager may have to consider segment-specific strategies.

TABLE 6
Choice Analysis

	Estimated Weights*	
Variable Name	1. Preference Alone	2. Conceptual Model†
Preference Index (β)	.88	.45
Autos per driver (α)		2.91
Percent Correctly Predicted	80.2	86.8
Percent Uncertainty Explained	56.6	68.4
Chi-squared statistic	289.7	350.1

χ^2 (Model 2 vs. Model 1) = 60.4 d.f. = 1 $p > .05$

*All coefficients are significant at the .05 level.
†Because the preference index and autos per driver are measured on different scales, the coefficients (.45 and 2.91) are not directly comparable in magnitude.

The procedure to test homogeneity is conceptually simple, although the statistics are complex. First, demographic and socioeconomic variables that represent potential segmentation variables are identified. In this case, age, number of drivers, number of autos in household, education, years of residence, occupation, driver's license, sex, marital status, trip purpose, number of adults in household, and income were selected. Next, for each phase of the conceptual model, parameters for each consumer segment were estimated and tested to see whether they were significantly different across segments.

Because no segments were identified for the Evanston general destination travel data base and because the technical details of segmentation analysis have been discussed elsewhere, we refer the reader to those references. In particular, a test of similarity of factor structure across segments is illustrated in Choffray and Lilien (1978). A likelihood ratio test of preference and choice is illustrated in Hauser, Tybout, and Koppelman (1981). For a review of these and other segmentation procedures, see Urban and Hauser (1980, pp. 259–266).

In this application, the homogeneity assumption was not rejected for either abstraction or aggrega-

[10] Recognize the Prob(i choose j |constraints) = 0 and that equation (4) implies independent marginal probabilities for the constraints.

[11] Bus and walk availability were not examined because these modes were available to nearly all respondents (the bus runs within three blocks of every home in Evanston and, except for some elderly or handicapped residents, walk is a viable mode).

tion. However, in other applications significant heterogeneity may exist. When this is the case, segmented models can help identify strategies tailored to the needs of homogeneous subgroups.

Outputs of the Analysis

The output of this market environment audit is a detailed description of competing modes' market positions. This information allows the manager to identify any undesirable market positions in the product line and provides insight regarding factors contributing to such positions. On the basis of this analysis, strategies for altering the market position of a particular product/service may be developed and evaluated. The conceptual model also assists the manager in this task. It suggests variables that stretegies should seek to modify and allows quantification of their impact. An example clarifies this process.

The marketing audit reveals bus to be in an undesirable market position. It is perceived to perform relatively poorly on important perceptual dimensions. As a result, bus is preferred and chosen only by a small segment of the population. To identify strategies likely to improve the position of bus, the variables in the conceptual model and their relationship are examined and strategies are generated to alter these factors. This process is illustrated for one strategy, an information campaign.

Specifically, the audit indicates that the limited choice of bus is strongly linked to low bus preference (Table 6). Lack of preference for bus, in turn, is found to be highly associated with a negative perception of the ease of travel via bus (Table 5 and Figure 2). This perceptual dimension is measured by the attributes: use to be on time, come and go as I wish, errands take little time, know how to get around, available when needed, get to destination quickly, and no long waits (Table 2). Thus, the market position of bus could be improved by improving perceptions of bus on these attributes. This could be achieved either by altering the physical characteristics (actual time, frequency, etc.) that contribute to these perceptions, or by attempting to alter the perceptions directly through some form of communication. The former approach is likely to be costly and may require research to test the causal link between physical characteristics and perceptions before expenditure is undertaken. The latter approach is likely to be lower in cost, and as such, may be tried as an initial means of improving bus market position.

