IMPLEMENTATION OF URBAN TRANSPORTATION DECISIONS: A SIMULTANEOUS CATEGORY MODEL

John W. Dickey, Division of Building Research,
Commonwealth Scientific and Industrial Research Organization, Australia; and
Robert C. Stuart, Division of Environmental and Urban Systems,
College of Architecture, Virginia Polytechnic Institute and State University

In recent years it has been a common occurrence for urban transportation decisions by planners and other professionals to be negated or even reversed by citizen groups or concerned public officials. In this study an attempt is made to identify those factors relevant to the political and technical complexity of an urban transportation problem, the acceptance or rejection of technical recommendations, and the likelihood of implementing any decision and time to implement any decision. A questionnaire was sent to various officials in cities throughout the country. The data from this questionnaire formed the basis for a nonparametric simultaneous category model known as IMPLEM. This model shows that the implementation-related factors are related not only to each other and to a variety of factors beyond the planner's control but also to the ease of communication fostered by the planner. Results of application of IMPLEM indicate, however, that the planner's influence through this means is relatively small.

•SOME of the most perplexing problems arising in any transportation planning endeavor center around attempts to implement chosen plans and designs. Usually planners have a difficult time predicting whether a certain planning decision will be carried out and, if so, how long a time period will pass before implementation is achieved. Furthermore, the planner generally is at a loss to know how to exert his efforts in order to get faster action and a better product.

One of the main hindrances to action is the vast complexity of most situations being faced. Political implications are almost always present, and even the technical tasks may be far from simple. With few exceptions it is nearly impossible for the planner to avail himself of any simple, general approaches that can be trusted to produce desirable results—implemented, beneficial urban transportation decisions—without the usual amount of agony involved. If this statement is true, and most cases seem to indicate that it is, then we should realize that any sound analysis of the implementation situation should focus on a large number of affecting factors and a correspondingly complex set of interactions.

In keeping with these directions, we have attempted to develop a multivariate model for the implementation process. This model is to be used to help the planner make predictions on matters such as the technical and political complexity involved in an implementation situation, the conformance of the final plans to the technical recommendations, and the time to implementation. What will be significant about this model is that it involves nominal variables, that is, ones measured in categories and not in continuums (this means that the usual parametric statistical techniques, such as multiple regression, will not be applicable). It also involves dependent variables that are related to each other. These two characteristics are combined into what is called a simultaneous (or stacked) category model, which is somewhat analogous to the simultaneous equation models often used in econometric analyses.

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A significant feature of this simultaneous category model is the identification and utilization of three types of variables: those over which the planner has direct control, no control, or indirect control. This feature makes it possible for the planner to make predictions about the impacts that various alternative strategies on his part would create, with these impacts taking place in the context of other factors beyond his control. It is hoped that this concept will become more meaningful through the example and detailed models to follow.

A SIMULTANEOUS CATEGORY MODEL: AN EXAMPLE

The actual simultaneous category model developed as part of this research endeavor is too complex for use in an example, and so another model, corresponding to a simple (and perhaps not too realistic) situation, will be explored at this point.

Suppose that a questionnaire survey has been undertaken and that data on four variables have been collected. These variables are type of government (strong mayor, town manager, or commission), major mode of transport (automobile or transit), major economic base (commercial or manufacturing), and predominant type of worker (blue collar or white collar). These variables are given in Table 1.

Suppose further that officials in 600 cities have responded to the questionnaire and have identified the category of each variable within which their city falls. This information then is used to develop a model to be used by a planner in a certain city to help predict the major economic base and the predominant type of worker affected by the mode of transport (assumed to be under planner control) and the type of government (assumed to be beyond planner control).

Analysis of the data indicates that the best cross-categorical relationships for predicting both the major economic base, Y_1, and the predominant type of worker, Y_2, are those shown in Figure 1a. Two items are of interest in regard to these relationships. First, each of the two dependent variables, Y_1 and Y_2, is a function of combinations of two other variables. For example, Y_1 (the major economic base) depends on the type of government, Z, and the predominant type of worker, Y_2. This can be seen in the first column of the first relationship (Fig. 1a) where, out of 100 cities having both a strong mayor type of government, Z1, and a predominantly blue-collar working force, Y_2A, 40 have a commercial major economic base, Y_1a, and the remaining 60 have a manufacturing major economic base, Y_1b. Other combinations of Z and Y_2 would lead to different proportions for the major economic bases.

The second item of interest about these relationships is that each dependent variable is a function of the other. The type of major economic base depends on the predominant type of worker and vice versa. This means that to predict either of these would require the simultaneous prediction of the other. The implication for the prediction process is that considerable attention must be given to the simultaneous handling of the interrelationships involved. However, as noted in the preceding section, complex interrelationships are to be expected in the types of situations being investigated in this study.

The output from the example simultaneous category model will be the probabilities of obtaining given categories of each dependent variable based on the settings of the

TABLE 1

VARIABLES IN HYPOTHETICAL SIMULTANEOUS CATEGORY MODEL EXAMPLE

Symbol	Variable	Category	Extent of Planner Control
Z	Type of government	Strong mayor, 1 Manager, 2 Commission, 3	No control
X	Major mode of transport	Automobile, I Transit, II	Complete control
Y_1	Major economic base	Commercial, a Manufacturing, b	Indirect control through influence of transport system
Y_2	Predominant type of worker	Blue collar, A White collar, B	Indirect control through influence of transport system

(a)

Z and Y_2

		1 A	2 A	3 A	1 B	2 B	3 B	
Y_1	a	40	20	30	80	50	70	290
	b	60	80	70	20	50	30	310
		100	100	100	100	100	100	600

X and Y_1

		I a	II a	I b	II b	
Y_2	A	10	100	50	140	300
	B	90	100	50	60	300
		100	190	114	196	600

(b)

Z and Y_2

		1 A	2 A	3 A	1 B	2 B	3 B
Y_1	a	.4	.2	.3	.8	.5	.7
	b	.6	.8	.7	.2	.5	.3

X and Y_1

		I a	II a	I b	II b
Y_2	A	.1	.5	.5	.7
	B	.9	.5	.5	.3

Figure 1. Data and resulting probabilities for example hypothetical simultaneous category model.

control variable X and the noncontrol variable Z. For instance, the planner in this example might want to know which type of major economic base and which predominant type of worker would be most likely if, under the manager type of government, Z2, he developed an automobile-dominant form of transport system, XI. The consequences of this strategy are found by first converting the frequencies shown in Figure 1a to probabilities as shown in Figure 1b. For example, if the major economic bases of 40 out of the 100 Z1, Y_2A cities are commercial, Y_1a, this would be 40 percent or a probability of 0.40.

