Behavioral Demand Modeling and Valuation of Travel Time

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Behavioral Demand Modeling and Valuation of Travel Time

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Introduction

Peter R. Stopher and Arnim H. Meyburg, Cornell University

The Conference on Issues in Behavioral Demand Modeling and the Evaluation of Travel Time provided a research forum to stimulate and channel future research of behavioral approaches in the areas of travel demand modeling and the inference of travel time values.

The conference, held in South Berwick, Maine, July 9-13, 1973, was sponsored by the Engineering Foundation, the Highway (now Transportation) Research Board, and the U.S. Department of Transportation. The Board's Committee on Traveler Behavior and Values planned the conference and sponsored the publication of this report.

The conference was organized around the 6 workshops that were charged with the following specific tasks within their identified areas:

1. Identify the present frontiers of research into or applications of the subject area;
2. Determine and justify what further research and development is needed;
3. Determine what specific directions the research or development should take, explore present hypotheses and approaches, and determine priorities; and
4. Discuss, rationalize, and develop approaches to specific problems with regard to the research and development.

This report of the conference proceedings contains a summary of recommended research, the position papers presented at the conference, and the workshop reports. Readers of these papers and reports will find overlap that unavoidably results when artificial barriers are imposed on the research framework considered by each author.

Summary of Research Recommendations

Peter R. Stopher and Arnim H. Meyburg, Cornell University

The workshops made 3 primary research recommendations.

1. The efforts of the U.S. Department of Transportation toward the collection of data to provide a basis for future research in travel demand were recognized and commended. However, a number of cautionary notes were sounded. One of the pressing needs in travel demand is for longitudinal data. The workshops strongly recommended that this need be considered in the design of the data collection effort. One of the workshops emphasized that there can never be "one data set to end all data sets." Experience is continually being gained in improving questioning procedures and both the quality and the content of the data. In addition, data needs for travel demand research are undergoing change as the research progresses. And there is no way to ensure that mistakes will not occur in the design of a data collection instrument. Therefore, a strong recommendation was made that there be a continuing data collection effort aimed at providing a central data bank for travel demand research.
2. Research and development of new travel demand models should proceed with a mix of short-range and long-range objectives. In the short range, new unconventional models should be included in the conventional Urban Transportation Planning Package, and new models should be developed as part of the ongoing planning processes being carried out by many urban regions. In the long range, a sound theoretical basis for the models should be developed and should provide for major research and development of the model structures in place of the ad hoc improvements made necessary by the application of the conventional model set. In this respect, caution was urged in trying to move prematurely from research to full application. An attempt to move too rapidly from the research laboratory to full field applications might be damaging to the models and induce unwarranted disenchantment with the entire approach by policy- and decision-makers and those charged with the responsibility of carrying out transportation planning studies.
3. The third primary recommendation concerned the dissemination of information on both current and future models. Only a small group of researchers are aware of current progress in disaggregate, behavioral travel demand modeling, and very few transportation planning practitioners know anything about the field. Moreover, the amount of research in this field is growing too rapidly for any one individual to be able to stay completely current in the entire field. Wider information dissemination and more educational programs are needed concerning the disaggregate, behavioral approach, and a careful and continuing review of work in the field should be initiated through some agency such as the U.S. Department of Transportation. A number of conference participants expressed an active interest in assisting in any short course

or seminar aimed at informing federal, state, and local planners about the modeling approaches and the areas of possible application and short-range practical research open to them.

A number of specific areas of recommended research are summarized in the following paragraphs.

1. The value of time can only be inferred from the travel choices of cost-time "traders," while most past research has indiscriminately lumped together traders and nontraders. Furthermore, the requirements for modal-choice modeling do not necessarily coincide with those for deriving values of travel time. Hence, a new research effort for values of travel time is recommended. It should be based on the recognition of the specific data requirements for valuing travel time.

2. Research is needed to extend the approach of disaggregate behavioral travel demand models to trip purposes other than work and to travel decisions other than the choice of travel mode.

3. Needed research concerning the structure of travel demand models includes the theoretical basis of the models and its transference to a mathematical structure; the choice of one simultaneous or several sequential models to represent the travel decision; the mechanism of equilibration (interaction of demand and supply); the interaction between other household decisions, such as home location and car ownership, and travel decisions; and the development of longitudinal rather than cross-sectional models.

4. With regard to the internal structure of the models, research is needed on the effect and structure of travel-decision alternatives, such as time of day, trip frequency, destinations, mixed trip purposes and tours, and nontransport substitutes. Research is also needed to characterize alternatives, with consideration given to both behavioral accuracy and the need for policy sensitivity, particularly with regard to new policy options and the introduction of new technologies.

5. Psychological scaling applied to transportation research is a promising avenue of research. Applications of scaling techniques to travel demand are in their infancy. As a result, a large number of research areas have a potential for far-reaching effects on travel demand modeling: identifying linkages between modal satisfactions and preferences and operational variables and design factors, thus supplying policy-sensitive information; identifying parameters of site selection and route choice decisions; determining sensitivity of travel decisions to activity importance; and using preference similarities as a basis for aggregation of disaggregate models.

Conference participants were in unanimous agreement that research should be encouraged and funded now. The momentum created by the Williamsburg Conference in December 1972 and augmented by this conference should not be lost by lack of follow-up in the sponsoring of research. Furthermore, these 2 conferences have jointly fostered an interchange of ideas and progress within the international community of travel demand researchers and thus provided a situation in which maximum progress and minimal duplication of effort are likely to occur. Most of these researchers are likely to continue their efforts in some way even if major sponsored support is not forthcoming. However, those conditions can lead to further fragmentation and duplication of research efforts if not to attitudes of futility. Professional transportation planners are currently disenchanted with using models because of the poor quality of existing operative models and their misuse (or incorrect expectations). Unless models can soon be developed that can be demonstrated to assist decision-making to a noticeable extent, the opportunity to regain respect for travel demand modeling may be lost for all time.

Keynote Papers

Challenges in Urban Travel Forecasting

David S. Gendell, Federal Highway Administration

Almost any transportation issue involves travel demand in one way or another. At any point, the transportation system is in equilibrium; the supply side is in balance with demand. Before changing the transportation system, we should understand how the changes will affect travel demand because that in turn affects service, socioeconomic conditions, public finances, and the environment.

During the 10 years that followed the passage of the Federal-Aid Highway Act of 1962, which required transportation planning in urbanized areas of more than 50,000 population, tremendous activity occurred in the field of travel demand forecasting. This work, which typically focused on a 20- to 25-year forecast period, was successful in several ways.

1. It led to the development of transportation plans in the urbanized areas in the United States and in many cities throughout the world;
2. The model assisted engineers and designers in designing and locating the Interstate Highway System;
3. Because of their mathematical base, the models allowed different practitioners to obtain the same or similar answers by using the same parameters;
4. The modularity of the models allowed one model to be improved in structure, theory, or computer technology without interfering with the use of the other models;
5. The models can be understood and applied by the average practitioner (more than 1,300 people have been taught these procedures in the Federal Highway Administration's 2-week Urban Transportation Planning Course); and
6. The models successfully forecast travel.

With regard to the last point, a number of studies calibrated travel forecasting models based on data collected 8 to 10 years ago. These models were then applied to current socioeconomic data, and the resulting travel was assigned to current-year networks. In each test area, the assigned traffic volumes matched current ground counts about as well as the assigned base-year data matched ground counts 8 to 10 years ago, in spite of average travel increases of more than 50 percent.

The traffic forecasting models were successful in the 1960s, but will they be just as successful in the 1970s? The problems are not the same, and the urban planning process will have to change to reflect current needs.

In city centers planning will be concerned with distribution systems, peripheral parking concepts, traffic-free zones, bicycle and taxi modes, and movement of goods. In other portions of cities, planning will be concerned with public transportation and concepts to keep traffic off local streets and to reduce the impacts of traffic on residential areas. Noise and air pollution must be reduced, and mobility must be provided for the transportation disadvantaged.

In the suburbs, planning will focus on 3 areas.

1. Land use controls so that land use intensity levels do not overload the sewerage, school, transportation, or other public facility systems. The ability to expand highway capacity is becoming more limited and may soon require that development be limited to that which can be accommodated by the transportation system. In travel demand estimation, system capacity will be the starting point, and the amount of demographic activity and land use will be the output. In addition, the clients for these efforts should be those who control urban development and those who build and operate the transportation system.
2. The impact of transportation improvements on development. The amount and form of development and the resulting life-style will become paramount in future years in making transportation decisions. Current models have some capability of dealing with these issues through an iterative process, which is costly and time-consuming, and most of the new direct demand models cannot deal with them at all.
3. Short-range or program-oriented roadway and transit improvements for the proper expenditure of available funds. The need for work in this area will be accentuated by the changing nature of federal aid for urban transportation.

Current or developing models, because of their regional orientation and cumbersome, costly, and time-consuming operations, cannot be easily used for this type of planning. We need simpler, quicker, and more powerful models.

There are also other problems with these models. They do not easily respond to the increasing number of legislative requirements, such as those of the Clean Air Amendments of 1970 for implementation of air quality plans or development of strategies for conserving energy resources. Both of these involve controlling travel demand, yet what is the best course of action toward this end? Is the current state of the art in travel demand forecasting adequate for evaluating transportation options such as vehicle licensing schemes, automobile-free zones, parking constraints, car-pool locator systems, staggered 4-day workweeks, staggered work hours, no-build alternatives, demand-responsive and dual-mode transportation systems, other new transportation systems, parking pricing and other pricing policies, priority lanes, flow metering and other traffic control schemes, increased fuel costs and fuel shortages, para-transit options such as jitneys and bus pooling, free transit, and changes in service or marketing?

The capability to evaluate these options or even the more traditional ones such as adding additional highway capacity is not entirely adequate. Perhaps the most frequently asked question involving the decision to build major highways concerns the amount of additional travel the improvement will generate. Although all travel forecasting procedures produce travel demand that varies with system supply, they seem unable to respond directly to this issue. The question is complicated by the fact that the change in supply also results in a change in land use. What is needed is the ability to predict the 2-way equilibrium among level of service or supply, urban development, and travel demand and to express the result in a way that is meaningful to the decision-maker.

That there is a clear need to move ahead in the area of travel demand forecasting is, therefore, readily apparent. But in what direction should we head? The earlier Conference on Urban Travel Demand Forecasting (1) led to a broad definition of the needs. The purpose of this conference was to further refine those needs and to develop concise recommendations. That requires each one to put aside loyalties to particular approaches and to develop a consensus on a direction for both practice and research requirements. For while the profession debates, decisions are being made that need sound forecasts.

The other element of this conference was the value of travel time. A clear distinction needs to be made between the value of travel time as used in determining the relation between time and cost in predicting travel behavior and the value of travel time as used in evaluating alternative transportation options. Considerable work has been undertaken in recent years in the former area. The value placed on travel time is found to vary with respect to factors such as income, trip purpose, segment of the trip (travel time spent in the vehicle and out of the vehicle), amount of time saved, and decision sequence (e.g., travel time for trip-destination decision is different from that for travel-mode choice). Although this work is important in the understanding of travel behavior, unfortunately the values are being used as the basis for evaluating alternative courses of action in the public sector. I believe that this is inappropriate in many instances and that the value of travel time should be a policy decision.

For example, assume that 2 transportation options are to be evaluated. One involves some form of high-speed transportation, and the other involves a demand-responsive urban transit system aimed at serving a poor area. The potential users of the first system value their time at $20 per hour, and those of the demand-responsive transit system value their time at only 50 cents per hour. An economic evaluation might justify the high-speed system but not the demand-responsive system. Should we, therefore, invest public tax money in the high-speed alternative and not in the transit option? I believe we should not.

The value of travel time used in investment analyses involving the expenditure of general tax revenues by the public sector should be a policy variable. In effect, the government says, public tax money will be invested in transportation improvements for which such expenditures are justified based on a value of travel time stated as a matter of public policy. If, in fact, segments of the population value time at a higher rate, 2 options appear to be open. First, the private sector might make the investment, recouping the invested resources through user charges. Second, the government might set up a mechanism through which the high-cost facility could be built and subsequently paid off by user revenues. In the latter case, the government would be justified in using the actual value of the potential user's travel time.

We must, therefore, make it clear that the appropriate value of travel time for use in public investment analysis should in some instances be a policy determination and point out that in analyses of the behavioral value of travel time the possible misuse of the product of the research has social implications.

Past efforts in travel demand forecasting were largely successful for the purposes for which they were intended, but the current transportation-related issues are far more complex and require a concerted effort on the part of the profession to meet the challenge.

We must make our work more understandable not only to decision-makers but also to practitioners who must apply the procedures. How many of these people understand the meaning of terminology such as multinomial logit, probit or discriminant analysis, behavioral, disaggregate, maximum likelihood method, stochastic, probabilistic, and utility maximization? The test of our effectiveness is how relevant our work is to solving the real-world problems they face.

REFERENCE

1. Urban Travel Demand Forecasting. HRB Spec. Rept. 143, 1973.

Behavioral Travel Demand Models: Some Basic Considerations

Raymond H. Ellis, Alistair Sherret, and Richard D. Worrall,
Peat, Marwick, Mitchell and Company

Travel demand forecasting has probably been subjected to more active and virulent criticism in recent years than any other phase of the transportation analysis process. The reasons for this are numerous but basically stem from a feeling that most existing models are cumbersome and unresponsive to changing analytical requirements.

Some critics have argued, with considerable cogency, that the most pressing current requirement is for a simpler, more aggregate set of models that are less ravenous in their data requirements, are less expensive and time-consuming to apply, and rapidly test a large number of different plans in a timely and responsive manner. Others have argued, with equal force, that a greater understanding of the basic mechanisms underlying travel behavior would lead to a completely new family of modeling techniques, employing varying analytical structures and each oriented toward a particular set of analytical issues and areas of policy concern.

Certainly, simpler, more malleable model structures that lead to more timely and less expensive forms of analysis are required. So too are models that may be used to address particular, relatively narrow issues at some considerable level of detail. Both of these requirements imply the need for a better and more organized understanding of the factors influencing travel behavior than we have at the moment. Both also imply a somewhat different approach to the whole question of travel demand forecasting and travel behavior research than has been embraced in the past.

These points emerged with some considerable clarity from the recent Conference on Urban Travel Demand Forecasting (1). We would like to take some of the initial recommendations of that conference as the starting point for these comments.

Our comments are deliberately eclectic, covering issues that it seems to us should be among those of greatest concern in any future programs of research, development, and application of models. They cover issues of an institutional and organizational nature as well as questions of technique and research orientation. Although the comments are not a comprehensive statement of the issues, we hope they may serve to provoke some fruitful discussion and argument.