A communication strategy that may enhance bus perceptions is one that informs residents about the bus system. This strategy will be most likely to influence bus perceptions if such perceptions are based on inaccurate or limited information regarding physical characteristics of the system. To determine the accuracy of consumers' knowledge about the system, subjects' beliefs about bus travel time, routes, and frequencies are examined. This analysis shows that, while estimates of travel time are quite accurate, consumers are not well informed about bus routes and frequencies. Therefore, an information campaign to improve knowledge in these areas and enhance consumers' confidence that they know how to get around Evanston by bus is one potential strategy for improving the market position of bus.

Once a strategy is identified, the models developed in the audit, coupled with managerial judgment, can be used to forecast the strategy impact. Judgment and any available data are used to identify the specific attributes likely to be altered and to estimate the magnitude of their change (the hypothetical modes may serve as useful upper bounds for such changes). For example, an information campaign is most likely to improve those perceptions based on inaccurate or limited information and enhance confidence in one's ability to use the bus system. The magnitude of the change in these attributes will be a function of the number of consumers who are uninformed or misinformed as well as the reach, frequency, and effectiveness of the communication itself. Using judgment and available data, the manager and the marketing analysts estimate how the strategy affects attribute ratings, such as those on know how to get around Evanston. After attribute rating changes are estimated, the analysis described in the marketing audit is rerun; factor scores are computed, equation (1) is used to forecast preference, and equation (5) is used to forecast choice probabilities. (See Hauser, Tybout, and Koppelman 1981 for technical details of the method.) Finally, choice probabilities are averaged (weighted by trip volume) and compared to existing market shares. In the Evanston application, this process was facilitated by the use of an interactive computer program that allowed both the analysts and members of the city manager's staff to make, discuss, and refine judgments. Forecasts made for the information campaign and other potential strategies appear in Table 7.

It might be argued that, because the strategy-to-perception mapping relies on managerial judgment, predictions like those in Table 7 could be generated without the analytic models. While appealing, such a simplification of the situation misses the central diagnostic purpose of the marketing audit. Prior to the analysis, the manager has a wealth of knowl-

TABLE 7
Forecasts of Strategy Impacts

Modification	Stage of Model Identification	Forecast Increase in Bus Ridership
1. Information Campaign	Perception/Preference	1.5% to 12.4%
2. Increase bus frequency 1 bus per hour	Physical Characteristics/Perception	3.4% to 19.0%
3. Reroute bus	Physical Characteristics/Perception	1.5% to 7.5%
4. Constrain auto availability	Behavior	2.9% to 15.5%
5. New service introduction	Perception/Preference	roughly 250%

edge about his/her product, but the technical analysis, indeed the whole process of planning, focuses that knowledge on specific strategies. The analysis within the marketing audit tells the manager about competitors, market position relative to competitors, consumers' feelings and preferences. This alone makes the analysis valuable. Beyond this, we have found that judgments are easier to make with respect to mode attributes than overall ridership, and the model's structure imposes a certain robustness on the estimates of ridership, yielding more realistic estimates than is possible without the model. Finally, the modeling process is evolutionary. Once the manager understands the basic marketing system, he/she can commission specific additional modeling efforts to fill out his/her understanding of the complete marketing system.

Conceptual Integrity of the Model

To this point we have argued in support of the particular model chosen on the basis of its consistency with the theoretical literature and its diagnostic potential. While these are compelling arguments, confidence in the model is increased further when the structure is supported empirically in the application setting. This helps insure that the model has been operationalized properly and that the model relationships actually exist in the field. In this section, we describe and illustrate two tests of the conceptual integrity of the model that can be performed after the data on model components is collected.

Correlation Test. If the conceptual model is correct, then variables at one level in the model should be most highly correlated with variables on the level immediately following. Physical characteristics should be most highly correlated with perceptions, perceptions should be most highly correlated with preference, and preference and situation constraints should be most highly correlated with choice. Thus, the model can be tested by examining the pattern or relative magnitudes of the correlations, irrespective of their absolute magnitudes. If repeated measures over time are obtained or if multiple operationalizations of each variable are used, then one might extend the correlational analysis to path analysis or simultaneous structural equations. (For a discussion of the use of structural equations in marketing, see Bagozzi 1980.) However, in doing so one must take account of the ordinal scaling of preference and the (0,1) scaling of choice. See Heckman 1978.