The next step is to isolate the boxes in the two probability relationships shown in Figure 1b that have to do with Z2 and XI. This leaves the relationships as shown in Figure 2. Now, because Y_1 is a function of Y_2 and vice versa, it is necessary, as mentioned previously, to solve these two relationships simultaneously to find Pr(a), Pr(b), Pr(A), and Pr(B), which are the probabilities that a given city (e.g., the one with which the planner in this example is concerned) will fall into categories Y_1a, Y_1b, Y_2A, and Y_2B respectively.

(a)

		2 A	2 B
Y_1	a	.2	.5
	b	.8	.5

(b)

		I a	I b
Y_2	A	.1	.5
	B	.9	.5

Figure 2. Relationships for Y_1 and Y_2.

It can be seen from the two-category relationships shown in Figure 2 that the expected value of each of the four probabilities is as follows:

$$Pr(a) = 0.2\ Pr(A) + 0.5\ Pr(B) \tag{1}$$

$$Pr(b) = 0.8\ Pr(A) + 0.5\ Pr(B) \tag{2}$$

$$Pr(A) = 0.1\ Pr(a) + 0.5\ Pr(b) \tag{3}$$

$$Pr(B) = 0.9\ Pr(a) + 0.5\ Pr(b) \tag{4}$$

Also

$$Pr(a) + Pr(b) = 1.0 \tag{5}$$

$$Pr(A) + Pr(B) = 1.0 \tag{6}$$

because it must be completely probable or possible for a city to fall into either category a or b for Y_1 or category A or B for Y_2. Equation 1 would arise from the first row in Figure 2a. If Y_2A is present (actually Z2 and Y_2A) and the probability of this is Pr(A), then in 20 percent or 0.2 of the cases we would expect Y_1a to occur. So, Pr(a) = 0.2 Pr(A). But we must also take into account the chance that we might have Y_2B, with probability Pr(B), instead of Y_2A. Thus, to get the expected (or weighted) value for Pr(a), we must add the two cases and divide by Pr(A) + Pr(B) = 1, thereby obtaining Eq. 1.

There are now four unknowns (the four probabilities) and six equations. Two of the equations, thus, are redundant and should not be used. As it turns out, the first four cannot be used together or else a meaningless solution arises. Therefore, to find the four probabilities, we could work in the following manner. Substitute Eqs. 3 and 4 into Eq. 1 to get

$$Pr(a) = 0.2[0.1\ Pr(a) + 0.5\ Pr(b)] + 0.5[0.9\ Pr(a) + 0.5\ Pr(b)] \tag{7}$$

which gives

$$0.53\ Pr(a) = 0.35\ Pr(b) \tag{8}$$

Now, substitute Eq. 5 into Eq. 8 to get

$$0.53[1 - Pr(b)] = 0.35\ Pr(b) \tag{9}$$

or Pr(b) = 0.60 and Pr(a) = 0.40. By a similar procedure, it can be found that Pr(A) = 0.34 and Pr(B) = 0.66. These results show that, under the given circumstances (Z2, XI), there is a 40 percent chance that the city under study will have a commercial major economic base; a 60 percent chance, a manufacturing base; a 34 percent chance, a predominantly blue-collar work force; and a 66 percent chance, a predominantly white-collar work force. If the planner did not like these results, he might switch the variable over which he has control (from XI to XII) and see whether any differences in the Y_1 and Y_2 category probabilities would occur. If he deemed the outcome of this change to be beneficial, he then would proceed to bring about a transit-dominant city (XII).

Thus, in this example of the hypothetical simultaneous category model, the planner is able to find the probabilities of different types of occurrences when each of these depends on (a) the other types of occurrences, (b) the uncontrollable aspects of the situation in which the planner operates, and (c) the control policies that the planner elects to follow. This overall concept forms the basis for the detailed simultaneous category model of implementation to be presented in the latter part of this paper.

RELIABILITY OF SIMULTANEOUS CATEGORY MODELS

In the preceding section, mention was made of the need for a measure or index of the reliability of the simultaneous category relationships. How much faith can we place in the previously calculated value of 0.40 for Pr(a)? Could it just as easily have been 0.50 or 0.20? This is the type of question that we will attempt to answer in this section.

Before proceeding, we must ask ourselves what characteristics of an index or measure of predictability would be desirable. First, and perhaps foremost, there must be some feeling on the part of the user as to how much predictability a given value of the index represents. Perhaps the most well-known and best understood index of a similar nature is the correlation coefficient, r, used with interval and ratio-scaled variables (1, see explanation of nominal, ordinal, interval, and ratio scales). This coefficient ranges from 0 to 1, with a value of 0.7 or more usually assumed in the social sciences to represent "good" reliability. (There is no concensus on the 0.7 value, however.) The index to be developed here has the same range as r and a roughly analogous interpretation.

Let us start in the development of the index by looking at the extremes in predictability for a two-category-by-two-category relationship. If we had 20 observations for the variable "response to planning" (either "great" or "terrible") as a function of the sex of the respondent, we could get either of the two extreme relationships shown in Figure 3a and b. In the first case it would be impossible to predict the response because both males and females feel exactly the same way (and are also equally divided) about planning. Our index thus should equal 0 in this situation. In the second case, the situation is completely different. All males think planning is great and all females think it is terrible, so that a prediction of the response can be made exactly by knowing the sex of the respondent. Our index thus should equal 1 in this situation.

(a)

Response	Sex: Male	Sex: Female	
Great	5	5	10
Terrible	5	5	10
	10	10	20

(b)

Response	Sex: Male	Sex: Female	
Great	10	0	10
Terrible	0	10	10
	10	10	20

(c)

Response	Sex: Male	Sex: Female	
Great	8	2	10
Terrible	2	8	10
	10	10	20

$\phi = 0.6$

Figure 3. Two-category-by-two-category relationship.