RECOMMENDATIONS FOR TRAVEL BEHAVIOR RESEARCH

One of the major purposes of the earlier conference was to develop a set of recommendations for future research in travel demand forecasting. Issues relating specifically to travel behavior were the concern of one workshop, which identified 11 major topics for future research (1, p. 115):

1. Behavioral response to low-capital options;
2. Evaluation of alternative marketing strategies;
3. Behavior of special user groups;
4. Definition, measurement, and treatment of attributes of transportation service;
5. Comparison of attitudinal and conventional forecasting techniques;
6. Monitoring of travel behavior;
7. Process of travel decision-making;
8. Activity patterns and destination choice;
9. Simultaneous estimation of service and demand;
10. Problems of aggregation and scale in travel analysis; and
11. Dissemination of research information.

The orientation, scale, and timing of the research vary considerably. Their total estimated budget comes to more than $4 million over a period of 3 to 4 years. The potential source of this money, perhaps not surprisingly, is not immediately identifiable. A cursory examination of the list suggests a number of themes that are central to several topics.

1. Considerable emphasis was placed on the need to develop a more coherent understanding of travel behavior from a variety of specialized perspectives. Emphasis was placed particularly on developing a better understanding of the potential impact of low-capital options, i.e., options involving relatively small levels of capital expenditures and dealing mainly with incremental changes in the service, supply, pricing, or marketing characteristics of existing transportation systems. Typical examples include car-pool schemes, priority transit schemes, parking and gasoline taxes, enhanced security provisions, improved vehicle design, alternative marketing strategies, short-range scheduling and service modifications, and marginal pricing changes. In a parallel vein, emphasis was also placed on the need to address more specifically the behavior and requirements of special user groups whose needs differ significantly from the norm and who are either ignored in current demand forecasting analyses or else simply lumped together with the rest of the population. Particular stress was placed on those segments of the population, the elderly, young, handicapped, and poor, whose behavior and use of existing systems is subject to identifiable constraints. In both instances, the emphasis was on the analysis of behavior at a highly disaggregate, specialized level rather than at a generic level, at least in the early stages of investigation.

2. There was considerable debate concerning the role that "attitudinal" analysis techniques may usefully play in the development of an improved understanding of travel behavior. The interest of the workshop members was reflected primarily in topics 4 and 5. The first of these focused on the need for a clearer identification of the salient attributes of transportation service, including the methods to be used in characterizing and measuring them and the mechanisms whereby they may be incorporated in either attitudinal or conventional model structures. Particular concern was expressed with respect to the definition of system-specific and system-common attributes, the stability and transitivity of user perceptions and attitudes toward alternative attributes, and the problems of extrapolating attitudes concerning existing systems to the analysis of new systems. The second focused on a comparison of the efficacy of attitudinal versus conventional techniques when applied to a single (or several) common test cases. Emphasis was placed in this latter case on a careful, comparative analysis of the viability, cost, and utility of attitudinal versus conventional techniques and on identification of those areas where each may be most appropriately applied in an operational context.

The message in this case is simple: There is a well-developed body of analytical techniques, derived mainly from the fields of market and consumer research, that appears to be highly appropriate to certain forms of travel behavior research. To date, its use has been explored only to a limited degree. It appears worthy of much closer examination.

3. One of the most common pleas of the behavioral analyst is for more and better

data. At present we are virtually ignoring one important source of such information, that is, information on traveler responses to the successive changes that are continually being implemented in transportation systems throughout the country. The problem is partly that we simply lack the appropriate mechanisms for collecting such data and partly that the necessary financial support is usually not forthcoming. The workshop proposed that a sample of case studies of existing systems be used to develop a systematic program for monitoring the impact on both long- and short-run travel behavior in response to selected changes in transportation service. The interest here was to capture information on operational changes in existing transportation services rather than to set up a set of explicit demonstration experiments. Particular emphasis was placed on low-capital options discussed above.

4. Existing information on travel decision process is extremely fragmentary largely because of the diffuse and uncorrelated nature of much existing research. To overcome the problem and to provide an effective, concentrated nucleus of research that might then serve as an effective foundation for the development of improved, more responsive demand forecasting models, a comprehensive program of basic research was recommended of the mechanisms underlying the travel decision-making process. This program would focus particularly on issues such as

a. Identification of the basic structure of the travel decision process and its relation to the established activity patterns and the characteristics of different decision units;
b. Development of a coherent, compatible set of behavioral data bases to serve as input to a variety of subsequent forms of analysis;
c. Identification of the sensitivity of travel decision-making to varying service parameters and other controllable factors under situations of at least quasi-experimental control;
d. Examination of the interrelations between long- and short-run travel investment decisions and between long- and short-run behavior;
e. Analysis of the interrelations between destination choice and trip purpose on the one hand, and route and mode choice and time of travel on the other; and
f. Consideration of potential short- and long-run substitution effects that involve the potential substitution of other forms of communication or interaction for current, physical movement.

The thrust of this recommendation was to guarantee (at least conceptually) that sufficient resources be made available, in one time and one place, to permit significant progress to be made in the development of improved behavioral analyses.

The above issues flowed only from one of the several workshops at the conference, but they serve to illustrate the combination of pragmatic and theoretical concerns that should underlie any future research program. We would like to pursue some of these issues in the remainder of this paper.

APPLICATION OF URBAN TRAVEL ANALYSIS RESEARCH

The absence of an appropriately funded urban travel analysis research program in the United States suggests that the priority that many planners associate with research in this area is not shared by decision-makers with the authority to implement such a program. In this context, it is useful to consider the potential justification for an urban travel analysis research program from the decision-maker's viewpoint.

During the past 10 years, the preponderance of the urban travel analysis research effort has been focused on regional planning analyses characterized by relatively coarse representations of the various urban transportation modes and relatively long forecast periods of 15 years or more. Research activity on these types of problems is understandable in the context of an urban transportation planning process that focused on highway capacity issues as it was evolved by the Federal Highway Administration. The crucial issues of urban transportation policy both now and in the future, however, involve concerns such as environmental policy and its transportation interrelations (with respect to the social as well as the physical effects of transportation), land use policy and its relations with transportation, and energy policy and transportation.

Inasmuch as the focus of national interest has shifted to issues associated with the environment, land use, energy utilization, and public transportation, there should be a corresponding refocusing of urban travel analysis research activities. If support is to be secured for an effective and meaningful urban travel analysis research program, it must be demonstrated to decision-makers that the results of this research will enable them to make better decisions with respect to these important and complex issues.

That an urban travel analysis research program is important to the achievement of national objectives can be illustrated by considering one specific research area. Partially in response to the critical issues identified above, national urban transportation policy has emphasized the development of an effective urban public transportation program for American cities. This emphasis is based on the belief that the environmental, social, and economic benefits are such that the general community should contribute to the development and support of the program. In other words, the rationale for developing an effective urban public transportation program stems from its contribution to the overall development of the community's objectives and not solely from a profit motive. The success of public transportation will, however, be ultimately judged on one overriding criterion: its ability to penetrate the urban travel market. The consequence of this observation is ineluctable: The marketing of public transportation cannot any longer be overlooked or deemphasized in a competitive environment in which the number of transit captives is increasingly diminishing.

Important elements of a public transportation marketing program include identification of target markets for public transportation—population segments that represent high potential sources of business; identification of the features and the stimuli most likely to influence the target markets; and assignment of priorities in the redesign of the public transportation service product.

Thus, one justification for conducting an urban travel analysis research program is based on the need to market public transportation more effectively. Unless an urban travel analysis research program is justified in this or similar terms, there is a strong danger that urban travel analysis research program proposals will be dismissed as irrelevant to national goals and merely reflecting the desire of researchers to conduct research in an area that they enjoy.

This perspective provides, in fact, an opportunity for an even broader urban travel analysis research program than was provided by the requirements of system level planning analyses. Many urban travel analysis research projects could be defined within this framework of marketing public transportation. Areas that are of particular importance include automobile car-pooling and increased automobile occupancy, vehicle equipment and terminal design, passenger's perception of personal security, schedule reliability, and image projected by transit operating personnel. Research projects should be designed to assess not only the impact of a given factor on the utilization of public transportation but also the normative issue of how the public transportation product should be designed.

IMPLEMENTATION OF URBAN TRAVEL ANALYSIS RESEARCH RESULTS

Perhaps more important than the identification of priorities for future research is the assessment of the results of the research that has been accomplished to date and the degree to which these research results have been implemented. Even if a research program were clearly related to national priorities, the program would not be sustained if the research results were not implemented. Nearly 5 years after the work of Lisco, Quarmby, and Stopher, behavioral, stochastic, disaggregate models are—with few exceptions—not being employed in operational planning studies and are largely discussed in research rather than operational planning contexts. Although aspects of behavioral, stochastic, disaggregate models do require further research, they can be usefully employed in modal-split and automobile occupancy analyses.

Thus, some of the research into behavioral, stochastic, disaggregate models has been completed and is available for implementation in operational planning projects, and there are distinct economic and technical justifications for using these techniques. Why then has the introduction of these techniques into operational planning practice been so limited, and what can be done in the future to encourage more rapid dissemination and implementation of research results? These are difficult issues that are not easily analyzed or resolved. Factors that contributed to the slowness with which these techniques have been implemented include the unavailability of a well-documented and efficient computer system, the general unavailability of well-qualified and trained personnel, and the absence of a professional consensus regarding the research findings to date.

If the urban travel analysis research program is to have any opportunity to be funded at an appropriate level, it should clearly include major elements relating to the implementation of research results. The following projects would contribute significantly to increasing the probability that these research results would be implemented:

1. A well-documented and efficient computer system that can be used in conjunction with behavioral, stochastic, disaggregate models (assuming that a professional consensus regarding the design of this system can be achieved) and that includes a calibration program, programs to assist in the preparation of a calibration data set, and programs to effectively apply the calibrated models;
2. Training programs that include short courses oriented to current practitioners and courses within the graduate programs of universities;
3. A program of demonstration planning projects that is specifically designed to field test the latest planning techniques—including new urban travel analysis approaches—within an operational planning environment and to demonstrate that these techniques can be effectively used to increase the quality of the transportation planning product; and
4. Techniques for applying behavioral, stochastic, disaggregate models that will exploit their advantages during the alternative-evaluation phase of a planning effort.

INSTITUTIONAL CONSIDERATIONS AND AN URBAN TRAVEL ANALYSIS RESEARCH PROGRAM

Implementation of a national urban travel analysis research program requires institutional changes at the federal level. To argue that the problem of implementing a research program would be solved if only the appropriate funding were available overlooks what may well be an important aspect of the problem, namely, that the federal government is not currently well organized to manage an urban travel analysis research program. The urban travel analysis research effort of the U.S. Department of Transportation is fragmented among various groups within the department (e.g., the Federal Highway Administration, the Urban Mass Transportation Administration, and the Office of the Secretary) and the National Cooperative Highway Research Program. Further, many of the issues that should be addressed within such a program are of major concern to a number of agencies outside the department, particularly the Environmental Protection Agency and the U.S. Department of Housing and Urban Development. Although a significant amount of coordination with respect to urban travel research does take place among these groups, the organization of an effective urban travel analysis research program requires a more developed institutional structure.

Thus, there is a need within the federal structure for an institution that would fund and manage a multimodal urban travel analysis research effort. This institution should clearly be designed to avoid even the suspicion of having a modal bias and for this reason should not be lodged in either the Federal Highway Administration or the Urban Mass Transportation Administration. Although multimodal research and policy studies related to urban travel analysis might be directly funded and managed by this new institution, this would not preclude the conduct of more mission-oriented urban travel analysis research efforts within the modal agencies. For example, the Urban Mass Transportation Administration might continue research projects specifically oriented to the problems of the transit industry such as the impact of the travelers' perceived security on their attitudes toward public transit. For those projects that continued within the operating administrations, this new institution would serve as a formal coordination point rather than as the program manager. The very applied nature of an urban travel analysis research program suggests that it should be placed within an operating department—probably the Department of Transportation—and not lodged in a more research-oriented environment where the perspective of the application of the research may be lost.

DISTINCTIONS BETWEEN MODELS FOR PREDICTION AND EVALUATION

In formulating mathematical models to estimate travel demand and especially the behavioral, disaggregate models, we need to bear in mind that different models may be appropriate depending on whether the primary aim of the analysis is prediction, evaluation, or design. The models may be different with respect to their structure or specification, their data requirements, the statistical estimation procedure used, and the method of their application.

If the primary aim of the model is predicting or forecasting some present or future level of travel demand, a 2-stage procedure is involved. At the first stage the model is specified and "estimated" (to use the terminology of the econometrician) or "calibrated" (to use that of the engineer) from a data set of observations on both the dependent and explanatory variables included in the model. The results of this first stage are best estimates of all the parameters of the model (i.e., the model coefficients) together with measures of the statistical significance that can be attached to the coefficients. At the second stage the model is "run" by inputting observed or predicted values for the explanatory variables to give predicted value or values for the dependent variables. The "goodness" of the model is assessed principally in terms of its overall explanatory power, that is, its ability to duplicate the values of observed dependent variables at the second stage. The estimates of individual model parameters derived at the first stage need not necessarily be of concern, provided that overall predictive ability of the model is acceptable.

If on the other hand the primary aim of the model is to aid processes of evaluation or design, the estimates of the structural parameters of the model and the errors of estimate associated with them are important. In the context of models to explain travel behavior and travel demand, the processes of evaluation and design may be considered to be much the same. In evaluation we are concerned with placing "values" on reductions in travel time and other transport system improvements; in design we are concerned with assessing what specific transport improvements will be most successful in effecting some desired objective. In both cases we are attempting to estimate the relative value or importance (however defined) of different transport system attributes. That being the case, the application of the model is essentially a 1-stage process in which we are interested only in interpreting the model coefficients in ways that are useful in evaluation or design. The second, predictive, stage is not necessarily of concern; but, in any case, in assessing the goodness of the model, predictive efficacy is secondary to the model structure and the significance of the individual structural coefficients.

For predictive purposes a perfectly satisfactory model might exclude any cost variable; but if a monetary value of time is required from the model to allow evaluation of alternatives, a cost variable must be included. Similarly, the form in which explanatory variables are entered in a model to allow good prediction (whether as differences, ratios, or whatever) may not allow meaningful interpretations to be placed on the coefficients. Consequently, for design purposes—for estimating the relative value of 2 specific attributes, for example—a model that is less good in a predictive sense is more appropriate if it allows useful inferences to be drawn from the coefficients.