Examination of the pattern in the correlation matrix for our data (Table 4) provides support for the model and does not reject it. Physical characteristics, travel time, and distance to the bus stop correlate most highly with mode perceptions. All perceptions except quickness/convenience and bus feelings correlate more highly with preference than with choice.[12] (Only bus feelings correlate significantly more with choice than with preference.) Preference correlates most highly with choice as does the situational constraint, autos per driver. And cost, which is both a physical characteristic and a constraint, correlates significantly with five of the six perceptual variables (as predicted by marketing theory), yet has its highest correlation with choice (as predicted by the concept of a budget constraint from economic theory).

Comparison of Preference and Choice Models. Further examination of the conceptual model entails comparing preference and choice formulations based on this model to those based on alternative structures. Preference models representing three different conceptual frameworks were estimated for

[12]These are only approximations because preferences and choice are not intervally scaled. It also is desirable for perceptions to be independent to avoid collinearity problems in the preference models. This is the case for perceptions that were factor analyzed together, but the mode perceptions and mode feelings are significantly intercorrelated. A check for the effect of this collinearity on the importance weights in the preference models was conducted, and the impact of multicollinearity was shown to be negligible. See Table 5.

TABLE 8
Comparison of Preference Models for General Travel Destinations

Variable Name	Relative Importance Weights*		
	Model 1	Model 2	Model 3
A. Physical Characteristics			
Cost	−.49	−.16*	
Travel time	−.01*	−.00*	
Distance to bus stop	−1.37*	−1.21*	
B. Mode perceptions and feelings			
Quickness and convenience		.26	.26
Ease of travel		.15	.15
Psychological comfort		.08	.08
Bus feelings		—	—
Car feelings		.32	.32
Walk feelings		.19	.19
Percent correctly predicted	74.6	80.2	80.2
Information	43.6	61.3	60.8
χ^2 statistic	223.1	313.6	310.9

χ^2 (model 1 vs. model 2) = 90.5 d.f. = 5 $p < .05$
χ^2 (model 2 vs. model 3) = 2.7 d.f. = 3 $p > .05$

*Starred coefficients are *not* significant at the .05 level.

our data base. These are reported in Table 8. Model 1 eliminates the mediating role of perceptions and directly maps the relationship between physical characteristics; travel time, distance to bus stop and cost, and preference. Model 2 eliminates the distinction between physical characteristics and perceptions and incorporates both in the preference model. Finally Model 3, which is consistent with our conceptualization, uses perceptions alone to predict preference. Statistical comparisons of the models for the variables in our data set support our model. Model 3 (perceptions → preference) surpasses Model 1 (physical characteristics → preference) and is not significantly different from Model 2 (physical characteristics and perceptions → preference).[13] Further, a model employing both perceptions and physical characteristics as predictors of preference is less desirable than one employing only perceptions because of potential interpretation problems resulting from multicollinearity between physical characteristics and perceptions.

[13]Model 2 is significantly better than Model 1 but not significantly better than Model 3. We, therefore, conclude Model 3 to be superior to Model 1.

Alternative formulations for choice models also were examined. Table 9 presents three alternative choice models for general travel destinations trips. Model 1 predicts choice on the basis of physical characteristics and situational constraints. Model 2 predicts choice from physical characteristics, situational constraints, and the preference index. And Model 3, which is based on our conceptual structure, predicts choice from situational constraints and the preference index. The findings parallel those for preference. For our data set, the conceptual model (Model 3) is superior to one using physical characteristics and situational constraints alone (Model 1).