A common approach in nonparametric statistics for measuring the predictability or reliability of relationships such as those shown in Figure 3a and b is to utilize the chi-square, χ^2, statistic (1, 2). This is calculated by taking the difference between the actual number of observations in each block of each table and the number that would occur if no relationship existed (the expected number). Each difference is squared (to eliminate negative differences that may cancel out positive ones), divided by the expected number, and then summed with the others. Thus

$$\chi^2 = \sum_{i=1}^{k} \sum_{j=1}^{m} \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{10}$$

where, for k rows and m columns,

O_{ij} = actual number of observations in row i and column j, and
E_{ij} = expected number of observations in row i and column j if no relationship exists.

The data shown in Figure 3a actually represent the case where no relationship exists, so that the values in each block are the expected values. If it were then desired to calculate the χ^2 value for data shown in Figure 3b, it would be done as follows: $\chi^2 = [(10 - 5)^2/5] + [(0 - 5)^2/5] + [(0 - 5)^2/5] + [(10 - 5)^2/5] = 20$. Because the relationship shown in Figure 3b has the highest possible predictability, its index should be 1.0, not 20. So why not divide the calculated χ^2 by its highest possible value for that relationship, which gives 20/20 = 1.0? Then, to adjust for the previous squaring operation, we should take the square root, $\sqrt{1.0} = 1.0$. This sequence of steps leaves a value for the best predictive relationship of 1.0, and of 010 for the worst. (Note that the χ^2 value for the relationship shown in Figure 3a is $[4(5 - 5)^2]/5 = 0$, which gives a value of $\sqrt{0/20} = 0$.) The formula for this index, known as the "phi coefficient," is

$$\phi = \sqrt{\chi^2/\chi^2_{max}} \tag{11}$$

where χ^2_{max} is the highest possible χ^2 value. The ϕ-value for the relationship shown in Figure 3c, which is intermediate to those shown in Figure 3a and b has been calculated as 0.6.

Two comments are in order insofar as dealing with matrices with several row and column categories. First, the expected number of observations, E_{ij}, can be calculated with the following:

$$E_{ij} = (n_i n_j)/N \tag{12}$$

where

n_i = total number of observations in row i,
n_j = total number of observations in column j, and
N = grand total number of observations.

Second, the χ^2_{max} value can be computed by means of

$$\chi^2_{max} = (k - 1)N \tag{13}$$

where, as before, k is the number of rows (or categories in the dependent variable) and N is the grand total number of observations.

SCENARIO FOR IMPLEMENTATION MODEL

There are many places in the planning process where the planner would have to be concerned with the implementation of a plan: in the solution formulation stage, in the evaluation stage, and, of course, in the actual implementation. In this section we imagine the planner to be in the following position: The problem has been identified, at least vaguely, either by the press, by a citizen group, or by the planner himself. In any case, no serious work toward making the problem fully known or developing a solution has been initiated, and the planner is trying to predict the amount of effort that lies before him if the problem is to be solved. What is the probability of implementing a solution? How long is it likely to be before implementation can take place? What will be the extent of technical and political complexity to be faced? In another vein, how should he, the planner or problem-solver, act so as to reduce or minimize the effort and time involved in implementing a solution? These are some of the crucial questions in front of the planner at this point.

A summary of the most significant considerations we feel would face the planner in this position are given in Table 2. The first variable, Y_1, deals with the question of how technical inputs would be handled. If the ultimate decision on a solution will rest almost entirely on political feasibility, then it would benefit the planner to spend his entire time in that arena and not in the technical development arena. Second, there are the variables of technical and political complexity, Y_2 and Y_3. If these are great, considerable effort toward implementation may be required on the part of the planner. Third, how will the planner's recommendations be accepted in relation to those coming from other agencies, Y_4, and those evolving from citizen groups of various types, Y_6? Conflicts here could impede implementation considerably. The fourth variable is the amount of revision expected in the planner's recommendations, Y_5. Finally, there are the questions of the likelihood of implementation, Y_7, and the time to implementation, Y_8. These latter two variables obviously are paramount to the planner, because, if implementation is unlikely or else is likely only in the distant future, it might be better not to get involved with the whole problem. Or, at least if the planner must get involved, he should have a rough idea of what lies before him. These, then, are the major factors to be predicted within the context of the scenario described earlier.

Of course, there are other considerations to be taken into account. The planner does have control over some factors that influence, indirectly at least, some of the eight dependent variables discussed in the preceding. Similarly, there are many factors completely beyond the planner's control. Because these also can affect the eight variables, it is necessary to specify the particular categories of these factors existing in a given situation and to determine which categories of the dependent variable are most likely to arise under these categories. Such circumstances were demonstrated in the hypothetical simultaneous category model example in which the type of government was beyond the planner's control.

QUESTIONNAIRE SURVEY

The data utilized to develop probability distributions of a form similar to those in the earlier example (Fig. 1) were collected through a survey questionnaire sent to planners, highway engineers, city managers, and mayors in metropolitan areas throughout the United States. Of the original 750 questionnaires, 151 were returned with information suitable for purposes of this research.

There were 132 questions on the survey, each relating to a certain urban transportation problem chosen by the respondent. While it is not practical to list all of the questions, in general they can be divided into the following groups:

Group 1—Those descriptive of the type of urban transportation problem being reported (e.g., transport mode involved and location of problem);

Group 2—Those indicating the type of factors considered by officials concerned with the problem (e.g., travel time, safety, and air pollution);

Group 3—Those indicating the different types of professionals involved (e.g., planners, lawyers, and architects);

Group 4—Those descriptive of the participants in the decision-making process and their influence (e.g., FHWA, UMTA, city manager); and

Group 5—Those descriptive of the urban area (e.g., SMSA population and total planned Interstate system).