In terms of the statistical estimation procedures employed, the distinction between predictive and evaluative models may be relevant to the extent that there are problems of misspecification and multicollinearity that give rise to unreliability and inconsistency in parameter estimates. If the model is purely predictive, low statistical significance levels associated with coefficients are likely to be of much less concern than if the coefficients themselves are the required output of the model.

These comments are not meant to imply that predictive and evaluative models should be different on theoretical grounds. Indeed quite the opposite is true. Ideally, one would expect a model that is a perfect predictor of behavior to contain all the factors that determine travel decisions in such a way as to reflect the relative values placed on them by the traveler. Further, to the extent that a model allows the outcome of any course of action to be predicted perfectly, it might be considered a perfect evaluation model. However, we are still a long way from developing perfect models. Moreover, even if one day perfect model constructs are available to us, practical and economic considerations such as data availability will always present constraints. The fact is that, practically speaking, we need to develop specific models to address specific problems and will often be required to adopt less than perfectly structured behavioral models. Certainly we should always be wary of predictive models that do not bear some recognizable and convincing relation to travel behavior; but, having said that, the distinction between models where prediction is the primary objective and models where coefficient interpretation is the primary objective is still a useful one to bear in mind.

In considering predictive models that involve a 2-stage process of estimation and application, we need to remember that, as inputs to their application, predictions must be made of all the exogenous variables included in the model. This being the case, we need to guard against the development of overly sophisticated models that can only be used in prediction if elaborate and expensive surveys are undertaken to predict the exogenous variables. This caution is made particularly with regard to the inclusion of psychometric, attitudinal, and perceptive data as explanatory variables of behavior in predictive models. Although it will probably often be true that the inclusion of such variables allows improved understanding and explanation of travel behavior, the difficulties of predicting the variables for other travel-choice situations may be so great as to invalidate the model in prediction.

DEMAND MODELS IN A CONSTRAINED TRAVEL ENVIRONMENT

Transportation planners have in the past been largely concerned with improving the transportation system so as to persuade travelers who have choices available to them to travel in a certain way. The obvious example is the attempt to persuade those with automobiles available to use public transport. Behavioral travel demand models have reflected this concern by concentrating on the modal- and route-choice decisions of travelers who are free to make such decisions.

However, we are now entering a period when policies to control travel will be increasingly pursued and when more and more travelers will find their mode and route choices much more limited by restraints on the use of private cars through legislation and pricing, by fuel prices and availability, and by other environmental pressures. Such constraints imply the need to produce estimates of travel demand in situations where travelers are faced with sets of choices rather different from those they have been faced with in the past. What this means for behavioral modeling is not altogether clear, but is something with which we should be concerned. Certainly the ways in which behaviorally based approaches to trip generation, attraction, and distribution modeling deserve attention. The estimation of how much traffic is generated by improved facilities and, on the other side of the same coin, the estimation of how much travel will be suppressed as travel choices are limited are important problems that have nowhere been satisfactorily tackled. However, in tackling these problems and others we have mentioned, we need to beware of directing all our energies to the development of improved and new models and neglecting the application of the models we have already developed.

Clearly, a great deal of research effort is required in many directions, but as transport planners we are being asked to help solve today's problems and to advise on policy decisions that cannot wait for the results of next year's research projects. Imperfect as they are, many of the behavioral models we have already developed can be of assistance in making better decisions, and we need to see to it that what knowledge we have already gained is put to practical use.

REFERENCE

1. Urban Travel Demand Forecasting. HRB Spec. Rept. 143, 1973.

Workshop Reports

1 Attitudinal Data

Michael J. Demetsky, University of Virginia

To properly view the role of attitudinal data in urban transportation planning, we enlarged the scope of this workshop from data requirements on comfort and convenience to include more extensive uses of psychological data in models of basic travel decisions. This more general scope arose from a consensus that behavioral analysis of travel choice has a much broader potential with psychological data than merely with subjective dimensions of modal attributes.

The major research objectives that were subsequently defined focused on the determination of basic travel choice variables and their ultimate relation with design factors and behavioral groupings. Thus, the goal of this workshop was to propose stages of research in the investigation and development of a forecasting methodology that associates observed travel behavior with the attitudes of the population toward system attributes and policy variables. It was further indicated that the attitudinal models must satisfactorily relate to the real world and provide a design-directing process in contrast to the present methodology that evolved as a resource-allocation process.

Discussion and references on the foundations for psychological models, the type of data obtained, and the basic measurement techniques are given in later papers by Michaels and by Golob and Dobson and are not repeated here. The behavioral theory advanced by these authors is that travel decisions are not neatly defined by a sequential process (i.e., generation, distribution, modal choice, and route choice) but arise from a complex interaction of considerations relative to making or not making a trip and choosing the destination, mode, and route. Accordingly, any model of travel behavior should accurately model the relevant decision process. In this respect, a valid model of the decision process must (a) include the variables on which people base their decisions, (b) possibly combine sets of these variables into more basic dimensions (multivariate techniques), and (c) describe how people actually use the dimensions or variables to make travel decisions. In this sense, the experimental design must determine as well as measure the relevant variables in a decision. For example, if comparisons of temperature and seating arrangement with other attributes show them to be important, they should be included in a representation of the decision process. Also, associated measures such as ratings on 0 to 1 scales are needed to relate how individuals perceive attributes at various physical degrees. These hierarchical (among attributes) and degree measures must then be interpreted in terms of broader characteristics, such as comfort, wherein there might be direct trade-offs between temperature and space as opposed to indirect trade-offs between temperature and travel time.

If users of contemporary transportation planning models are to be able to implement research results, an evolutionary process of behavioral model development is recommended. This strategy can be initiated by improving the modal-choice methodology.

Here, the modal-choice model, which derives choice patterns on the basis of behavioral measures rather than, or in addition to, physical dimensions, should be investigated to provide a true abstract representation of travel modes to facilitate predictions of demand for new as well as existing modes. By directly or indirectly incorporating appropriate measures such as comfort, convenience, and reliability into the prediction algorithm, a significant increase in the explanation of variance over existing models will result.

BEHAVIORAL ASSUMPTIONS

Existing disaggregate modal-choice models, which are calibrated by regression, probit, or logit techniques, hypothesize that people trade off certain quantities of variables and that they maximize their satisfaction (or minimize their dissatisfaction); that is, utility theory applies. Other interpretations of the decision mechanism are possible, however. For example, one alternative viewpoint states that people rank in order the basic attributes and, if mode A is superior to mode B on the most important dimension, mode A is chosen. Another theory of travel-choice behavior hypothesizes that people do not optimize but "satisfice." That is, if both modes A and B are satisfactory on a given attribute (perform adequately relative to a minimum threshold), there is no trade-off with respect to that attribute. Consequently, each of the 3 interpretations may be correct in different circumstances. For example, in studies on the value of time, people are assumed to trade time for money in urban travel. The time factor is dominant regarding business travel and the air mode, and air conditioning is a "satisficing" attribute. The behavioral process must, therefore, be understood if any realistic model is to be consequently derived and, hence, the underlying behavioral assumptions are critical.

Furthermore, disaggregate modal-choice models, which are based on the trader hypothesis and use direct measures of time and cost, have provided a means to estimate the value of travel time, which has become an important consideration in project evaluation. This process becomes more complex when indirect psychological measures of these system attributes are used. In this case, concepts of utility theory intervene and transform attitudinal assessments into indexes of satisfaction for competing modes. These indexes or utilities are then correlated with observed choice behavior to explain fundamental decision processes. Therefore, the key element in the psychological model is the index of satisfaction, which is founded on attributes such as comfort and convenience as well as on time and cost measures. The utility transformation is derived from the explicit behavioral assumptions that underly the model, and if, for example, the trader assumption prevails, then the value of time estimates will be indicated in the intermediate utility transformation.

DATA CONSIDERATIONS

The data requirements for models based on behavioral measures to predict transport demand are potentially fewer than those for current models. This conclusion is founded on the observation that, if preferences are measured and behavioral groups established, the findings from a limited number of studies can be generalized to provide a universally applicable set of behavioral axioms regarding travel choices. It is recognized that there are many complications in reaching such a goal, particularly aggregation considerations (the definition of behavioral groups) and interarea consistencies among these classifications. However, the potential benefits from behavioral models are encouraging and, hence, problems anticipated at this early stage of investigation should not discourage future research.

Specific data must be based on the particular choice process being analyzed and, accordingly, measure certain individual needs. In transportation planning the basic phenomena that must be measured include frequency of activity (trip generation), preference structures of destinations (trip distribution), satisfaction with modes of travel (modal split), and a preference structure for routes of travel (route assignment). Analysis of these processes requires that a single survey provide attitudinal or preference data, socioeconomic information, and travel-choice behavior. Surveys should be longitudinal in nature to reflect changes in travel behavior relative to system changes and individual attitudes. With respect to complete data needs, the proposal by the U.S. Department of Transportation to collect a disaggregated data set was welcomed by workshop members. It was further recommended that a central data library be established to relieve researchers of the data collection problem. Several small survey projects that relate choice situations would be more expeditious to behavioral model development than large areawide surveys. This conclusion reflects the need for a survey design more detailed than past designs because, even though the transportation planner lacks a controlled environment, he or she must be careful to derive demand hypotheses from individuals who do have alternative choices available.

Techniques are well established for the collection of travel data and relevant socioeconomic information on trip-makers and will not be discussed here. Rather, the collection methodology exclusive to psychological data is addressed.

METHODOLOGY

Primary psychological information is gathered via scaling procedures that include the following: paired comparisons, rating scales, ranking data, and binary data. These techniques differ in degree of cost and sensitivity of measurement and should be tested and compared in problem applications to arrive at a consensus on techniques for specific applications (i.e., modal satisfaction versus preference structures of destinations). The questionnaire must provide reliable information on travel needs (preferences or how attitudes ideally relate to individuals) and satisfaction with given options (perceptions). Because the task of questionnaire design is extremely demanding in content and detail, experts should be consulted. In this respect, a handbook to assist planners in questionnaire design should ultimately be developed.

The psychological measures found should then be subjected to diagnostic analysis, i.e., hypothesis formulation and citation of groups that exhibit similar choice behavior, and eventually incorporated into the development of predictive models. The data are first scaled via univariate or multivariate techniques (see Golob and Dobson paper in this Special Report), and then individuals are aggregated into behavioral groups. At this point, no prior assumptions should be made to relate behavior to socioeconomic groups because it is a fundamental goal of this approach to seek classes on the basis of behavior and then relate them to demographic groups. The scaled data are combined to produce utilities or measures of satisfaction that must be related by some mathematical structure to observed choice (a behavioral prediction model).

The resulting model must be thoroughly examined regarding its capacity for realistically handling the following major methodological requirements:

1. Specifications of class boundaries for homogeneous groups;
2. Validation from longitudinal data to show sensitivity to changes over time; and
3. Sensitivity of behavior to changes in transport systems, technology, and controls.

The findings should also be tested and validated in case studies, particularly with respect to before and after data from controlled demonstration projects.

RECOMMENDED RESEARCH

The aforementioned study design is recommended for application to travel-choice modeling in an incremental fashion. The workshop recommends that initial, or short-term, research should be concerned with the incorporation of psychological dimensions of level of service into the modal-choice model to make it more complete than the existing models. The goal is to determine the important behavioral factors underlying mode choice and the establishment of a mathematical formulation for the model. Here psychological data would be transformed to indicate modal satisfaction, which in turn would be used to indicate mode choice. At this initial stage of study the relations between behavioral sets and the traditional classifications employed in transportation planning should be investigated. Finally, the linkage between perceived attributes with manipulatable operational variables and design factors should be made.

In the intermediate state, the psychological model should be applied to the activity site selection and route-choice decisions. In the former case, a cognitive space for travel will be rendered. Various travel spaces, such as the preference structure by activity type (trip purpose) and geographic location, and activity spaces by travel mode can be investigated.

A behavioral route-choice model should be designed to diagnose particular elements relative to the route-choice decision so that an association is provided between the traveler and his or her environment. Such an association is not incorporated into conventional diversion approaches based solely on travel time and distance.

In the long-term phase of investigation into a true behavioral modeling system, the trip generation stage should be broadened to show sensitivity to activity importance and, consequently, need to travel. Such a methodology should be designed to show the relative effects on total travel demand that result from innovative social-technological schemes such as shopping via cable TV, working at home, and reducing the workweek.

Finally, if the above research provides successful models, the sequential decision models should be interrelated to define a realistic behavioral structure of the elements involved in travel decisions. Thus, the end product may be a completely new planning process with true behavioral foundations.

The research has been recommended in the described incremental fashion to integrate the results into the conventional planning process and, consequently, to slowly introduce the practitioner to the new models. The workshop concurs that the research must be useful and yet basic to achieving the broad goal of an improved planning methodology.

2 Aggregation Problems

David R. Miller, Barton-Aschman Associates, Inc.

In the context of this workshop, the aggregation problem is primarily one of statistical inference for predictive purposes. Classic transportation modeling involves aggregation over geographic zones. Sample points consist of geographic areas, and the dependent variables of primary interest are travel flows among areas. Dissatisfaction with geographic aggregation (and aggregate analysis in general) has grown in part from the realization that zones are not homogeneous populations and, hence, are not appropriate units for aggregation.

Disaggregate, stochastic transportation choice models have developed rapidly in recent years (2, 3). These models estimate the probability that an individual traveler will select a mode, based on characteristics of the traveler, the environment, and the available choices. Research in this field has concentrated on improved understanding of the travel-choice process and consequent explanation of the effect of changes in choice characteristics (e.g., level of service) on travel choice.

As a logical extension, Burnett, in his paper in this Special Report, and others (1, 2, 3, 4) have directed attention recently toward the application of disaggregate models to prediction of future travel behavior. The basic problem of aggregation associated with use of disaggregate stochastic models appears at this point: It is the development of a procedure for expanding individual probability-of-choice estimates to describe travel-choice behavior of groups.

Disaggregate modeling did not create the problem; it merely makes it explicit. For example, consider a disaggregate modal-split model based on a nonlinear relation between the probability of a traveler's choosing mode A and a vector representing a combination of characteristics of the trip by mode A or mode B and the trip-maker—a logit model, for instance. The traveler's initial position on the curve crucially affects the sensitivity of his or her response to changes in the vector of characteristics of the trip (for instance, a shift in the level of service). Without information about the distribution of travelers along the logit curve, inferences about the aggregate behavior of a group of travelers are highly unreliable. The mean value will not do. Suppose half the travelers were in fact at the 0 to 5 percent probability end of the curve and the other half at the 95 to 100 percent probability end. The sensitivity of response for either group to service changes is, in fact, low; yet, using the mean value of the distribution would lead to the (incorrect) inference that there was high sensitivity to changes in service.