Summary. The results of the correlation and model comparison tests suggest that the model relationships in fact exist in the application setting and support the contention that the components have been measured appropriately. (Similar support for the conceptual model also was obtained in analysis of the other two Evanston data bases; see Hauser, Tybout, and Koppelman 1981; Koppelman and Lyon 1981.)

The Role of the Model in Further Research

The initial marketing audit should be the beginning, rather than the end, of research. At a minimum,

TABLE 9
Comparison of Choice Models for General Travel Destinations

Variable Name	Relative Importance Weights*		
	Model 1	Model 2	Model 3
A. Physical Characteristics			
Cost	−.31	−.34	
Travel Time	−.01*	.00*	
Distance to Bus Stop	−.56	−.10*	
B. Preference Index		.44	.45
C. Situation Constraints			
Autos per Driver	5.01	4.17	2.91
% Correctly Predicted	86.8	87.3	86.8
Information	65.6	69.3	68.4
χ^2 Statistic	335.6	354.6	350.1

χ^2 (model 1 vs. model 2) = 19.0 df. = 1 $p < .05$
χ^2 (model 2 vs. model 3) = 4.5 df. = 3 $p > .05$

*Starred coefficients are not significant at the .05 level.

it must be repeated at regular intervals to keep management abreast of changes in the environment. More often the audit uncovers some undesirable aspects of the firm's market position. Once management has designed and implemented a strategy to address these problem areas, research is necessary to monitor the strategy impact. The conceptual model in Figure 1 can play an important role in the research as well. It suggests the dependent variables to be measured in the evaluation and assists in diagnosing any strategy failure. Moreover, the accuracy of the model in forecasting strategy effects can provide insight for model refinement. In this section we illustrate the role of the conceptual model in a post-strategy audit and consider the strengths and weaknesses of the model.

The Strategy

As discussed in the previous section, an information campaign was identified as one strategy that could help improve the market position of the Evanston bus service. This strategy was selected for actual implementation over alternative strategies on the basis of its predicted effect on ridership, cost and ease of implementation, consistency with city goals, and feasibility of evaluation. These features made it a good starting point for managerial action.

The implemented bus information campaign involved four components designed to increase awareness of bus routes and schedules and encourage bus use for trips within Evanston:

- Bus route maps and timetables were sent to each city household along with a cover letter from the city manager.
- Bus stop signs with graphics of the bus routes were erected. (Previously few signs had appeared and these did not contain route information.)
- Posters showing a map of the city with color coded bus routes superimposed on it were distributed to banks, offices, and stores around Evanston. Merchants marked their location on the map and then displayed the poster in their establishment.
- The research on the travel behavior of Evanston residents and resulting information campaign was featured in several local papers.

This campaign was judged likely to increase bus ridership by altering knowledge about and perceptions of bus. First, it was expected to improve residents' actual knowledge of routes and timetables for the bus, as well as their perception that they know how to get around Evanston by bus. Also, it was anticipated that knowledge of bus routes and timetables would improve ratings on no long waits, little effort involved and on time. Because these attributes are important aspects of two mode perceptions that determine preference and choice, quickness and convenience, and ease of travel, improvements on these factors were expected to increase bus ridership by 1.5% to 12% (as indicated in Table 7). However, the bus system would have to perform adequately in order to maintain this increased ridership.

The Post-Strategy Audit

A multistage effort was undertaken to determine the impact of the strategy and the adequacy of our conceptual model.

Before/After Surveys

First, surveys were used to measure the model components that could not be observed unobtrusively or through archival data. Two weeks before, two weeks after, and one month after the strategy surveys measuring respondents' knowledge, mode perceptions, and mode preference were conducted with separate random samples of Evanston residents.[14] Respondents to the different surveys did not differ significantly in their demographic profiles. Therefore, the samples were considered sufficiently similar to allow across-sample comparisons to detect strategy effects. Table 10 summarizes these comparisons.