TABLE 2

DEPENDENT VARIABLES IN IMPLEMENTATION MODEL

Symbol	Variable	Category
Y_1	Technical-political consideration of dominant factor	1. Left almost entirely to technical solution 2. Handled largely as technical problem 3. Given generally equal technical and political consideration 4. Handled largely as problem of political feasibility 5. Handled almost entirely as problem of political feasibility
Y_2	Technical complexity	1. Simple 2. Fairly simple 3. Average complexity 4. Above average complexity 5. Very complex
Y_3	Political complexity	1. Simple 2. Fairly simple 3. Average complexity 4. Above average complexity 5. Very complex
Y_4	Interagency conflict over technical recommendations	1. Single, essentially technical set of recommendations with any interagency conflict resolved 2. Technical recommendations of two or more agencies with conflict unresolved prior to decision 3. No prior technical recommendations
Y_5	Conformance of decisions to recommendations	1. Decision closely conformed 2. Decision conformed with minor changes 3. Major changes were made 4. Decision reversed recommendation
Y_6	Professional-citizen influence on decision	1. Decision based entirely on recommendation of professional personnel 2. Decision based largely on recommendation of professional personnel 3. Decision based equally on recommendation of professional personnel and decisions of opposing citizen groups 4. Decision based largely on decisions of opposing citizen groups 5. Decision based entirely on recommendation of opposing citizen groups
Y_7	Implementation likelihood	1. Definitely 2. Probably 3. Uncertain 4. Unlikely 5. Never
Y_8	Time to implementation	1. 0 to 26 weeks 2. 27 to 104 weeks 3. 105 to 182 weeks 4. 183 to 260 weeks 5. 261 to 364 weeks 6. 365 or more weeks

These five groups were in addition to the group given in Table 2. An important point about the questionnaire, and possibly one of its greater limitations, was that no explicit definitions were supplied to the respondent. What was "average" political complexity to one respondent may have been "fairly simple" to another.

DEVELOPMENT OF THE IMPLEMENTATION MODEL (IMPLEM)

To develop the urban transportation plan implementation model, called IMPLEM, by using the data collected through the survey questionnaire, required first that the 132 potential answers be classified according to whether each was (a) under direct planner control, (b) a dependent (indirectly controlled) variable, or (c) outside the control of the planner and, thus, either known at present or predicted exogenously. For example, assuming (as has been done in the scenario) that the problem has just become apparent to the planner, we would expect that he would know the type of problem, its location (group 1), and certain facts about the urban area (group 5). He probably would not know, and thus would have to predict exogenously, factors such as the future involvement of different types of officials and professionals (group 3) and whether these people would be influential (group 4). As work on the problem progressed, many of these factors would become known. Thus, scenarios different from the one employed here would evolve. (See the final section of this paper for an outline of proposed research in this direction.)

As for the planner's own influence, it has been assumed that he has direct control over only three items: his own participation in the planning or problem-solving process, the extent of communications, and the means of initiation of problem identification. These assumptions do not allocate to the planner a very dominant role in the decision-making process. However, because most planners and planning agencies are advisory in nature, stronger assumptions probably are not warranted.

Having identified the possible dependent (indirectly controlled), directly (planner) controlled, and uncontrollable variables, we can establish the IMPLEM model. This model provides predictions of probabilities that certain categories of each dependent variable will occur given certain categories of the planner-controlled, uncontrollable, and other dependent variables.

The IMPLEM model was developed as follows:

1. Each of the eight dependent variables given in Table 2 was cross-categorized with each of the 131 other variables in the survey questionnaire.
2. The ϕ-value for each of the cross-categorized relationships was calculated.
3. Various combinations (or stackings) were created of those categorical variables that, when cross-tabulated with a given dependent variable, gave high ϕ-values. These stacked variables were then cross-categorized with the particular dependent variable.
4. The combination of variables that, for a given dependent variable, gave the highest ϕ-value was chosen as the most appropriate.

The eight resulting categorical relationships and the corresponding ϕ-values are given in symbolic form as follows:

$$Y_1 = f(Y_2, Y_6, X_1);\ \phi = 0.72 \tag{14}$$

$$Y_2 = f(Y_3, Y_7, X_1);\ \phi = 0.60 \tag{15}$$

$$Y_3 = f(Y_2, X_1, Z_4);\ \phi = 0.70 \tag{16}$$

$$Y_4 = f(Y_1, Y_5, Z_3);\ \phi = 0.77 \tag{17}$$

$$Y_5 = f(Y_1, Y_4, Y_6);\ \phi = 0.76 \tag{18}$$

$$Y_6 = f(Y_1, Y_3, Y_5);\ \phi = 0.74 \tag{19}$$

$$Y_7 = f(Y_2, X_1, Z_4);\ \phi = 0.68 \tag{20}$$

$$Y_8 = f(Y_4, Z_1, Z_2);\ \phi = 0.53 \tag{21}$$

TABLE 3

PLANNER-CONTROLLED AND UNCONTROLLABLE VARIABLES IN IMPLEMENTATION MODEL

Symbol	Variable	Category	Symbol	Variable	Category
X_1	Communications	1. Good, free exchange of ideas 2. Satisfactory 3. Average 4. Poor; impeded by various obstacles	Z_3	Involvement and influence of state highway agency	0. Not involved 1. Just a participant 2. Influential 3. Initiated and influential 4. Initiated but not influential
Z_1	Location of problem condition	1. Area-wide 2. Central business district 3. Central city 4. Suburban 5. Exurban 6. CBD, central city 7. Central city, suburban 8. Suburban, exurban	Z_4	State of public information	1. The decision did not require any public information 2. Public information was desirable but nonexistent 3. Information given to private citizens effective, but not over mass media 4. Mass media coverage elicited no response 5. Strong mass media was combined with high degree of public information and response
Z_2	Total number of factors considered in making decisions	1. 1 to 10 2. 11 to 20 3. 21 and more			

As it turns out, the eight dependent variables are most highly related to a set of five other variables given in Table 3. Only one of these five communications, X_1, is under planner control. This factor is active in four of the eight relationships. The four uncontrollable factors are (a) location of problem condition (known), (b) total number of factors considered in making decisions (to be predicted exogenously), (c) involvement and influence of state highway agency (to be predicted exogenously), and (d) state of public information (to be predicted exogenously). (It is unfortunate that the latter three variables must be predicted outside the IMPLEM model because this reduces the reliability of the model's outputs. However, this situation can be attributed more to the type of scenario assumed than to the type of model developed.)

This brings us to consideration of the eight categorical relationships. These are given in Tables 4 through 11. The first row in Table 4 is used as an example to show that we are dealing with a situation in which variable Y_2, technical complexity, falls into category 1, simple; variable X_1, communications, falls into category 1, good, free exchange of ideas; and variable Y_6, professional-citizen influence on decision, also falls into category 1, decision based entirely on recommendation of professional personnel. Under these circumstances, there was only one response or observation, and it indicated that variable Y_1, technical-political consideration of dominant factor, fell into category 3, dominant factor given generally equal technical and political consideration.