By contrast, aggregate models implicitly assume that the travel behavior of each member of the group can be described by identical linear functions and that the population is well represented by the group mean value of the characteristics vector or some similarly arbitrary assumption. Conventional, aggregate modeling buried the distribution problem that disaggregate modeling makes explicit and, therefore, unavoidable.

An additional issue discussed in the workshop, though perhaps somewhat less fundamental, is the role of attitudinal variables in explaining travel choice. Traditional transportation modeling has confined data collection to objective measures of socioeconomic and environmental characteristics of people and transportation systems. Research is currently under way to investigate the potential of attitudinal variables for predicting travel behavior. Hensher, Golob, and the General Motors Research Laboratories are conducting this research in the expectation that attitudinal variables will prove to have better predictive power than the other variables in common use. In this research, there is a problem of separating groups of travelers according to their attitudes and other characteristics and of disaggregating so as to maximize between-group and minimize within-group variance.

Other aggregation issues, such as the aggregation of trips by purpose, by traveler-descriptive variables, or trip-descriptive variables, are common to both aggregate and disaggregate modeling. These issues were largely excluded in the workshop's deliberations—a decision made in the interest of limiting the scope of the workshop to manageable proportions and not with the intention of implying that these other issues are not worth further research and discussion.

PROPOSED TECHNIQUE

The workshop discussed a technique that appears promising for dealing with the aggregation problem made explicit in behavioral models. Workshop members substantially agreed about the outlines of the technique but were divided about what its most promising application is. One view was that the most promising application of the technique is for forecasting mode choice with respect to specific, incremental changes in service levels on parts of a network. The other view was that, properly applied, the technique might be used for much broader travel demand forecasting.

The approach proposes that the individual be maintained as the basic unit of analysis and that individuals be grouped to reflect some notion of a (Marshallian) representative person. This approach contrasts with the traditional aggregation interpretation where grouping by physical zone changes the basic unit of analysis (from the individual to the zone). Aggregation in the traditional approach may be viewed as a hierarchical ordering of horizontal layers in which an individual belongs to one of the mutually exclusive elements of the set that constitutes each layer. For example, an individual resides in a town, which in turn is located in a county within a state. The ordering may be viewed graphically as follows:

region
subregion
physical zones
individuals

By contrast, individuals in the proposed approach are aggregated only into those subgroupings that are meaningful with respect to the question at hand. The groupings, for example, might be according to attitudes, to socioeconomic strata, or to some other probably nongeographic attributes. An individual, accordingly, may become part of different population subgroups for different purposes.

The selection of the individual as the basic decision unit, rather than the household, is based on the premise that the individual maximizes utility (or some other function) subject to household constraints. Household decision-making is somewhat more nebulous and perhaps less appropriate to analyze. To illustrate this, consider the importance of having information on the number and availability of cars in a household. Although such information may be useful in determining the total number of trips made by the household, the picture changes when individual trips are considered. Choice of mode by an individual for a particular trip may be constrained by the availability of an automobile for that particular trip, which in turn is a function of previous decision-making by other individuals. It is possible that individual utility maximization may lead to household utility maximization, but not necessarily. In any case, the individual, having been identified as the basic decision unit, should be maintained as this unit at subsequent stages of travel-choice modeling.

The immediate advantage of the proposed approach is that it should permit consideration of the influence of household variables on the individual and the influence of variables directly related to the individual on the household choice process. By contrast, adopting the household as the unit of analysis excludes an important aggregation problem: summation of individuals within a household. There is little evidence to suggest that there is any more homogeneity between members of a household with respect to certain relations (e.g., convenience of mode or cost with number of trips) than there is between individuals of entirely different households.

Grouping along socioeconomic, nongeographic lines requires no further explanation; the variables used are familiar ones. Attitudinal groupings, however, are somewhat less familiar. Examples of attitudinal variables that might be used in grouping are as follows:

1. Importances people place on the characteristics of means and opportunities for travel in making transportation-related decisions (such as automobile ownership, residential choice, trip timing and frequency, mode and route choice, and destination choice);
2. Perceived satisfactions with characteristics (attributes) of existing travel means and opportunities;
3. Awareness of the existence of various means and opportunities;
4. Predispositions to react in certain ways to various stimuli; and
5. Stated intentions to behave in certain ways to changes in other of their attitudes or to changes in the supply of opportunities or means.

Automatic interaction detection was cited as a computer technique useful in determining "best" groupings of representative individuals. The need for the grouping technique (whatever technique may be selected) can be described mathematically as follows (1). Let us assume we are able to estimate a model of the general form

$$P_{ij} = f[\{E_j\}, \{L_j\}, \{Q_j\}] \tag{1}$$

where

P_{ij} = probability of individual j choosing alternative i,
$f[]$ = function of the enclosed terms,
$\{E_j\}$ = vector of environmental characteristics facing j,
$\{L_j\}$ = array of service characteristics for all available choices facing individual j, and
$\{Q_j\}$ = vector of the characteristics of individual j.

Such a model may be in the form of a single mathematical expression or a set of expressions applying to different groups of individuals. It would be a simple task to estimate N_i by the relation

$$N_i = \sum_j P_{ij} \tag{2}$$

if it were possible to predict all of the relevant variables as observed or perceived by each individual. Short of this, a more realistic procedure is to group the population according to population groups that are consistent with the included characteristics, compute the mean or central values of each of the characteristics for each group, and obtain the overall estimate from

$$N_i = \sum_J N_J P_{iJ} \tag{3}$$

where

N_J = number of individuals in group J, and
P_{iJ} = probability choice structure of individuals in group J.

Travel behavior prediction based on a disaggregate mode-choice model requires, in addition to a model of the general form specified in Eq. 1, a population distribution forecast model that assigns proportions of the population to subgroups described by the characteristics of group members. Various means can be developed for population distribution forecasting. At the least, the distribution could be assumed to be identical to the present one or, alternatively, related to means in the same way at present. Either of these assumptions is at least as good as the implicit assumptions contained in aggregate models.

Once the disaggregate mode-choice model and the population distribution forecast are developed, specific issues can be studied by the following technique. (It is at least theoretically possible to apply the mode-choice model from a different but reasonably similar area rather than to develop a new model for each region studied.)

1. For each zone of interest, apply the disaggregate choice model to a representative individual from each population subgroup identified in the population distribution model to estimate the probability of the selected choice, e.g., use bus, for members of that subgroup;
2. From the population distribution forecast model, estimate the number of persons in each subgroup; and
3. Multiply the probability of the selected choice for members of each group by the number of persons in each group and add up over all of the groups to estimate the total number of persons choosing the option studied.

An alternative application of the disaggregate model is based on the assumption that attitudinal variables will be found to be closely associated with, for example, socioeconomic characteristics. In this application individuals would be first identified by characteristics and then surveyed to determine whether their travel patterns made the use of a proposed new facility probable. (In the approach described in the preceding paragraphs, geographic location is likely to be one of the initial criteria for selection of "representative" individuals.)

Consider the planning questions revolving around the design of a line-haul transportation facility within a single corridor of a metropolitan area. First, population subgroups are defined on the basis of the multiplicity of behavioral, socioeconomic, environmental, physical, and attitudinal criteria addressed through the classification technique described above. Suppose that these groups were found to be differentiated primarily with respect to a subset of data available from census data sources in interaction with some variables concerning attitudes and existing behavior. Then, the geographical subregion census data would be statistically processed to allow identification of these data, and a second succinct survey (perhaps a telephone inquiry) would be designed to gain both the key attitudinal and behavioral data and the subset of trip patterns under study. Finally, point-coordinate systems would be used to derive inferences for the total population of interest, i.e., those in certain subgroups residing or working in the subregion.

In theory, this approach could be used on an areawide basis as well as for investigation of problems like the single line-haul facility. However, considering the developmental nature of the initial applications, subregional studies are judged more appropriate applications for the present. An important advantage of the proposed technique is that it permits focusing only on certain population subgroups and eliminates the need to formulate predictions for total populations.

It is granted that the procedures described will be difficult to apply in practice. Compromises will have to be made that introduce bias and error. Nevertheless, the final result, once expansion to regionwide predictive models occurs, will be an aggregate model that is more accurate than existing models, is sensitive to changes in service and population characteristics, and allows the magnitude of bias to be estimated. Such a result will justify the effort necessary to continue development of both the underlying disaggregate models and aggregation procedures outlined here.

SOME NOTES ON THE DATA QUESTION

One of the charges to the workshop concerned data requirements for modeling procedures discussed above. Data on travel behavior, socioeconomic characteristics, the travel environment, and attitudes are being collected in various ways now. One of the data problems is that at present the appropriate questions for attitude data collection are not the subject of general agreement. By contrast, the travel behavior and socioeconomic data are generally standardized and have been for a number of years. Research is under way to refine attitude data collection procedures. The two issues to be resolved are (a) which attitudes are to be measured and (b) how they are to be measured. The object of the research is to achieve a reasonable degree of consensus on the set of attitude questions to be asked—much in the same way that present home-interview survey questions have been standardized.

Finally, the workshop noted that disaggregate methods of travel forecasting should not be promoted as promising data collection requirements substantially lower than those of conventional aggregate techniques. It is possible, but not necessarily true, that data requirements may be reduced. A far more likely outcome is that a researcher will confront a trade-off between data collection requirements lower than present ones but with models yielding the same level of accuracy as present aggregate techniques and data collection requirements as substantial as present ones but with models yielding higher levels of accuracy. At least the possibility for the trade-off will exist with further development of the disaggregate models.

ATTITUDINAL MODELING IN PERSPECTIVE

The workshop felt that attitudinal research should be put in proper perspective to avoid the charge of having ignored existing and relatively valid techniques. It currently appears that the inclusion of attitudinal data, along with socioeconomic, environmental, and other objective data, will yield better predictions of travel behavior than those that can be achieved by excluding attitudinal data. This, however, is a hypothesis currently under investigation. It is possible, for example, that a consistent one-to-one mapping between some set of objective characteristics and attitudinal variables in individuals will be found. Should this be the case, a decision on which data to collect should be made on the basis of explanatory and predictive ability. It is also possible that attitudinal research may prove useful in predicting changes in behavior over time—to the extent that those changes are associated with predictable changes in attitudes in the population.

DIRECTIONS FOR FURTHER RESEARCH

Some of the directions for further research suggested by the workshop have been foreshadowed in the discussion above. Among the areas recommended for near-term research are the following:

1. Theoretical argument supporting the case for development of aggregate models based on the ability of disaggregate choice analysis to capture behavioral effects and to take account of changes in the distribution of the population among subgroups;
2. Selection of methods of population classification consistent with their reference to change in environmental characteristics;
3. Selection of a standardized set of attitude questions;
4. Analysis of the effectiveness of alternative classification schemes, which includes (a) selection of variables and their groupings and structure and (b) comparison of classification of individuals by individual characteristics directly to spatial units and of a 2-stage regionwide classification and spatial distribution procedure;
5. Analysis of the question of one-to-one mapping between attitudes and socioeconomic characteristics;

6. Development of overall measures for error and bias based on the errors involved in both the classification and behavioral description portions of the model structure;
7. Reduction of gaps between explanatory and predictive powers of models through selection of appropriate aggregation techniques, in conjunction with disaggregate modeling techniques, aimed at demonstration of the ability to forecast travel behavior through application to zones not included in the original model development; and
8. Comparison of the effectiveness of models based on aggregate and disaggregate analysis.

Completion of these tasks appears to be a requisite for further development of aggregate models based on behavioral analysis. Furthermore, it will provide a basis for trading reduced error and bias for increased development cost. Ultimately, the set of models selected for general use will be those that have the most desirable combination of cost, ease of use, and sensitivity properties.

REFERENCES

1. Koppelman, F. Prediction With Disaggregate Models: The Aggregation Issue. To be published in a forthcoming Transportation Research Record.
2. Reichman, S., and Stopher, P. R. Disaggregate-Stochastic Models of Travel-Mode Choice. Highway Research Record 369, 1971, pp. 17-23.
3. Stopher, P. R., and Lisco, T. E. Modelling Travel Demand: A Disaggregate Behavioral Approach, Issues and Applications. Proc., Transportation Research Forum, 1970.
4. Talvitie, A. Aggregate Travel Demand Analysis With Disaggregate or Aggregate Travel Demand Models. Proc., Transportation Research Forum, 1973.

3 Policy Issues

Eugene D. Perle, Center for Urban Studies, Detroit

This workshop was concerned with the applicability of disaggregate behavioral travel models in demand estimation and value of time studies. We were concerned especially with their usefulness in aiding policy decision-making and planning in special situations.

Discussions were stimulated by papers by Lisco and by Hartgen and Wachs, both in this Special Report. Lisco addressed problems involved in the concept of travel time valuation and the determination and application of travel time values. Hartgen and Wachs considered the practical requirements of demand modeling in special context planning and the appropriateness of disaggregate travel demand models in such situations.

FUNDAMENTAL POINTS

No one model or package of models is universally applicable to all transport planning problems. Depending on the problem being addressed, models will differ with regard to the basis for and complexity of their formulation, the level of data disaggregation involved in their calibration, the level of data disaggregation involved in their application, and so on. This is as true of what we have termed behavioral disaggregate models as of any other class of model. Moreover, different models may be appropriate depending on whether the primary concern is prediction, evaluation, or design.

We need to build models that are explicitly directed toward particular policy or planning issues. This means that variables under the control of or sensitive to the policy in question must be included in the model and that the scale of modeling effort involved with regard to model construction, data collection, calibration, and application must be commensurate with the nature of the decision being considered. Moreover, the speed of response of the models must be appropriate to the time frame within which the decisions have to be made.

Transportation system attributes, especially those other than simple time and cost variables, need to be included in travel demand estimation models on the basis of what attributes are important to travelers in their travel decisions if satisfactory explanations of behavior are to be achieved. At the same time system attributes must be included in models on the basis of what attributes are important to the policy-maker if they are to be useful in aiding policy decisions. Environmental and other external costs, for example, may be of major concern to the policy-maker but of little importance to the individual in making travel decisions.