In general, the survey results support judgments regarding the effects of the information strategy on knowledge about and perceptions of the bus system. Knowledge of the nearest bus stop, off-peak bus frequency, and whether or not the bus route nearest one's home went to downtown Evanston all improved, though only the effect for knowledge of the nearest bus stop was statistically significant. Perhaps this can be attributed to the bus stop signs, as a function of their ongoing nature, being a stronger and more memorable communication than information on routes and timetables. Also consistent with our expectations were the significant improvements observed in perceptions of the effort required to travel by bus, and the length of wait at bus stops. Further, perceptions of the on-time

[14] 300–600 questionnaires were mailed out for each of the three surveys. Response rates for each were approximately 21%. Comparisons of the demographic profiles for the three samples showed no significant differences.

TABLE 10
Before-After Evaluation of Bus Information Campaign

Variable	Pre-Strategy	Post-Strategy	Significance of Pre-Post Difference
1. Knowledge of Bus System (% correct)			
a) Know bus stop nearest home	86.7%	95.9% (2 wks. later)	[a]
		94.6% (1 mo. later)	[a]
b) Know off-peak bus frequency	36.7%	43.0%	—
		45.4%	—
c) Know that bus goes to downtown Evanston	77.9%	86.8%	—
		78.5%	—
2. Perceptions of Bus System†			
a) Traveling by bus requires a lot of effort	3.72	3.22	[b]
		3.17	[b]
b) There is generally a long wait when traveling by bus	3.72	3.31	[b]
		3.47	[a]
c) If I had to be somewhere on time, I would not travel by bus	3.34	3.26	—
		3.25	—
d) I know how to get around Evanston by bus	2.69	2.90	—
		2.87	—
3. Preference for Bus: % stating bus as most preferred mode	8.8%	11.6%	—
		5.4%	—

†Lower numbers indicate more favorable evaluations; for item d the scale was reversed in order to make it comparable to other items.
[a]Significant at .05 level.
[b]Significant at .01 level.
(z test for proportions was used to test knowledge and preference effects, t test was used to test perception effects.)

performance for bus improved, but not significantly. In contrast, there was no significant change in respondents' perception of their knowledge of the bus system. The absence of any effect on this variable may be attributable to the campaign improving residents' actual knowledge *and* making them aware that they were less familiar with the bus system than they had previously believed. Finally, first preference for bus showed a temporary increase (within the predicted range) and then a decline, although neither of these effects were significant.

Before-After Ridership Counts

While the data from the surveys is not inconsistent with the model predictions, the small samples make it difficult to obtain significance for some of the effects. Therefore, two types of aggregate data were used to gain further insight about the strategy. First, the local transit authority conducted onboard ridership counts for one week before and one week after the strategy on two of four routes. A 4.4% increase in the average weekday ridership was found, suggesting that the strategy did have the predicted impact on actual ridership. However, because this data only was collected on two routes for one week before and one week after the strategy, and because random or seasonal variation potentially could account for the difference observed in these ridership counts, longitudinal ridership data was also examined.

Time Series Analysis

Time series analysis was used to analyze the longitudinal bus ridership data. This analysis first identifies patterns in ridership data for the extended pre-strategy time period, and then identifies changes in these patterns that occur after strategy implementation. If an appropriate control is available (e.g., ridership data for a similar city, but one unaffected by the strategy), it can assist the researcher in modeling nonstrategy fluctuations in ridership.