Several points about the type of relationship given in Table 4 should be brought out. First, and probably most obvious, there are some combinations of the Y_2, X_1, and Y_6 variables that have no observations falling within their domain (and thus are not given in the table). Furthermore, most of the combinations that do have observations have only a very few. These conditions arise here because of the shortage of data coming from the survey. Even though 151 observations are usually more than adequate for calibration of most parametric models (e.g., regression), cross-categorical models require much more in the way of informational inputs. Not having these data is a definite drawback that will reflect on the precision and reliability of the probability values derived from the observational frequencies.

A second point of concern about the cross-categorical relationships is that, in certain cases, some of the data may not be useful and may have to be discarded. This occurs, for instance, when observations fall into the nebulous "other" or "no response" categories found in most surveys. These categories have not been given in Table 2 and have been eliminated from the relationships established here leaving, in the case of Table 4, a total of 134 observations with which to work.

A final comment relates to the complexity of the cross-categorical relations like those given in Table 4. In the simultaneous category example situation given previously, the expected value of the probability of an observation falling within a given category of a dependent variable is a simple function of the probabilities associated with another dependent variable. Equation 1 is a good illustration of this case. In contrast, the

TABLE 4

CATEGORICAL RELATIONSHIP FOR VARIABLE Y_1

Category of Variable			Number of Observations in Variable Y_1 Category					Category of Variable			Number of Observations in Variable Y_1 Category				
Y_2	X_1	Y_6	1	2	3	4	5	Y_2	X_1	Y_6	1	2	3	4	5
1	1	1			1			4	1	1	2				
1	1	2			1			4	1	2		1	4		
1	1	4				2		4	1	3		1	1	1	
1	2	5					1	4	2	1	1	1			
1	3	1		1				4	2	2			2		
1	4	2			1			4	2	3			2	2	
2	1	1	1		1			4	3	2			1	1	
2	1	2	1	1		1	1	4	3	3		1	1		
2	1	3			1			4	3	4					1
2	1	5			1			4	4	1		1			
2	2	1	1	1				4	4	2	1	1		1	
2	2	2		1	1	1		4	4	3			1		
2	3	1			2			4	4	4					1
2	3	2			2	1		5	1	1	2	2			
2	4	2	1		2			5	1	2	1		1	1	
3	1	1	3	2				5	1	3		1	1		
3	1	2	3	1	4			5	1	4			1		
3	1	3	2	2	1			5	2	1		2	1		
3	1	4					1	5	2	2		1	2		
3	2	1		2	1			5	2	3			2	1	
3	2	2	2	3	4			5	2	4	1				
3	2	3			4			5	3	2			1		
3	2	4			1			5	3	3			1	1	
3	3	1	1					5	4	2			1	1	
3	3	2		2	1	1		5	4	3				1	
3	3	3	1		1			5	4	4	1				
3	4	1				1		5	4	5					1
3	4	2			1										
3	4	3				2									
3	4	5			1										

TABLE 5

CATEGORICAL RELATIONSHIP FOR VARIABLE Y_2

Category of Variable			Number of Observations in Variable Y_2 Category					Category of Variable			Number of Observations in Variable Y_2 Category				
Y_3	X_1	Y_7	1	2	3	4	5	Y_3	X_1	Y_7	1	2	3	4	5
1	1	1	1	1	1	1	1	3	4	3			1		
1	2	1	1	1	1			3	4	4			1		
1	3	1		1				4	1	1		1	4	2	2
1	3	2		1				4	1	2			1	2	
1	4	1			1			4	2	1		1	4	2	2
2	1	1		4	3	1		4	2	2		1	1	1	
2	1	3	1					4	3	1			2		
2	2	1		2	2	1	2	4	3	2	1	1			
2	2	2			2			4	4	1				1	1
2	4	1		1				4	4	2				3	
2	4	2			1			5	1	1	1		1		1
3	1	1	1	2	7	2	3	5	1	2					4
3	1	2		1			2	5	1	3					1
3	1	4	1					5	2	1			1	1	2
3	2	1		1	5	2	2	5	2	3				1	1
3	2	2			4		1	5	3	1					2
3	2	3				1		5	3	4					1
3	3	1		1	2	2		5	4	1			1		
3	3	2		1	1	3		5	4	2			1		3
3	4	1	1	1	1			5	4	3			1	1	1

TABLE 6

CATEGORICAL RELATIONSHIP FOR VARIABLE Y_3

Category of Variable			Number of Observations in Variable Y_3 Category					Category of Variable			Number of Observations in Variable Y_3 Category				
Y_2	X_1	Z_4	1	2	3	4	5	Y_2	X_1	X_4	1	2	3	4	5
1	1	3	1					3	4	3					2
1	1	5		1	2		1	3	4	4			1		1
1	2	1	1					3	4	5			2		
1	4	5			1			4	1	1	1				
2	1	1			1			4	1	3			1	1	
2	1	3		1				4	1	5		1	1	3	
2	1	4		1				4	2	2				1	
2	1	5	1	2	1	1		4	2	3			1		
2	2	2				1		4	2	4			1		
2	2	3	1			1		4	2	5		1	1	2	2
2	2	4		1	1			4	3	1			3		
2	2	5		1				4	3	4				1	
2	3	1			1			4	3	5			2		
2	3	2				1		4	4	1				1	
2	3	4	2					4	4	3				1	
2	4	1			1			4	4	4				1	1
2	4	5		1	1			4	4	5	1			1	
3	1	1		1	2			5	1	1	1				
3	1	3			1	2		5	1	2					1
3	1	4			2			5	1	3				1	
3	1	5	1	2	3	3	1	5	1	4					2
3	2	1		1	4	1		5	1	5			4	1	3
3	2	3			1	2		5	2	1			1	1	1
3	2	4	1		1	1		5	2	4		1		1	
3	2	5		2	3	1	1	5	2	5		1	2	1	2
3	3	1				2		5	3	5					3
3	3	3				1		5	4	1				1	
3	3	4			1	1		5	4	4					1
3	3	5			2	1		5	4	5					3
3	4	1		1											