Behavioral disaggregate travel demand models are generically no different from other demand estimation models. Compared to other travel demand models, they are behavioral only in degree. The models developed in the past, whether growth factor models, gravity models, shortest route models, or whatever, are all attempts to model travel behavior. In current models, we are attempting merely to provide a more complete specification of behavior. Similarly, their level of disaggregation is a matter of degree. All statistical estimation models employ data that are disaggregated at some level. Using data that are collected at the level of the individual traveler to calibrate a demand model has significant advantages of economy in data utilization. However, the calibration is no different in kind from that using data aggregated at, say, the household or traffic zone level. In transportation planning we are rarely interested in the travel behavior of individuals as individuals, and even if models are calibrated from data at one level of disaggregation they will often be applied at some other level of disaggregation.

Inasmuch as behavioral disaggregate models are basically no different in kind from any other travel demand models, they are not incompatible with the models used in existing travel demand estimation procedures. In particular, there is no conceptual reason why behavioral demand models cannot be integrated into the generation-distribution-modal split-assignment logic of the urban transportation planning (UTP) models for certain kinds of analyses. The view that behavioral disaggregate models and the UTP models are necessarily incompatible is a mistaken one.

Because behavioral disaggregate models are generically like other models, we have to be concerned with all the problems, difficulties, and requirements of models in general. For example, models are always imperfect representations of the real world and will always be dependent to some extent on the peculiar supply and demand characteristics underlying the data from which they are calibrated. They can never, therefore, be completely general in their applicability, although behavioral disaggregate approaches hold a greater promise of our being able to develop models that are transferable to different situations. Models should be soundly based both logically and empirically. The assumptions and logic of policy-oriented models should be made as clear as possible and be understandable by the policy-maker. The confidence level that can be associated with models and their outputs should always be made clear. Models should be as simple as possible and consistent with the nature and complexity of the issues being addressed.

CONCEPTUAL ISSUES

Travel time savings only have value with respect to their activity contents. Strictly speaking, time cannot be saved; it can only be transferred from one activity to another, and the value associated with the transfer of time from one activity to another depends entirely on the relative utility or disutility of the activities involved. Thus, a minute of travel time saved on the journey from work to home may be valued more or less highly than a minute of travel time saved on the journey from home to work depending on how pleasurable the activities are that are or could be indulged in at either place. A minute saved on a journey by bus will be valued by a traveler more highly than a minute saved on a journey by automobile if riding in a bus is considered less pleasurable than riding in an automobile. A minute saved on an automobile journey in congested traffic may be valued more highly than a minute saved on an automobile journey in free-flowing traffic, and so on.

The recognition that only savings in time spent doing something can practically be considered to have value has many implications for value of travel time models. Basically it means that only times of similar activity contents can be aggregated, compared, or valued together. A frequently voiced criticism of past value of time studies has been that they have shown wide variation in results. Although many of the criticisms of methodology are undoubtedly valid, the criticisms of the results may be less so. To the extent that the different studies considered savings in time spent in different ways, they should be expected to produce different values. Many models have recognized the significance of activity content in time valuation by considering walking, waiting, and in-vehicle time separately. Future models both to predict travel demand and to evaluate system improvements perhaps need to be structured in terms of an even finer stratification into different kinds of time—for example, time spent traveling in comfortable conditions and time spent traveling in uncomfortable conditions. Empirical constraints of data collection may, however, pose major difficulties.

The problem of how to measure and include in models attributes of travel other than time and cost—especially qualitative measures of comfort and convenience—is of current concern to many researchers. The fact that most attributes of travel are experienced over time may provide a solution to this problem of measurement: In some instances it may be appropriate to model an attribute such as comfort not in terms of the relative level of the attribute itself but in terms of the relative time spent experiencing a given level of the attribute.

A continuing point of contention among some researchers is the issue of whether a monetary value of time or of time savings is a meaningful concept at all. It can be argued that time cannot be transferred between individuals, nor bought nor sold in a marketplace, nor saved for use in a future period. Each person has neither more nor less time than 24 hours a day, and this passes at a constant rate. How then can economic theories of marketing be appropriate to the peculiar and nonmarketable good of travel time? Such conceptual issues can only be settled by a consideration of the activity content of peoples' time. The distinction, if any, between the value of time and the price of time is an issue that has yet to be finally resolved. So, too, are questions of the value of small amounts of time and the relation between average and marginal values.

Should perceived or objectively measured values of time, cost, and other attributes be included in models? Perception is the basis of traveler behavior, and so perceived values should be used to best explain and predict choice. But if the purpose of the model is economic evaluation of the costs, benefits, and resource allocations associated with transport alternatives, objective attribute values should be used. Pragmatically speaking, moreover, the difficulties of predicting peoples' perceptions will generally require objective values to be used. The development of models expressing the relations between perceived and objective variable measurements may become an important aspect of future travel demand models.

An advantage of behavioral modeling approaches is held to be that they allow models to be developed that are transferable to situations other than the ones for which they were calibrated. Implicit in this objective is the feeling that there are universal or generalizable patterns of traveler behavior. This feeling has been questioned and is perhaps likely to continue to be a point of some contention.

CURRENT POLICY ISSUES

We have concluded that demand estimation models must be developed to assist in specific policy or planning questions and that no one model or class of models can be expected to answer all questions of policy. Consequently, to give any meaningful answer to the general question of what the implications are for behavioral disaggregate demand modeling of current policy questions without considering specific policy questions is impossible. Nor is it possible to assess the appropriateness of behavioral disaggregate demand models in general for answering policy questions in general. We will not, therefore, attempt to give answers to these questions here, either in general terms or with regard to specific policy questions. We do, however, feel it is worthwhile to restate some of the current policy issues that models will be required to address and that should consequently determine the direction of future modeling efforts.

As transportation planners we are likely to be increasingly concerned with situations in which severe constraints are applied to the environment in which travelers must make their travel decisions and in which the transportation system must operate. The most obvious of these constraints are more stringent environmental standards for air pollution and noise levels, more expensive and less easily available fuel, and political and social pressures associated with these and other environmental issues. Given these constraints, the most important policy issues will be those dealing with how and to what degree travel demand should be controlled to achieve environmental objectives such as air quality or fuel conservation. Some of the policy options that have been and will be considered as means of controlling travel demand are as follows:

1. The availability and price of fuel may be controlled;
2. The use of the private car may be restrained in other ways such as by increasing parking charges, by charging for the use of road space through congestion tolls, licenses, or other road-pricing schemes, or by prohibiting private cars on certain streets at some or all times of day;
3. Public transport ridership may be encouraged by reducing or eliminating fares, by improving frequency, comfort, reliability, and other characteristics, by marketing such improvements, and by providing public transit with operating advantages over private transport by the provision of exclusive lanes and other priority schemes;
4. New transportation systems such as people movers, personal rapid transit, demand-responsive transportation, and jitney systems will be considered as will low-capital options such as incentives to encourage car pooling; and
5. The "do-nothing" option by which road congestion is itself allowed to control demand will inevitably, by default, arise as a policy option.

In evaluating alternative policies to control travel demand, policy-makers will have major concerns about the effects on travel generation in absolute terms; that is, how much travel will be suppressed or generated as the result of implementing a particular control policy, and what will be the effects on origin-destination distribution patterns? Assessment of the likely effects on land use redistribution will be important, especially the movement of employment and other activities into or out of the city center. Of major concern, also, will be the implications for the movement of essential goods and services in the city.

DIRECTIONS FOR FURTHER RESEARCH

A number of issues of modeling concepts, methodologies, and policy requirements have been mentioned in previous paragraphs, each of which implies the need for further research and development effort in specific areas. Underlying most of these is a basic need for an improved and deeper understanding of the motivations and rationales underlying traveler behavior. Especially important is the need to improve our understanding of the way in which travelers perceive the characteristics of both travel alternatives and the activities for which trips are made and the relative importance that they attach to those characteristics in making their travel decisions. Although the dominant feeling of the workshop was that future model development efforts should emphasize the need for simplicity and policy orientation in model application, we would agree that there is certainly a place and a need for continued "pure" research of travel behavior. An emphasis on consideration of the activities that do or could take place over time may be an important and fruitful avenue of such further research.

Further research is required into several aspects of the question of what attributes of travel alternatives should be included in travel demand estimation models, and how. The question of whether the model is to be used primarily in predicting or in evaluating the economic benefit associated with changes in travel mode characteristics will be important. The question of what travel attributes should be included in models should be considered from the viewpoint of the traveler or the viewpoint of the policy-maker depending on the problem being addressed. The question of whether perceived, objective, or other "attitudinal" attribute measures are appropriate will also depend on the problem being addressed. Policy variables may be included directly and explicitly in the model, or they may be included indirectly as attributes to which travel behavior responds. Two-stage modeling approaches may be implied in which the effects of policy decisions on travel attributes and the effects of travel attributes on travel behavior and demand are modeled sequentially. The appropriate model form in any situation must be developed with regard to specific planning decision issues.

The increased emphasis on policies to control travel demand in urban areas has a number of implications for the requirements of future demand estimation models. Behavioral modeling approaches need to be applied to the trip generation, attraction, and distribution phases of demand estimation as well as to modal choice. The problem of how to estimate the absolute increase or decrease in travel resulting from changes to the transport system will become even more pressing when traffic restraint policies must be assessed. The changes in the distribution of land use and land use activity resulting from changes in the transport system are a closely related and equally important area where further model development work is urgently required. For example, the effects of traffic restraint on the movement of business activity out of the central business districts of cities are likely to be a major concern of policy-makers in the future. Behavioral modeling approaches based on the home and work location decision-making behavior of individuals or firms may be appropriate in addressing these model development needs.

SOME PRACTICAL SUGGESTIONS

In the last 10 years, a great deal of research has been done on issues associated with behavioral travel demand models and value of time estimation. Research findings have been fairly effectively disseminated through transportation research journals, research reports, and conferences. We have reached the point where this body of literature is too great for any one researcher to review comprehensively. As future research and development work is completed and reported and as the results of the application of models to practical planning issues become known, there will be a pressing need for the comprehensive review and dissemination of research findings in the field.

The function of information dissemination should be undertaken by a single central agency. This agency should (a) prepare and publish independent critical reviews of all work done internationally in the behavioral demand modeling field; (b) summarize and compare in a consistent way the assumptions, methodology, and results of different model development efforts; and (c) publish relevant research findings in the form of comprehensive guidelines and manuals for data collection and model application and update these guidelines as further research results indicate.

The function of information dissemination and coordination might most effectively be accomplished by an agency of the federal government, such as the U.S. Department of Transportation. The dissemination and coordination of research information in the field would be an important complement to the function of the federal government as a supporter of travel demand model research and development.

In making this suggestion, we recognize there are likely to be reservations among both researchers and practitioners concerning the role of a federal agency as the arbiter of research activity. These reservations, which were held by some members of the workshop, apply particularly to the extent to which a government point of view can be expected to be a truly independent one. Furthermore, the practical constraints of the availability of suitably qualified personnel within existing agencies may preclude their adding such a task to their other responsibilities and commitments. Nevertheless, we feel there is a need for a positive and authoritative dissemination of research information on the subject of behavioral demand modeling and that a federal government department may best direct and support such an activity.

The UTP package of computer models, which is currently maintained by many state and local planning agencies, is cumbersome and inappropriate for most of the planning and policy issues that we currently face. Even so, maintaining those models frequently consumes large resources of trained and qualified personnel. Because so many of their people are occupied in maintaining the UTP model, many planning agencies are prevented from developing more appropriate planning tools. Short of abandoning the current UTP models altogether, there is no easy way out of this circle. However, it seems clear that the present state of affairs often represents a poor use of manpower resources. During the conference, we heard pleas for increased government support of behavioral modeling efforts. While supporting these pleas, we feel that the manpower resources and funds already available for planning model development could and should be put to much better use by redeploying some resources away from the maintenance of large-network UTP models to the development and application of more responsive, policy issue-oriented behavioral models of travel demand.

4 Structure of Disaggregate Models

Antti P. Talvitie, University of Oklahoma

The workshop had 2 tasks: to broadly identify areas where more research is needed and to give specific directions to research in these areas.

STRUCTURE OF TRAVEL DEMAND MODELS

Fundamental theoretical work is needed to extend established theories of consumer behavior to travel demand and travel choice. Many existing demand or choice models consistently violate the established principles of consumer behavior as expressed in current theories. This is particularly true with the urban transportation planning (UTP) model system; alternatively, overly restrictive assumptions are introduced into the models to overcome the limitations of data availability or coefficient estimation.

The second topic that urgently needs attention concerns the identification of the behavioral structure on which the statistical choice models—logit, probit, and truncated linear—are based. The workshop discovered that starting with 2 sets of axioms regarding choice behavior it is possible to arrive at the same explicit mathematical expression. This raises the issue of whether the statistical models measure behavior based on stochastic transitivity (as defined by Luce) or absolute transitivity (as defined in microeconomic theory). The reader is referred to the excellent workshop resource papers in this Special Report for further study of these 2 approaches.

The third topic involves the choice of simultaneous or sequential models. A number of problems, both theoretical and practical, are associated with the use of sequential models. Members of the workshop found it difficult to justify sequential choice behavior by using a priori reasoning. Furthermore, empirical evidence suggests that the ordering of choices significantly affects the model coefficients. The workshop concluded, however, that further research is required to reveal how consumers make their choices from among the alternatives and whether and how these choices are ordered.

The fourth topic needing more research concerns the problem of the supply side of transportation. Almost all models used for the analysis of travel demand to this day neglect the fact that there are 2 types of decision-makers in the travel market. The failure to account for this may, therefore, have led to the calibration of models reflecting not the behavior of the consumers but the behavior of both consumers and suppliers. Thus, research is needed to ascertain whether the supply side should be brought into the model building process and, if so, how.

The fifth topic, which is difficult to separate from the previous ones, is the problem of equilibration (assignment) of demand and supply. Route choice cannot be separated from choice of mode and other trip decisions. Thus, research is needed to ascertain that procedures exist that produce a unique equilibrium of demand and supply; at present no such method exists.

The sixth topic is the need for a more thorough understanding of the relations between travel-related decisions such as automobile ownership and household location on the one hand and trip-making decisions on the other. The location behavior of other activities should also be studied concurrently.

The seventh topic, which is not unrelated to the research tasks enumerated above, concerns the modeling of travel and related behavior over time. The workshop members felt that dynamic models are theoretically sounder than static models; consequently, the enormous challenge of a dynamic approach should be accepted.

SPECIFICATION OF VARIABLES IN THE MODEL

The first topic concerns the need to uncover how relevant alternatives are structured and conceived by the trip-maker. These alternatives include frequency of trip, time of day of trips, possible destinations, mixed trip purposes and tours, nontransport substitutes, or any combination of them. Although this research appears formidable, it may not be impossible. Members of the workshop produced evidence that suggests that the travel patterns of individuals are stable and focus on far fewer alternatives than is generally believed and that more than a third of the trips have multiple destinations and purposes (tours). These observations are also of importance in projecting travel behavior over time.