Before discussing the time series analysis, we comment briefly on an alternative method for evaluating the impact of transit system changes. Blattberg and Stivers (1970) present a mathematical modeling approach in which the researcher first

identifies and sets values for all exogenous variables (other than the system change or strategy) that are likely to influence ridership. Parameter estimation is done using ordinary least squares, generalized least square, or minimum sum of absolute errors. After the model is identified using pre-strategy data, it is used to make post-strategy predictions for ridership. The matrix of differences between predicted and actual post-strategy ridership is used to compute a test statistic for the strategy impact. The major differences between this approach and the time series approach we used lie in (1) identifying the exogenous variables and (2) testing the strategy impact. The Blattberg and Stivers approach is dependent on the identified exogenous variables. In contrast, the time series analysis derives these variables through analysis of the patterns in the series. Systematic stochastic variation in the series may be accounted for in the model even if the cause of that variation is not apparent. This is particularly true when a control city is used. In addition, the time series approach incorporates the strategy into the model itself, allowing a measure of the increase in variance explained as well as a test of the significance of the strategy. Both approaches allow testing of various assumptions regarding strategy dissemination, such as lagged effects, etc. These were examined in our analysis and are discussed in detail in Tybout and Koppelman (1980).

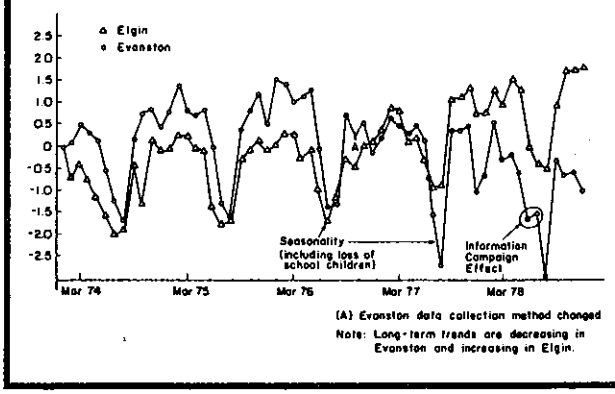
The use of time series analysis versus the Blattberg-Stivers methodology versus another statistical technique is a research tradeoff based on data availability, computational capability, and professional judgment. However, it is managerially important that some analytic technique be used to evaluate explicitly the impact of any identified strategy.

The steps in our time series analysis are summarized below.[15]

Identification of the Selected Time Series. Average weekday bus ridership in Evanston for each month from January 1974 to December 1978 was selected as the series. This particular index of ridership was chosen because it is unaffected by variations in days per month, and it avoids mixing weekend and weekday data. (Assuming the patterns of weekend and weekday ridership are different, combining the two would impair modeling.)

[15]It is interesting that both in our analysis and in the Blattberg-Stivers analysis, the effect of an information campaign is more apparent and better understood with the statistical model. (In Blattberg and Stivers the effect of the information campaign appeared to be insignificant when weather, trend, seasonality, school vacations, Christmas, and special shopping nights were not modeled.)

FIGURE 3
Standardized Average Weekday Ridership Data by Month for Elgin and Evanston



Selecting a Control Series. The objective is to identify a data series that is similar to the Evanston one and that is subjected to the same exogenous events that may influence bus ridership (e.g., weather, energy shortages, and areawide economic conditions). Average weekday bus ridership for Elgin, Illinois, fulfilled these criteria.

Visual Inspection of the Data. Average weekday ridership data was standardized separately for each city and then plotted on the same graph (see Figure 3). Examination of this graph leads to several observations. First, the patterns for Evanston and Elgin are similar, although ridership in Elgin shows a slight upward trend and ridership in Evanston shows a slight downward trend. This suggests that Elgin is an appropriate control for Evanston.[16] Second, a clear seasonal pattern is evident in both series and is particularly strong in the Evanston series. A contributing factor to this seasonality may be school children's use of the public bus system in place of any private school bus system. Third, the strategy appears to have had some, albeit temporary, impact on ridership. In the years prior to the campaign, ridership in both series always dropped dramatically from June to July. In 1978, this pattern continued in the Elgin series, but was reversed, temporarily, in the Evanston series.