TABLE 7

CATEGORICAL RELATIONSHIP FOR VARIABLE Y_4

Category of Variable			Number of Observations in Variable Y_4 Category			Category of Variable			Number of Observations in Variable Y_4 Category		
Y_1	Z_3	Y_5	1	2	3	Y_1	Z_3	Y_5	1	2	3
1	0	1	5			3	1	3	1	1	
1	0	2	2	1	1	3	2	1	1	1	
1	1	1	4			3	2	2	1		
1	1	2	1			3	3	2	3		
1	2	1	2			3	4	2	1		
1	2	2	1			3	4	3		1	
1	2	3	1			4	0	1	3		
1	3	2		1		4	0	4	1		
2	0	1	5	1		4	1	1		1	
2	0	2	2	1		4	1	3		1	
2	1	1	1			4	1	4		1	
2	1	2	2	2		4	2	1	1		
2	2	1	3			4	2	2		1	
2	2	2	1			4	3	3	1		
2	3	1	1			5	0	1	1		
2	3	2	2			5	0	3	1		
2	4	1	1			5	0	4	1		
3	0	1	5			5	2	2	1		
3	0	2	5			5	4	1		1	
3	0	4	2								
3	1	1	7	1							
3	1	2	7	1	1						

TABLE 8

CATEGORICAL RELATIONSHIP FOR VARIABLE Y_5

Category of Variable			Number of Observations in Variable Y_5 Category				Category of Variable			Number of Observations in Variable Y_5 Category			
Y_1	Y_4	Y_6	1	2	3	4	Y_1	Y_4	Y_6	1	2	3	4
1	1	1	6	2			3	1	3	3	3		
1	1	2	4	1			3	1	4				1
1	1	3	1				3	1	5	1			1
1	1	4		1	1		3	2	2	2			
1	2	2		1			3	2	3		1	2	
1	2	3		1			3	3	3		1		
1	3	3		1			4	1	2	3			
2	1	1	5	4			4	1	3			1	
2	1	2	5	1			4	1	4				1
2	1	3	1	2			4	2	2	1	1		
2	2	1	1				4	2	3			1	1
2	2	2		2			5	1	2		1		
2	2	3		1			5	1	4	1			
3	1	1	3	2			5	1	5				1
3	1	2	6	11	1		5	2	4	1			

expected value of the probability that Y_1 falls into a given category (Table 5) is a function of several other variables. For example, the probability that Y_1 will fall into category 1 depends on the categories of variables Y_2, X_1, and Y_6 jointly. In other words,

$$Pr\{Y_1 = i\} = f[Pr\{Y_2 = j \wedge X_1 = k \wedge Y_6 = \ell\}] \tag{22}$$

where $Pr\{Y_1 = i\}$ is the probability that Y_1 falls into category i and $Pr\{Y_2 = j \wedge X_1 = k \wedge Y_6 = \ell\}$ is the probability that $Y_2 = j$ while $X_1 = k$ and $Y_6 = \ell$. Because the value of the $Pr\{Y_2 = j \wedge X_1 = k \wedge Y_6 = \ell\}$ probabilities is not known, the total number of probability values to be determined are increased as is also the size of the set of simultaneous equations to be solved. The additional equations linking the dependent variable

TABLE 9

CATEGORICAL RELATIONSHIP FOR VARIABLE Y_6

Category of Variable			Number of Observations in Variable Y_6 Category					Category of Variable			Number of Observations in Variable Y_6 Category				
Y_1	Y_3	Y_5	1	2	3	4	5	Y_1	Y_3	Y_5	1	2	3	4	5
1	1	1		1	1			3	3	1		3			1
1	2	1	1					3	3	2	1	5			
1	2	2	2	1		1		3	4	1	1	1	2		
1	3	1	2	2				3	4	2		4	3		
1	3	2			1			3	4	3			2		
1	4	1	1					3	5	1		1			
1	4	2		1	1			3	5	2		1	1		
1	5	1		1				3	5	3		1			
1	5	3				1		4	2	1		1			
2	1	1	1					4	3	1		1			
2	2	1		1	1			4	3	4				1	
2	3	1	3	2				4	4	1		1			
2	3	2	3	1	1			4	4	2		1			
2	4	2	1	2	2			4	5	1		1			
2	5	1	1	2				4	5	3			2		
3	1	1		2				4	5	4			1		
3	1	2		1				5	1	1				1	
3	1	4					1	5	1	4					1
3	2	1	2	1	1			5	3	1				1	
3	2	2	1		1			5	3	2		1			
3	2	4				1		5	5	4					1

TABLE 10

CATEGORICAL RELATIONSHIP FOR VARIABLE Y_7

Category of Variable			Number of Observations in Variable Y_7 Category					Category of Variable			Number of Observations in Variable Y_7 Category				
Y_2	X_1	Z_4	1	2	3	4	5	Y_2	X_1	Z_4	1	2	3	4	5
1	1	3	1					3	4	1		1			
1	1	5	2		1	1		3	4	3	1	1			
1	2	1	1					3	4	4			1	1	
1	3	1			1			3	4	5	1		1		
1	4	5	1					4	1	1	1				
2	1	1	1					4	1	3	3				
2	1	3	1					4	1	5	4	2			
2	1	4	1					4	2	2		1			
2	1	5	5	1				4	2	3	1				
2	2	2	1					4	2	4			1		
2	2	3	1	1				4	2	5	5		1		
2	2	4	2					4	3	1	1	2			
2	2	5	1					4	3	4			1		
2	3	1	1					4	3	5	1	1			
2	3	2		1				4	4	1		1			
2	3	4	1	1				4	4	3	1				
2	4	1	1					4	4	4		1	1		
2	4	5	1	1				4	4	5	1	1			
3	1	1	3					5	1	1	1				
3	1	3	1	1				5	1	2		1			
3	1	4	3					5	1	3	1				
3	1	5	10					5	1	4	1		1		
3	2	1	4	1				5	1	5	3	5			
3	2	3	2	1				5	2	1	1	1	1		
3	2	4	2	1				5	2	4	2				
3	2	5	5	2				5	2	5	5				
3	3	1		1	1			5	3	5	2			1	
3	3	3			1			5	4	1	1				
3	3	4	1	1				5	4	4			1		
3	3	5	3					5	4	5		3			