Another topic concerns the way in which the alternatives themselves are characterized. The variables in a travel demand model are normally divided into 3 groups: socioeconomic, activity (attraction), and level-of-service variables. The workshop devoted only a token of time to the socioeconomic variables. The consensus was that for social and other reasons division of the travel market into segments is mandatory, and research is in order to support the composition of these segments.

One of the important aspects in characterizing the alternatives is the way in which the alternative destinations are defined. The current practice of using the number of jobs (by type if necessary) to characterize destinations may or may not be the best way. The workshop felt that it is not the best way and strongly suggested more research in this area.

Another important concern in characterizing the alternatives is the inclusion of the right level-of-service variables in the model. The workshop members felt that past models placed too much emphasis on curve fitting and not enough on incorporating into the models those variables that are under the control of planning authorities or private operators and may, thus, be used in formulating transport policies. In addition, the members of the workshop felt that new situations and policy variables should be anticipated and ad hoc techniques should be used in specific cases without undue fear as a part of the normal model-building process. Some of the variables that have been ignored in the past are traffic management measures, pricing, location and provision of parking, licensing, shared-ride and freight taxi, bus lanes, car pooling, reliability of service, and schedule delay.

The variables that are functions, e.g., travel time as a function of volume, number of lanes, signalization, and access control, should be quantified.

Not only is the inclusion of the right variables in the model important but also the way in which they are mathematically represented in the equations. The observed stability of individual travel patterns and supporting evidence of the existence of response thresholds (i.e., a change of certain magnitude is needed before it is recorded) suggest that behavioral models may not assume continual travel response. This observation is especially important for strategic and short-range planning purposes. Further diagnostic research pertaining to this problem is clearly called for.

The research projects described briefly above in this and the previous section cannot be successfully conducted by using existing data. Therefore, a government-funded data collection effort should be undertaken in 2 parts. The first part should include a diagnosis of what needs to be measured and small diagnostic surveys to measure responses of travelers and nontravelers to identified relevant variables. Some of the surveys might well be attitudinal surveys to identify the relevant variables.

A specific research institution should be selected to manage the sampling design and the necessary diagnostic research. That institution should be required to appoint an advisory group to direct the sampling design and to act as a steering committee for all of the diagnostic work required to probe which factors enter into decisions relating to trip-making behavior.

The end product of this first part would consist of a detailed sample design, including appropriate questions directed toward the measurement of all those parameters that are known or that are thought to be relevant to trip-making behavior. This would form the basis for the second part, which is detailed and continuing surveys. The second part should probably be done under separate contract and not necessarily involve the same research institution.

All the data should be made generally available to further develop and test disaggregate behavioral models to ultimately replace the present UTP model system.

PRACTICAL APPLICATION OF NEW KNOWLEDGE

Employment of new travel demand models in practice is of paramount importance because the current UTP model system is theoretically, empirically, and computationally unjustifiable. The separate models in that system as well as the system itself (and we mean the latest versions of it) can only be marginally improved. The structure of the model system is rigid. It accepts only one type of modular sequence and cannot be applied with confidence. Clearly, research in this field should concentrate on developing models with sound theoretical bases.

Several things, however, can be done now before new models are developed to help bring the new models into common use. The first is the incorporation of measures of accuracy for each model separately as well as for any sequential grouping of models in the UTP system (and also for the new models, of course) to provide an adequate insight into the actual performance of the model or model system. The accuracy should pertain to measures such as product of interest, zonal interchanges, and path volumes and not to popular but useless measures such as trip length frequency, expressway link volumes, and vehicle-miles of travel.

In addition, greater use can be made of existing behavioral models—aggregate and disaggregate—in dealing with a limited range of planning problems. Models are already in existence that can be used to deal with problems such as provision and pricing of parking, changes in frequency of public transit, closing of lightly used stations or stops, fare changes, air pollution controls, and energy consumption.

The third thing that can be done now is to allow and encourage those ongoing studies that want to develop new models to update their plans to do so. Because the current 2-front effort, using what exists and developing new and better methods besides, has failed to produce meaningful changes in models within a reasonable time period, merging the 2 fronts in some transportation studies to help the change take place is the sensible thing to do.

The initiative should come from the study itself, and the first of these attempts are likely not to meet our highest expectations. Therefore, the enterprising agency should be granted a bargaining position with the federal government with respect to time deadlines and study costs. Although this suggestion does not detail in step-by-step fashion how a practicing agency can develop and employ new models, it does describe the atmosphere in which useful and healthy progress can occur.

5 Traders Versus Nontraders

Reuben Gronau, Hebrew University, Jerusalem

The terms traders and nontraders in the context of the analysis of modal split date back to one of the first studies in this field (1). Beesley distinguished between travelers who faced a choice between a faster but more expensive mode and a slower but cheaper mode (the traders) and between travelers who faced a mode that was both faster and cheaper (the nontraders). In his sample of about 1,100 travelers, less than 30 percent belonged to the first group. The percentage of traders in other samples was even lower (2, pp. 49-53). Furthermore, it was found that estimates of the value of time based on the sample as a whole differ significantly from those attained in a sample consisting exclusively of traders.

Given the large fraction of nontraders in the population and given their effect on the estimates of the value of time, which is the right method of estimation? If it is necessary to exclude nontraders, an additional question must be answered: Can one use the estimates of the value of time (estimates based solely on traders) for the valuation of the benefits of projects that also involve nontraders? The answers to these 2 questions are the focus of this paper.

To an economist the distinction between traders and nontraders or, more specifically, the existence of nontraders may verge on sacrilege because economists believe that all people are born to be traders. We trade services (labor and capital) for money and money for goods and services. Thus, their specific situations and not their characteristics make persons nontraders. It is therefore worthwhile to generalize Beesley's definition and examine some of its ramifications.

Given a situation where a person has to choose between n alternatives on the basis of k characteristics, we have to distinguish between those cases where there is 1 alternative (among the n) that is perceived to be dominant (i.e., is superior in all k respects) and the case where there is not. In the first case the person is a nontrader; in the second case the person is a trader. Let me start with some of the most trivial implications of this definition.

When n = 1 (i.e., there is no choice) the person is a nontrader.

The definition hinges on the existence of a dominant alternative and is independent of the actual choice made. Thus, if a person seems to behave illogically, i.e., if a person is in a situation where a dominant alternative exists but still chooses an inferior one, he or she is still defined as a nontrader (in this case an illogical nontrader).

Trading or nontrading is not a property of the person but relates rather to the situation. A person may face a dominant mode of travel (say, car) and hence be a nontrader where the choice of modes is concerned, but be a trader where the decision about which route to take is concerned. Furthermore, the situation that makes a person a nontrader may be the outcome of a trading decision. Thus, the location of the household, which is a major factor in the determination of the feasible alternatives, is in the long run not exogenously given, but is often decided on the basis of a comparison of (among other factors) the cost of traveling (including the opportunity costs of time) versus the cost of housing.

The classification of the population into traders and nontraders depends on the number of characteristics k. Travelers who may be considered to be nontraders if the decision process is confined to $k = k_0$ characteristics may be regarded as traders if the decision set is expanded to $k > k_0$ characteristics. An increase in k may, therefore, convert some nontraders into traders (the opposite cannot happen).

Finally, though the distinction between traders and nontraders may seem to be an objective one, it is not necessarily so. Our definition depends on the "perceived" characteristics that may differ from the objective ones [this is particularly true in the case of the cost of cars (see the paper by Beesley in this Special Report) and where the measurement of time is concerned (6)]. Thus, we talk about perceived dominance rather than objective dominance.

The existence of nontraders does not create any difficulties in the prediction of the modal split. On the contrary, the greater the percentage of nontraders in the population is, the easier the tasks facing the forecaster are. In the extreme case where the population consists solely of nontraders and where the forecaster predicts the modal split on the basis of traveling time and costs, the odds for a correct prediction exceed 9:1 (the illogical nontraders being, in general, less than 10 percent of the nontraders).

The distinction between traders and nontraders becomes important when one tries to analyze the general decision procedure determining travel choice. Specifically, this distinction is important when one tries to estimate the value of time. Assume that a person makes a modal choice on the basis of a generalized cost function, Π, and prefers mode 1 to mode 2 if

$$\Pi_1 < \Pi_2 \tag{1}$$

This cost function consists of 2 parts, the money cost, P, and the opportunity cost of time, KT (where T is traveling time and K is the value of time).

$$\Pi = P + KT \tag{2}$$

The decision criterion governing the choice of mode calls for the choice of the faster mode (mode 1) if

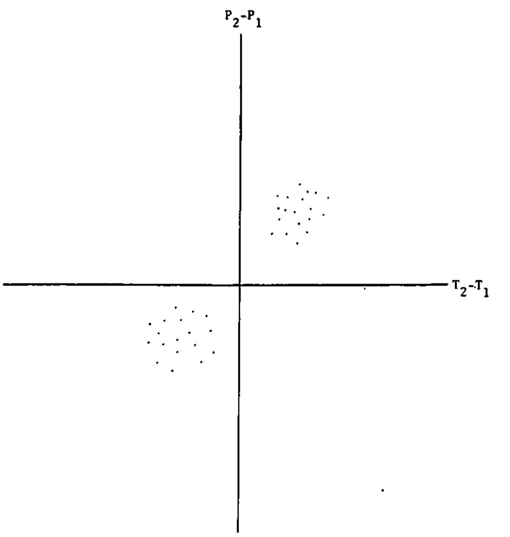
$$K > (P_1 - P_2)/(T_2 - T_1) = K^* \tag{3}$$

i.e., the faster mode is preferred if the value of time exceeds K^*, the ratio of the money costs differential to the time differential. The faster mode is always preferred when K^* is negative, i.e., when the faster mode is also the cheaper ($P_1 < P_2$). Thus, the choice of nontraders is consistent with any value of K as long as the value of time is positive. Put differently, the behavior of nontraders does not have any informational content as far as the value of time is concerned. This is particularly true in the case of illogical nontraders (i.e., those who face a negative K^* but choose the slower mode) because they clearly act according to different rules.

How does the existence of the nontraders affect the estimation procedure of the value of time K? As we emphasize above, nontrading is a property of the situation, not of the person. Thus, though a traveler may be a nontrader when it comes to modal choice, he or she may be a trader in a different context. The value of time may be irrelevant to the decision on what mode to travel by, but it may still affect the number of trips the nontrader takes. Assuming that the generalized cost function, Π, affects the demand for trips by a given mode, one may infer the value of time from the estimated demand function (3, 5), regardless of the percentage of nontraders in the sample.

The more common method of estimating the value of time, however, is based on data reflecting binary choice. How should nontraders be treated in this estimation procedure? It is obvious that the illogical nontraders have to be removed from the sample because their behavior clearly contradicts the model, their choice being made on more than 2 characteristics. But what about the logical nontraders? Admittedly their behavior cannot teach us anything about their price of time, but does it impair our procedures?

If nothing else, simplicity and the saving in computation cost call for the exclusion of irrelevant data (particularly if a nonlinear iterative estimation procedure such as probit is employed). But it seems that there are far more serious reasons for removing the nontraders from the sample. Thus, let us assume a population consisting exclusively of logical nontraders, some of them choosing mode 1 and some choosing mode 2. Diagrammatically the first group is concentrated in the first quadrant of the sketch below, while the second group is located in the third quadrant. Using discriminant analysis to discriminate between these 2 populations should provide a perfect match.



Moreover, though there are an infinite number of lines separating the 2 populations, the discriminant analysis picks 1 line—the one that yields the greatest variance between samples relative to the variance within samples. Thus, if, for example, one regresses a binary variable (0, 1) on K^* to obtain an estimate of the value of time, there will be nothing in the results to warn the analyst that all the values of K^* are negative. The outcome (i.e., the slope of the discriminant line) will be interpreted as the value of time, though it clearly is merely a technical result. Mixing data of traders and nontraders, therefore, yields biased estimates of the value of time.

To prevent this kind of bias, one must exclude the nontraders from the sample. But the distinction between these 2 groups is based on perceived characteristics. This makes it all the more important to collect data on the perceived costs and time of travel. Only these kinds of data will allow the analyst to escape the pitfalls of nontraders.

Finally, can one use estimates of the value of time derived from a sample of traders for the evaluation of the benefits of, say, a road improvement that is also used by nontraders? The answer at this point seems clear. The value of time depends on the socioeconomic characteristics of the traveler—income, age, education, family composition [the determinants of the value of time are discussed in a somewhat different context in another report (4)] as well as the time scarcity facing the traveler at a given moment (e.g., an emergency). This value is intrinsic to the person and independent of the transportation choice faced. On a first approximation, travelers with the same socioeconomic characteristics whose trip purposes are the same have the same value of time. The exclusion of nontraders from the estimation procedure does not impair the applicability of the results so long as the estimates of the value of time are adjusted for possible differences in the socioeconomic characteristics of traders, nontraders, and new entrants.

REFERENCES

1. Beesley, M. E. The Value of Time Spent in Travelling: Some New Evidence. Economica, Vol. 32, May 1965, pp. 174-185.
2. DeDonnea, F. X. The Determinants of Transport Mode Choice in Dutch Cities. Rotterdam Univ. Press, Rotterdam, 1971.
3. Gronau, R. The Value of Time in Passenger Transportation: The Demand for Air Travel. Columbia Univ. Press, New York, 1970.

4. Gronau, R. The Effect of Children on the Housewife's Value of Time. Journal of Political Economy, Vol. 81, No. 2, Pt. 2, March/April 1973, pp. S168-S199.
5. Demand Analysis for Air Travel by Supersonic Transport. Institute for Defense Analyses, Washington, D.C., Dec. 1966.
6. Reichman, S. Subjective Time Savings in Interurban Travel: An Empirical Study. Highway Research Record 446, 1973, pp. 21-27.

6 Extension of Present Methodology

Paul Shuldiner, University of Massachusetts

The 3 sections of this report are methodology, application, and strategy. The first 2 sections draw heavily on the resource papers by Brand, Burnett, and Gilbert in this Special Report. The last section reflects the discussions and issues raised during the conference.

A word is perhaps in order regarding some of the words used with regard to demand models. It is assumed that the underlying motive of our efforts is to build "better" models of travel choice and that better models require greater behavioral content. It then follows that models that deal most directly with true behavioral units, that is, disaggregated models, are called for, and that leads us almost inevitably to probabilistic rather than deterministic mathematical structures. We leave for others the questions as to whether we should speak of probabilistic or stochastic processes and whether aggregate models cannot capture certain behavioral qualities of society more effectively and with greater fidelity than disaggregate ones.