Formal Modeling. Modeling of the series was undertaken to quantify the relationships described in Step 3. The PACK time series program was used in this stage of the analysis. After verifying that Elgin was a valid control, the Evanston series was

[16]Trend components can be accounted for by time series analysis. Elgin is a good control city because it is subject to environmental variables that are similar to Evanston.

modelled as a function of this series. This model, which explained 82.4% of the variation in the Evanston bus ridership data, took into account seasonality, one-month lagged effects, and other factors shared by the two series. However, the model did not control for one factor unique to Evanston and known to influence bus ridership, the proportion of nonschool days per month. Therefore, a dummy variable representing months and half-months when school is not in session was added to the model. This revised model provided a good fit to the data, explaining 85.4% of the variation in the Evanston series. Then, the effect of the bus information campaign was tested. If the strategy had a significant impact on ridership, then a variable representing this strategy should be significant when added to the nonstrategy model. This was the case. Moreover, inclusion of the strategy variable raised the variance explained to 89.1%. The net effect of the campaign was a 14.2% increase in July ridership. However, this effect decayed completely in August.

Interpretation

On the basis of the survey, ridership counts and time series analyses, we concluded that the short-run results of the strategy were as predicted. Knowledge, relevant perceptions, and actual ridership all increased. Furthermore, the total pattern of results for these variables cannot be explained readily by any nonstrategy factor.

In contrast, the rapid and complete decay of the increase in ridership was unanticipated. It is, however, informative and indicates that the strategy was inadequate to sustain the increase it generated. There are two plausible explanations for the rapid decay: the short duration of the campaign may not have been sufficient to produce enduring changes in well-ingrained habits (a strategy design problem), or the campaign may have been effective in stimulating trial, but poor service undermined repeat usage (a service performance problem that must be corrected before any communication strategy can be effective). Management can now focus either on trying a longer term communication strategy or undertaking research to measure physical characteristics, and map the link between these characteristics and perceptions. In view of the dangers associated with promoting what may be a poor service, the latter strategy is preferred.

In this section we have illustrated what the conceptual model can and cannot do. It can serve as a framework for developing and forecasting the effects of strategies. It is our belief that this framework enhances managerial decision making. However, the model cannot insure the strategy outcome in a real world setting. This is because until it is tested, any strategy involves judgments and assumptions about background factors not explicitly modeled. Evaluating the actual impact of the strategy tests the validity of the assumptions made, and in so doing, directs further research and long term managerial policy.

Conclusions

This paper has discussed a marketing audit based on a conceptual model of consumer behavior. It has summarized theoretical support for the model and has evaluated its application in a marketing decision environment.

The results of this research suggest that this model is conceptually sound and managerially useful. Application of the model provides detailed data for determining market position and designing strategy to modify that position. By measuring model variables (physical characteristics, perceptions of the object attributes as well as more general object related feelings, preference, situational constraints, and choice), and mapping their relationships, managers are able to identify a full range of strategies for altering behavior. These include strategies altering physical characteristics as a means of affecting perceptions and/or preference, strategies modifying perceptions and preference without altering physical characteristics, and strategies simultaneously targeting physical characteristics, perceptions, and preference. Further, the model assists managers in selecting among these strategies because it provides a framework for generating predictions of strategy impact.

The conceptual model also is useful when evaluating the impact of strategies. Careful monitoring of changes in model variables can provide a diagnosis of strategy performance. This is important input for future strategy design and research.

However, we do not wish to claim too much for the model. It is a tool for decision making. As such, it is designed to insure that important consumer variables are considered and to organize the manner in which these variables are viewed. While this may reduce uncertainty in decision making, it by no means eliminates it. The identification of marketing strategies requires creative, insightful marketing managers who can use models to aid, not replace, decision making.

Finally, the conceptual model in Figure 1, the specific measurements in our surveys, and the specific statistical techniques for consumer analysis and strategy evaluation are by no means unique.

We believe that a variety of theoretical and analytic models in the marketing literature can and do help managers make better decisions. The informed manager selects those models and measurements that are right for the specific circumstances of the managerial problem being examined.

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