TABLE 11

CATEGORICAL RELATIONSHIP FOR VARIABLE Y_8

Category of Variable			Number of Observations in Variable Y_8 Category						Category of Variable			Number of Observations in Variable Y_8 Category					
Z_1	Y_4	Z_2	1	2	3	4	5	6	Z_1	Y_4	Z_2	1	2	3	4	5	6
1	1	1		1	1			1	4	1	2		1	1			
1	1	2		4	2		3		4	1	3	1					
1	1	3			1	1			4	2	1		1	1			
1	2	2		2	1			1	4	2	2						1
1	2	3		1		1			5	2	1		1				
1	3	3	1						5	2	2		1			1	
2	1	1			1				6	1	1	1					
2	1	2	1	1					6	1	2	1	3				
2	2	1			1				6	1	3		1				1
2	2	2					1	1	6	2	1						1
3	1	1	6	7	1				6	2	2			1		1	1
3	1	2	3	9	1	4	1	5	6	3	2	1					
3	1	3	2	1	1	1		2	7	1	1	2	1	1	1		
3	2	1	5	1	1		1		7	1	2	1	3				1
3	2	2	1	2	3	2	1	2	7	2	1		1				
3	2	3		1					7	2	2	1	3				
3	3	1		1	1				7	3	1						1
3	3	2		2				1	8	2	1			1			
3	3	3			1												
4	1	1	1	1				1									

category probabilities and the $Pr\{Y_2 = j \wedge X_1 = k \wedge Y_6 = \ell\}$ probabilities are derived from general rules of probability (4) and are presented in Eq. 23. These tend to be fairly complex.

$$Pr\{Y_2 = j\} + Pr\{X_1 = k\} + Pr\{Y_6 = \ell\} = 3Pr\{Y_2 = j \wedge X_1 = k \wedge Y_6 = \ell\}$$
$$+ 2 \sum_{\substack{m \\ m \neq j}} Pr\{Y_2 = m \wedge X_1 = k \wedge Y_6 = \ell\} + 2 \sum_{\substack{n \\ n \neq k}} Pr\{Y_2 = j \wedge X_1 = n \wedge Y_6 = \ell\}$$
$$+ 2 \sum_{\substack{p \\ p \neq \ell}} Pr\{Y_2 = J \wedge X_1 = k \wedge Y_6 = p\} + \sum_{\substack{n \\ n \neq k}} \sum_{\substack{p \\ p \neq \ell}} Pr\{Y_2 = j \wedge X_1 = n \wedge Y_6 = p\}$$
$$+ \sum_{\substack{m \\ m \neq j}} \sum_{\substack{p \\ p \neq \ell}} Pr\{Y_2 = m \wedge X_1 = k \wedge Y_6 = p\} + \sum_{\substack{m \\ m \neq j}} \sum_{\substack{n \\ n \neq k}} Pr\{Y_2 = m \wedge X_1 = n \wedge Y_6 = \ell\} \quad (23)$$

The indexes m, n, and p are substitutes for j, k, and ℓ respectively.

Using the IMPLEM Model: An Example

To illustrate the use of the IMPLEM model, we will assume certain conditions for the uncontrollable variables Z_1, Z_2, Z_3, and Z_4 and set the planner's strategy for the controllable variable X_1, remembering that we are working within the context of the scenario outlined previously. Let us set $Z_1 = 4$, the problem is located in a suburban area; $Z_2 = 1$, the total number of factors considered in making relevant decisions and between 11 and 20; $Z_3 = 3$, the state highway agency will initiate work on the problem and be influential in decision-making; and $Z_4 = 1$, the decisions made will not require any public information. Under these conditions, suppose that the planner chooses action $X_1 = 1$; i.e., he allows good communications and the free exchange of ideas. What will be the probabilities that various categories of each of the eight dependent variables will arise? What, for instance, will be the probability that the political complexity of the situation will be very complex, $Y_3 = 5$?

To answer these questions, we must set up the simultaneous equations evolving from the IMPLEM model. Note first that, with certain variables in the model fixed, there will be a reduction in the number of cross categories. For example, one can see that all those combinations given in Table 4 of Y_2, X_1, and Y_6 that do not involve $X_1 = 1$ can be eliminated because the corresponding $Pr\{Y_2 = j \wedge X_1 = k \wedge Y_6 = \ell\}$ probabilities will be zero. Thus, the relationship given in Table 4 can be collapsed to that given in Table 12. (Those relevant combinations without any associated observations have been added in Table 12 so that a comprehensive set of categories is utilized in the predictive effort.) Similar reductions can be made in the other relationships in the IMPLEM model except in conjunction with variables Y_5 and Y_6, each

TABLE 12

CATEGORICAL RELATIONSHIP FOR VARIABLE Y_1 WHEN $X_1 = 1$

Category of Variable			Number of Observations in Variable Y_1 Category				
Y_2	X_1	Y_6	1	2	3	4	5
1	1	1			1		
1	1	2			1		
1	1	3					
1	1	4				2	
1	1	5					
2	1	1	1		1		
2	1	2	1	1		1	1
2	1	3			1		
2	1	4					
2	1	5			1		
3	1	1	3	2			
3	1	2	3	1	4		
3	1	3	2	2	1		
3	1	4					1
3	1	5					
4	1	1	2				
4	1	2		1	4		
4	1	3		1	1	1	
4	1	4					
4	1	5					
5	1	1	2	2			
5	1	2	1		1	1	
5	1	3		1	1		
5	1	4			1		
5	1	5					

of which is a function of three other dependent variables.

With these changes there would be 283 probabilities to be determined; 38 for the categories of each dependent variable and the rest for the joint probabilities generated in each relationship in Table 3. Consequently, 283 equations would be needed. These would consist of the following:

1. The expected value equations for each category of each dependent variable (the number of these used for each dependent variable would be one less than the number of categories for that variable as in the example in the beginning of this paper);
2. The equations showing that the sum of the category probabilities for each dependent variable should equal one; and
3. The equations of the form of Eq. 23, with one equation for each joint probability in each of the eight relationships.

With the 283 unknown probabilities and the 283 equations, it would be possible to use the usual simultaneous equation computer programs to find the value of each probability. However, in the IMPLEM model as it is made up with the present set of data, the likelihood of some of the probabilities being zero is great. This would mean that the matrix of coefficients for the variables in the equations would be singular and thus could not be handled by most simultaneous equation programs that utilize Gaussian reduction. We have found it easiest to use a linear programming routine with the cost coefficients set equal to one for the 38 dependent variable category probabilities and equal to zero for the joint probabilities. Because the equations of the second type mentioned in the preceding are present in the constraint set, this approach would give a value of 8.00 (1.00 for each dependent variable) for the objective function. Any deviation from 8.00 would immediately indicate a problem somewhere in the data or computer program. (Because there is a unique solution to the 283 simultaneous equations, it really does not make any difference as to what cost coefficients are used. We have found the preceding coefficient set to be useful for the reasons cited.)