METHODOLOGY

Primary concerns in the area of methodology revolve around problems of aggregation and the relative advantages—and behavioral validity—of direct versus sequential models of travel choice. The aggregation problem (not without some justification at times appearing as the "aggravation" problem) is an inherent concomitant of the disaggregated approach just as the "ecological fallacy" is a natural hazard in aggregative procedures. We have, it seems, in forsaking areal aggregations for more discrete analyses gone from the unsupportable to the intractable. (As one of the authors put it, "There is a sporadic but by no means pervasive recognition that the problem of the ecological fallacy has been replaced by the problem of finding ways to add together models for different individuals in different locations at different times.") That individual behavior can more accurately be observed at the individual level goes almost without saying; that models of such behavior will provide more accurate predictions of future aggregated actions in geographic space has not yet been proved.

Two approaches to dealing with the aggregation problem were discussed by the workshop. The first involves a compromise in which individual behavioral units (e.g., persons or households) are grouped on the basis of similarities in socioeconomic and other presumed behavior-determining attributes rather than lumped together as a consequence of geographic proximity. This approach reduces but does not obviate the danger of generating spurious correlations between group attributes and group travel behavior and still leaves unsolved the problem of aggregating these subgroups into areally specified populations. A second suggested approach relies on mixing probability distributions for individual decisions to obtain predictions of choice decisions for a heterogeneous group comprising such individuals.

Whether these and other similar efforts will lead to techniques for overcoming the problem of aggregation remains to be seen. It may be that the problems associated with aggregation will prove to be no less serious—and no less fundamental—than those associated with ecological correlations; indeed, the two may simply be mirror images of each other. In any case, it is hard to argue with the conclusion that "...finding a plausible, mathematical, operational and logical resolution of...the aggregation problem seems the most crucial question for modeling travel decisions other than mode choice."

Striking very close to the heart of the behavioral approach to travel choice modeling is the issue of sequential versus simultaneous models. The 4-step sequence of trip generation, distribution, mode choice (or, if we wish to enter into what has been called "the most actively debated issue in modal split," we may transpose the order of the distribution and mode-split steps), and assignment models, so long the mainstay of the urban transportation planning (UTP) process, has in recent years been questioned and, in some instances, successfully challenged by models that treat these 4 steps as a single (simultaneous) decision. Fundamental to this issue is the question of whether travel decisions are made as a whole or step by step in some sequence based on the relative importance of each step to the traveler.

Under either assumption, identification and valuation of transport system attributes remain central issues. Direct demand models in which the parameters associated with each attribute are estimated simultaneously involve no strong assumptions regarding travel choice sequence but tend to be very complex because of the vast number of combinations of alternatives at each level. Models of this type may be simplified by limiting sharply the number of system attributes that are assumed to influence travel choice behavior.

Alternatively, strong (one might suggest heroic) assumptions may be made about the separability of travel choices in the interest of fashioning more simple models. In keeping with the separability property of the Independence of Irrelevant Alternatives Axiom, it may be assumed that the trade-offs at the margin between attribute variables that govern one travel choice do not vary between travel choices. This assumption allows separation of travel choices and a more easily estimated model but still requires an a priori determination of travel choice sequence (or an iterative process) to ensure that the relative marginal utilities among attributes are equal for each travel choice.

Since no attempt is made in estimating the classical UTP chain of models to ensure equality of trade-offs among attributes in each step, significantly different results will follow from different choice orderings. However, if the marginal utilities are preserved at each step, choice ordering will not influence the results and the models can be applied in any order or combination. Conversely, if all choices are estimated simultaneously, the conditional and marginal probabilities of travel choice may be derived and separate submodels or combinations may be applied in any sequence desired.

Closely associated with the issue of separable travel choices is the problem of choice set definition. It would seem, for example, that mode and route choice decisions are logically connected and might profitably be modeled as a joint decision. However, because of the separability property and because of the strong similarity of alternative routes within a given mode, combining these 2 choice sets may lead to erroneous conclusions. The example of the "red bus, yellow bus" problem in certain mode-abstract models also applies. It would appear that judicious use of common sense rather than blind obedience to arbitrary mathematical structures may be of some use in overcoming this dilemma.

It might help in these situations to rely on choice-specific rather than choice-abstract models, particularly when one is dealing with mode choice. The presumed ease with which new, even exotic, models can be introduced into a multiple-choice situation may be more than overbalanced by the restrictions on market-share ratios and cross elasticities imposed by the structure of these models. Realistic (but untestable) a priori assumptions about the differential impacts of new modes might be preferable to empirically testable models based on unrealistic and overrestrictive assumptions and separability conditions. Choice-specific models would likely be less useful in situations other than mode choice where the irrelevance of many alternatives is of far greater importance.

No such simple remedy is available when one is dealing with the identification of choice sets for models of spatial choice. The assumption that all individuals (or aggregations of individuals, for the problem exists at all levels of disaggregation) share the same choice sets is insupportable, yet it forms the basis of all aggregate and most disaggregate trip distribution models. True, we have adjusted our models so that they no longer send ghetto blacks to executive jobs in nearby office towers, but assumptions of universal knowledge and universal opportunity still underlie most spatial-choice models in use today. The natural attenuation of knowledge with distance may minimize this problem in models that make use of an impedance function of one kind or another, but that is a very blunt instrument for the job of delineating choice sets for all but the most ubiquitously distributed activities.

Associated directly with the development of disaggregate probabilistic models of travel choice behavior is the need for improved procedures for testing the statistical validity of the estimates that are obtained through the use of such models. Standard statistical tests appropriate for the standard least squares formulations are not well-suited to the newer class of models. A corollary to this problem is the need for estimation techniques that yield better classification criteria and aid in the selection of explanatory variables.

We should not leave this discussion of methodology without raising some basic questions concerning the fundamental nature of the models that we call "behavioral." As put most forcefully by Burnett, "By far the most serious difficulties for the development of disaggregate, behavioral models of travel stem from the dubious status of the mind as an object of scientific inquiry." (It has been said, with no little justification, that our models of trip-making are Newtonian but that our understanding of the process is pre-Aristotelian. Might it not be self-deluding to think that, simply because our models are now clothed in Freudian garb, our understanding of travel behavior has suddenly leapt ahead by 2 centuries?) If it is true that words describing mental processes are alternative words for overt behavior, then studies of perceptions, attitudes, and preferences may not be analyses of the causes of overt travel behavior and may be inherently and unavoidably tautologies. In the presence of such possibilities, it may be wise to treat behavioral models as nothing more than plausible, convenient constructs for the prediction of travel choices.

The above concerns strengthen the position that disaggregate models can, at best, describe the mean behavior of a group of individuals on the basis of observations of individuals whose actions can be assumed to represent a group with similar traits. Such an interpretation would suggest that even behavioral models can be expected to provide good predictions only in choice situations that closely parallel the situations used in calibrating the model and only for groups whose attributes are not too dissimilar to those whose mean traits are represented in disaggregate observations. As a corollary, it might be argued that disaggregate behavioral models are better suited for explicitly determining aggregation criteria than for predicting. If we cannot escape the ecological fallacy completely, at least we can learn to live with it.

APPLICATION

One of the obvious questions relating to the extension of present disaggregate behavioral models is the set of travel choice situations to which such models might usefully be applied. Disaggregate models of the sort that concerned this conference were first developed for, and have for the most part been applied to, mode choice, particularly the journey to work. Their extension to other trip purposes and to other travel decisions is well justified, if not inevitable.

It may be convenient for the purposes of this discussion to divide travel decisions into 2 broad categories: (a) spatially oriented decisions, which include destination choice and route choice; and (b) mode choice. Related to both categories are decisions pertaining to trip frequency and trip purpose. These 2 categories are not so separate as the above division might imply, as evidenced by the earlier discussion of separable versus simultaneous models. Nevertheless, investing certain travel decisions with a high degree of spatial content allows for the convenient introduction of a wide variety of disaggregate behavioral models derived from theories of intraurban spatial-choice behavior.

Looking at the issue from a somewhat different point of view, we may identify certain trip purposes—namely, shopping, recreational, and social travel—as representing significant opportunities for application of disaggregate behavioral models. Together these trip purposes constitute about 40 percent of total travel and, in contrast to the journey to work, are governed by behavioral influences not so readily subsumed within classical economic theory. In trips of this type, route and destination choices fluctuate over time and trips are often multipurpose; the sequence of activities varies from trip to trip. The complexity of such travel invites, if not demands, application of disaggregate behavioral models.

There is yet another way of looking at the need and opportunity for extending the use of the newer types of models. By and large, travel modeling has concerned itself with the "average" man. For a variety of reasons, this has resulted in an emphasis, perhaps an overemphasis, on the travel behavior of white males with steady jobs. Recent concern for the handicapped notwithstanding, there are large segments of society whose travel behavior and travel needs have, at least insofar as travel modeling is concerned, been treated with benign neglect. A useful but by no means exhaustive list of such ignored travel includes shopping trips, especially those made by women; work trips by those who are employed either irregularly or for less than a full day; trips by children (from, say, 6 to 17) other than those by school bus; and all non-home-based trips.

Recreational travel of all sorts constitutes an increasingly important travel market and, therefore, an important area of inquiry. Tourism now accounts for a significant proportion of externally derived income in certain areas of the country. As leisure time and disposable income continue to rise, recreational travel will become an even more significant factor in the transportation investment decisions of many states. Although we tend to think of rural areas when we think of recreational travel, the need to understand (model) better urban recreational trip-making should not be ignored. Coney Island, or for that matter Times Square, probably attracts far more trips than do all national parks combined. And urban recreation travel is undoubtedly as rich in behavioral content warranting disaggregate analysis as is its country cousin.

The final point to be made about extending the sphere of application of disaggregate behavioral models deals with the socioeconomic context within which transport investment and travel choice decisions are made. In these days of "oil diplomacy" on both the foreign and domestic fronts, it is naive to assume, explicitly or implicitly, that transport investment decisions, and the travel choices that follow, are not inextricably bound up in the social, economic, and political life of the nation. The logical consequence of this argument is that transport planning, and the travel choice models that aid in this planning, must be sensitive to long-run (and perhaps short-run) changes in tastes (e.g., the ecological issue and the bicycle craze), taxation (e.g., higher gas taxes, parking fees), equal opportunity in housing and employment, income maintenance, transit operating subsidies, and a host of other influences that are normally ignored by most travel-choice equations.

The above argument also suggests that the dichotomization of travel choice into long-run and short-run classes may obscure important real-world behavior. This is not to suggest that only general equilibrium models that capture the interaction of everything with everything else should be allowed. It is to suggest that a somewhat more open mind is needed to deal with the fuzzy gray area in which the short run and the long run merge. For example, the decision to buy (or sell) a car when a second member of the family gets a job is a "middle-run" decision that is influenced by earlier long-run decisions (where to live and work) and will influence subsequent short-run travel choices. As another example, it is reasonable to assume that people who use public transit (a short-run choice) do so not only because they happen to live near a bus line but also because they have other characteristics that predisposed them to locate near the line they use (a long-run choice).

STRATEGY

There are few things that cannot be improved and, as the foregoing sections would suggest, disaggregate behavioral demand models do not yet fall into that select number. There was general agreement that considerable research is needed and that an improved data base is an essential ingredient in any such effort. Agreement was not reached, however, as to the best way to go about gathering these data, nor was the nature of the research effort specified. Principal areas of disagreement centered about the scale and timing of data acquisition and on how new model developments should relate to the classical methods gathered under the UTP rubric. The brief statements that follow make no pretense of summarizing this debate or of offering a balance of views expressed. They were presented as a part of the workshop's report to the plenary session and are repeated here as such.

Relation to the Current Set of UTP Models

As imperfect as the classical approach may be, the models are in widespread use and will serve as the standard against which newer disaggregate behavioral models will be judged. A mixed strategy of parallel, and perhaps competitive, research to improve elements of the UTP package while wholly new models of travel choice behavior are developed may prove to be not only the soundest but also the most feasible course of action. Perhaps this could best be done in an operational rather than in a pure research context. However, it would certainly be unwise, given past experience in this respect, to attempt to build and apply a complete system of disaggregate behavioral models as a part of an ongoing transportation study. Rather, models for specific travel choices or for a portion of a region should be developed and supported in the background by more prosaic but more predictable models of the classical type. It would be well to be able to show by means of such competition that the newer approaches not only are sounder theoretically and more elegant mathematically than present models but also provide answers more cheaply, more accurately, and more quickly to questions that public administrators require answers to.

Data Collection

There is little question that more and better data are badly needed if significant progress is to be made in the development of disaggregate behavioral models of travel choice. In this regard, the efforts of the U.S. Department of Transportation are to be applauded. However, the case is strong for a continuing rather than a massive one-shot effort. In the first place, the most useful data for these kinds of studies are time series data, preferably before and after. Furthermore, we must be willing to conceive of the possibility of our making mistakes in the specification of data sets and in the design of data collection instruments. There is no way of ensuring against such mistakes, but we can put ourselves in a position to learn from them. By trying to use the data gathered through our first efforts, we can learn how to improve the data as well as the travel choice theories that should provide the basis for subsequent data collection efforts.

Concluding Remarks

It may be of value to contrast the present proposals for large-scale research efforts in travel choice modeling and data acquisition with the development of what has become the urban transportation planning process. By and large the original models were developed on an incremental basis by people who were seeking answers to pressing problems that they had the responsibility for solving. These people were practitioners, not researchers, and they developed tools that satisfied them as to their usefulness. I am uneasy over the prospects of moving in force directly from the research laboratory to the field of battle. The hazards of making major mistakes and of discrediting what, if done more slowly, could be a continuing process of significant improvement are not to be ignored. The danger is real, and it speaks for the mixed strategy.

Conference Papers on Attitudinal Data

Behavioral Measurement: An Approach to Predicting Transport Demand

Richard M. Michaels, Northwestern University

Although several transportation technologies compete for passengers in both intraurban and interurban markets, the competition is highly biased. In intraurban travel, highway transportation dominates transit; in interurban, air transportation dominates rail. Furthermore, travelers in either market make choices on several bases and do so consistently. It is this overt choice behavior that is measured in modal-split analyses.