Results From the Example Situation

The left side of Figure 4 shows the probabilities that result when the uncontrollable and planner-controlled variables are set as indicated previously. With the planner trying his best to create good communications, the following turn out to be most highly probable:

1. The dominant factor will be given generally equal technical and political consideration ($Y_1 = 3$);
2. The problem will be of average technical and political complexity ($Y_2 = 3$, $Y_3 = 3$);
3. A single, essentially technical set of recommendations will be forthcoming with interagency conflict resolved ($Y_4 = 1$);
4. The decision eventually made will conform to the recommendations with only minor changes ($Y_5 = 2$);
5. Professionals and citizen groups will have about equal influence on the decision ($Y_6 = 3$); and
6. The decision will definitely be implemented but in a time period of between 183 and 260 weeks ($Y_7 = 1$ and $Y_8 = 4$).

The broken line in Figure 4 connects the most highly probable categories.

These results are not unexpected, given the planner's anticipated strategy for the situation in which he would most likely find himself. It looks as though he would be spending a great deal of time communicating between the highway department and suburban citizens in an attempt to iron out a few apparently significant difficulties that, in the long run, will not prove to be any hindrance to implementation. A relatively long time will be required, however, for a compromise to be reached.

As a basis for comparison, a prediction also was made of the conditions that would be most likely to occur if the planner did his best to impede communications. Would this change the technical or political complexity of the situation? Would the likelihood of implementation be lessened? The answer to the first question appears to be "yes"

$X_1 = 1$

Communications are Good: Free Exchange of Ideas

Category	1	2	3	4	5	6
Y_1	0.26	0.30	0.39	0.02	0.03	
Y_2	0.11	0.20	0.36	0.16	0.17	
Y_3	0.33	0.12	0.55	0.00	0.00	
Y_4	0.71	0.29	0.00			
Y_5	0.30	0.65	0.01	0.04		
Y_6	0.25	0.35	0.36	0.01	0.03	
Y_7	1.00	0.00	0.00	0.00	0.00	
Y_8	0.00	0.15	0.36	0.49	0.00	0.00

$X_1 = 4$

Communications are Poor: Impeded by Various Obstacles

Category	1	2	3	4	5	6
Y_1	0.11	0.27	0.31	0.31	0.00	
Y_2	0.00	0.32	0.04	0.32	0.32	
Y_3	0.00	0.04	0.32	0.64	0.00	
Y_4	0.89	0.11	0.00			
Y_5	0.27	0.42	0.31	0.00		
Y_6	0.27	0.38	0.34	0.00	0.00	
Y_7	0.63	0.37	0.00	0.00	0.00	
Y_8	0.00	0.05	0.15	0.50	0.00	0.00

Uncontrollable conditions: $Z_1 = 4$, $Z_2 = 1$, $Z_3 = 3$, and $Z_4 = 1$

Figure 4. IMPLEM model probabilities associated with two planner strategies under one set of uncontrollable conditions.

but to the second, "no." As can be seen on the right side of Figure 4, there has been a shift in technical and political complexity (Y_2 and Y_3). These have both changed from category 3, average complexity, to category 4, above average complexity. The influence of the planner's strategy seems to display itself significantly only in these two shifts, however (with the exception of Y_6 that changed almost imperceptibly from category 3 to 2). There has been very little change in any of the remaining variables. Thus, it would appear that, on the whole, the differences in effect that the planner can achieve by controlling communications are relatively minor. This does not mean, however, that the planner, if faced with the situation hypothesized here, should not bother to exert any effort. The effects of better communication, while minor, are all beneficial (in terms of reduced technical and political complexity). Moreover, we would guess that it would be rare that any single professional operating in the pluralistic public decision-making environment that exists in metropolitan areas of the United States would have an extremely significant effect on a transportation decision. This would mean, then, that it is a summation of a multitude of minor efforts, such as the planner's efforts, in this example, to reduce complexity, to conform to recommendations, and to seek greater probabilities and shorter times for implementation.

SUMMARY

The main objective of this research has been to develop and illustrate the use of a model capable of reliably predicting the impact of planner strategies relating to implementation of urban transportation decisions. The scenario used as a backdrop to the model has the planner pictured in the position of just having had initial contact with a particular urban transportation problem. He now has to decide what strategy to use to obtain the most desirable states of certain variables of interest—political and technical complexity, handling of his recommendations, and time and likelihood of implementation. Of course, the planner must act within the framework of some known or predicted factors beyond his control. The significant ones of these turn out to be (a) the location of the problem condition, (b) the total number of factors considered in making decisions, (c) the involvement and influence of the state highway agency, and (d) the state of public information.

The IMPLEM model's categorical relationships are shown to be reasonably reliable for making predictions of the probabilities of occurrences of certain implementation-related events, given the preceding uncontrollable conditions and the planner's strategy for handling communications (the only variable of significance over which he has a high degree of control). Phi-values for the eight relationships in the IMPLEM model range between 0.50 and 0.80, values that are satisfactory for social science research but certainly not outstanding.

A hypothetical example set up to demonstrate the use of the IMPLEM model produces some interesting results. Although general conclusions certainly cannot be drawn from one application of the model, it does point to the possibility that the effect of the planner's actions on implementation-related matters is fairly minor. Nonetheless, the impact is positive. The creation of better communications by the planner will help to decrease political and technical complexity. It is for these kinds of useful predictions that the IMPLEM model has been developed.

FURTHER RESEARCH

It should be remembered that the IMPLEM model has been developed under certain assumptions that have not been fully explored. Of prime significance is the fact that only one scenario was proposed: that in which the planner was at the beginning of the problem-solving process and was looking forward to determine the chances of implementation. Many more scenarios and situations are possible, and these open the way for a variety of research endeavors:

1. A study of the evolution of implementation probabilities as more becomes known about various exogenously predicted variables;
2. A study of implementation probabilities if the probabilities of different categories of the uncontrollable, exogenously predicted variables are used (instead of using one category with certainty for each of these variables);
3. A study of planner strategies (use of his control variables) in an evolving situation such as in Siegel's work (1);
4. A study of strategies for other professionals and the competitive aspects of these strategies;
5. A study of how to achieve consideration for certain of these factors; and
6. A study of implementation probabilities if the planner were to take over and control certain variables that he now does not control.

These and many other investigations are possible, indicating the great number of aspects yet to be researched. If these were to be done, however, it would be highly desirable to collect more data. There is not enough of the present data to develop a simultaneous category model that could be counted on to produce consistently reliable results.

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