A more fundamental question that arises from the obvious is, What are the determinants or the factors that lead travelers to make the choices that they do? This question underlies most of the research during the past 5 years in the area of behavioral mode choice modeling. Essentially, these models are concerned with predicting the probability of a mode selection based on factors that operate within individual travelers and that determine the observed choice behavior. The issue addressed, however, is far more general in mode choice than in mode selection and applies in theory to trip generation and distribution. In fact, that mode choice can be separated from trip generation or trip distribution does not seem conceivable. They are all part of a common process.

In the end, what is observed in the transport domain as demand is a derivative of some more fundamental behavioral processes operating in time and space. Transportation in this sense is mediated behavior. Because of the nature of the organization of space, some connecting system has to exist to link activities in which people need to engage. Consequently, linkage systems are necessary, but involve financial costs and also psychological costs partly because they incur delays to satisfaction and partly because they require an expenditure of energy that can constrain participation in those activities that generate the travel.

There is a converse to this that is immediately apparent. Those linkage systems that reduce these psychological costs will become attractive to travelers. Indeed, the brute force technologies currently employed for transportation can be easily categorized in terms of these costs and their share of the travel market predicted. Travel time, which is sort of a lumped constant reflecting all the disutility sets, is still a quite acceptable overall predictor of mode choice. This is true in behavioral as well as aggregate models.

In fact, supporting what people in the aggregate overtly choose uniquely defines transportation history in the United States. This national policy has led to inordinate investments first in railroads, then highways, and then aviation. If one could just get a new technology started that travelers would choose, one would predict that government would invest in its development.

Unfortunately, the traditional policy has emerged with some internalities as well as externalities that have caused serious concern about the investment tradition in transportation. The social, physical, and economic costs have become too large. The national policy, in essence, has produced a divergent solution—one in which transportation has come to dominate rather than serve social ends. Consequently, there has been a recent movement that asks another kind of question, What are the basic functional requirements that people really need from transportation? To put it another way, How do we design a transport system that optimally meets the requirements of people in fulfilling their basic needs? In the end, the study of behavioral response to transportation is a fundamental means to answer this question. One can make a fairly strong case that the 2 current classes of behavioral research in transportation are converging to this end (12). One class, of course, is the mode choice models, and the other is the attribute analysis class. Both are progressing and appear to be coming from opposite directions to provide some overall probabilistic model of trip generation and distribution.

At its simplest, the behavioral approach to transportation choice makes 3 classes of assumptions. One is that people are motivated to travel because of intrinsic needs of the household that can only be satisfied by physical movement to sites that can satisfy those needs. A second class of assumption is that choice behavior is based on subjective perception of the utility of the transport options that may or may not be related to "objective" criteria. The third class of assumption is that, although choice behavior may change, the basic process by which choice decisions are made will not; within any defined population of people, basic variables determining that choice process are universal.

Before considering the transport choice process, we should define a few key terms that are used frequently in behavioral analysis of transportation. The 3 most important are attitude, preference, and choice. It is important to distinguish among these because they essentially represent a hierarchy of behavioral process that underlies overt observable action.

Attitudes are predisposing tendencies to act on abstract stimuli. They are the behavioral response to certain classes of objects, concepts, or actions. At the very least, the response will be emotion inducing; at the most, it will be action inducing. The strength of an attitude may be defined in terms of the probability of overt response to the arousing concept. In general, attitudes are predisposing biases toward aspects of the social environment, generally learned in a social context. Much of the history of social measurement is concerned with the development of methods for analyzing and scaling attitude sets (4, 14, 16).

Preferences may be defined as the ordering or scaling of alternative satisfiers of a need or need set. People find by direct and vicarious learning that a range of objects or activities can satisfy physiological or psychological needs. Through direct experience with these sets, the individual will scale the members according to their efficiency in satisfying a need to fulfill a deficiency. Preferences thus emerge out of an active experience in search of need satisfaction. The scaling of a set of alternatives defines the abstract preference among alternatives. This scaling represents an ideal ordering of alternatives within the individual's or group's cognitive field. For example, in a study by Bowlby, preferences were determined for grocery stores accessible to residents of the area. The residents were able to scale their preferences for the set of which they were aware, even though there were several others that they might have known.

Choice may be defined as the operational selection of a specific satisfier to meet the individual's needs. Choice is the observable behavioral process—the end point of the selection process. There is not necessarily a direct relation between choice and preference. Preference represents the individual's ideal selection; choice represents the real selection. The disparity exists almost universally because of the constraints imposed on the individual either externally or internally. For example, an individual may have a preferred doctor, but in an emergency will select an alternative because of the constraints of time or accessibility. In general, people will always try to make choices in correspondence with their preference sets. Where large and consistent disparities exist, emotional response is a likely consequence, and an organized attempt to change the life state may follow.

From this discussion, we can view the behavioral process as one that provides the basis for satisfying needs. Attitudes are the underlying biases toward social objectives that constrain or direct the orientation of individuals toward certain sets of objects that have value. Preferences are the ordering by the individual or group of the members of those sets according to their perceived capability to satisfy needs. Choice is the selection process by which individuals or groups actualize the satisfaction of their needs. In complex social systems, not only are there constraints on alternatives, there are also mediating systems between needs and their satisfier sets. Transportation is one of these mediating systems. Consequently, transportation systems themselves must take on values and, thus, generate a set of attitudes. One would expect that these attitudes would be attached both to the alternative modes as entities and to their abstract attributes.

If transportation is a mediating variable between needs and satisfaction, then its component systems must be viewed as part of a larger behavioral process. To say this is to imply that how and why people use transportation alternatives can be explained only by an analysis of the subjective perceptions of these systems and the psychological measures of their necessity and sufficiency. This, in turn, suggests the inadequacy of traditional models based on objective or extrinsically measurable variables of system performance. Travel time ratios or differences, cost, safety, and the like presume an evaluation process based on extrinsic variables of systems and a direct relation between these objective measures and the psychological decision process. Neither of these appears sufficient, especially the latter. There simply is overwhelming evidence that the relation between objectively derived measures of physical process and behavioral performance is rarely linear. The more complex the physical process is in which a behavioral transaction occurs, the more indirect is human response. This is especially true in the domain of attitudes, preference, and choice behavior.

Consequently, if one desires to construct a model such as trip generation, distribution, or mode choice, validity and reliability are likely to be higher when such a model is constructed on the basis of behavioral measures rather than physical measures, especially when the latter are selected simply because they are convenient or easy to measure. This conclusion applies, of course, only in those nontrivial cases where choice exists. For example, automobile availability should be a good predictor of mode choice simply because it determines whether travelers have a choice. It describes the trivial case. Clearly, it can and does say nothing about satisfaction with transportation, nor will it predict what people will do if they are given new options, i.e., choice alternatives.

If one accepts this argument, then it becomes essential to enter the domain of direct measurement of human attitudes, preferences, and choices. It means that models must be constructed that are based on these kinds of processes rather than the prosaic methods and expedient measures that have characterized traditional transport planning models. This leads to the question of how one measures behavioral processes and how one defines the user's process of judgment in the transaction with his technological systems—in our case, transportation.

Basically, the problem has 2 major dimensions. One is the identification and measurement of the psychological or subjective variables that determine the perception of the utility, positive or negative, of transportation. The other is how these measures may be combined to produce a prediction of what technologies people will use and how they will use them. What is important is the combination of the metrics of a multidimensional set of variables in ways that will produce reliable estimates of travel demand and the factors that will cause that demand to change.

The first problem of identification and measurement is where the behavioral modeling field is in transportation. At its heart, the issue is concerned with how measurement of behavior is to be done operationally. Since one is dealing in a qualitative domain of attitudes and preferences, the problem becomes one of developing measuring instruments for such dimensions. Fortunately, a half century of psychological research has gone into the problem, and hence both a body of theory and a technique are available.

There are 2 problems that inhere in this domain of measure. One relates to measure properties per se. The other relates to the correspondence between observation and the underlying psychological scaling process. In regard to the first, it is important to keep in mind that any measure may have 1 or more of 3 properties: (a) Numbers applied to a set have some order and consistency to that ordering; (b) distances among members of the set are ordered, that is, they have the properties $(a - b) = (c - d)$, $(a - b) > (c - d)$, and $(a - b) < (c - d)$; and (c) the series has an origin that is real and determinate. Scales having one or more of these properties will define a scale class. There are 4 such classes, but only 3 have properties of interest for measure purposes.

One class is called an ordinal scale in which the units on the metric define only position. Thus, the single prediction that such a scale provides is that $A > B > C$. A common example of an ordinal scale is Mohs' hardness scale in which hardness of a material is located in a series of classes running from 1 to 10. A material having a hardness of 6 means that it is harder than a material having a hardness of 5 or less. However, there is no way to tell how much harder 6 is than 5. Simple rank-order scales, or similar categorizing scales, are all minimally ordinal. For scales of this type, the only appropriate statistical inference techniques are the nonparametric ones.

The second class includes scales having interval properties in addition to order. These properties permit the distance over the scale range to be defined so that any distance located at any point on the scale will be equivalent to the same distance located at any other point on the scale. Such a scale class makes allowable the algebraic operations of addition and subtraction, but not multiplication or division. Fahrenheit and centigrade temperature scales are common examples of true interval scales; the 0 points on both of these scales are purely arbitrary. For true interval scales, parametric statistical techniques may be used as tests of inferences.

The third class may be termed a ratio scale. This scale has not only order and distance properties but also a determinate 0 point. The decibel scale is an example, the Kelvin scale of temperature is another. The characteristic of a true ratio scale is that all algebraic operations are valid—multiplication and division as well as addition and subtraction.

Clearly, no matter what process one desires to measure, the higher the scale class order is, the more general can the mathematical operations be and the more precisely can inferences be drawn from a set of measures of a process. To measure attitudes and preferences, we must develop scalars that have interval properties, at least. We want to know how much more preferred one alternative is than any other member of a homogeneous set. If we can scale the value, desirability, or satisfaction that people perceive in a set of alternative activities or modes of transport to such activities, we can predict the probability of what people will travel to, when, and by what means. We will have developed a behavioral demand model.

The determination of the application of the scale class to any form of psychometric measure is a purely theoretical one. That is, using any measuring instrument, whether the human response function has interval or ratio properties depends on a theory of the human scaling process that underlies the observed response. Basically, there have been 2 theoretical positions that have been developed in psychology during the past 40 years. One is attributable to Thurstone who defined the law of comparative judgment. This essentially says that the quantity or quality of an object in the domain of human judgment is a stochastic variable, normally distributed such that the mean value defines the perceived quantity or quality. Further, the variability of this psychological response distribution defines the probability of judgment taking on any particular value different from the expected value. This is called the discriminal dispersion. Hence, when 2 objects are compared on the same psychological continuum, it becomes possible to define a distribution of differences that itself must be normally distributed with an expected value equal to the perceived difference between the 2 distributions and a variance equal to the sum of variances of the 2 distributions (assuming independence). The derivation of this law is such that, if it is valid, in any particular case, then the scale class of the domain must be an interval one. Thus, if a group of people are asked to judge the differences among all possible pairs of a set of objects, they will generate a set of psychological response numbers that order that set of objects in terms of subjective value. These numbers form a true interval scale, within sampling error, whenever the set of differences derived from the distributive law are equivalent.

The law of comparative judgment has been the basis for most attitude and preference scaling during the past 40 years. Pair comparison, categorical judgment, and summated ratings are all formal methods for generating and validating true interval scales of human attitudes and preferences. Each involves a specific procedure for generating psychologically consistent measurement instruments. These procedures are necessary when one realizes that a scalar domain is being tapped with objects or stimuli whose denotative form may not, and usually does not, bear any direct relation to that underlying psychological domain. One does not know why a particular item on a battery evokes the psychological response that it does. All that one knows is that such an item generates a response that is part of a continuum having interval properties. For example, let a group of people be asked to respond to an item in Likert-scale form: Transit is less convenient than automobile. If this is a discriminating item, then all it says is that people who agree with this statement have a more negative attitude toward transit than those who disagree with it. One cannot infer directly that respondents are scaling convenience. They may be, but the scaling process does not allow that inference to be made in this case. All we know is that an item phrased in such a fashion evokes a feeling in the respondent that reflects his or her bias toward the subject of the battery. This indirect relation between the objective evocative stimuli and the emotional response of the respondent to it does not necessarily negate the utility of the scale that the methods produce. People's attitudes may predict observed behavior as well as or better than any other measure, objective or otherwise. For example, it may be possible to determine people's preference scale for a set of alternative routes through a network. This may be just as efficient a means of doing traffic assignment as going through the horrendous procedure of solving a minimum-time path algorithm.

The second theory underlying human judgment is that developed by Stevens. Basically, this theory is that the basic judgmental process is a ratio one; that is, human observers scale quantitative or qualitative objects directly in terms of the perceived magnitude of the stimulus. In effect, the judgmental process follows a power law, such that perceived magnitude, R, is related to the scaled object or quantity, S, according to the relation, $R = kS^x$. Basically, the theory is derived from Weber's law. In practice, it is based on the assumption that the subject can reliably determine the ratio between 2 stimuli. Its basic application, until 1950, was in the domain of psychophysics. Not until Comrey developed the method of ratio rating could the theory be generalized to qualitative as well as physical stimuli. Basically, however, the process is simply one of asking a respondent to rate, by using a direct ratio estimate, how much more preferable or valuable one stimuli is relative to another. In Comrey's method, an $M \times M$ matrix comprising a set of independent estimates of the ratios for all pairs of stimuli is constructed. The marginals are then used to generate the average ratios among the stimuli and, hence, the ratio scale of the stimuli. Ekman generalized the procedure and provided a more economical means of determining the ratios, but the basic principle is the same.

In general, ratio scales are simpler to construct than most of the interval scales. In theory, they have more power than interval scales and are more general. Stevens has suggested that ratio scales for preference and attitudes represent the most general scaling law of which the law of comparative judgment is a special case. The importance of the power law theory is that it permits the scaling of human judgment such that any unit on the scale has not only position and distance but also a proportional relation among the units. That is, an element with a scale value of 2 is not only 4 units less than an element with a scale value of 6 but also a third as great. Thus, in a preference scaling of a set of trip destinations, we can determine how many times more preferred A is than B. Such a scaling should provide a means of developing more simply and reliably a trip distribution model than any of the current objective models.

This discussion has been concerned with unidimensional scaling methods. It should be obvious that methodologically either the law of comparative judgment or the law of ratio judgment can be used for multidimensional scaling as well. One of the major problems in measuring human judgment in social contexts, like transportation, is that many objects, activity sites, and linkage systems have more than 1 attribute that determines attitudes or preferences. The simple scaling methods assume a single, unidimensional psychological continuum. This is neither a necessary nor even a realistic assumption to make, especially in complex situations. It is reasonable to assume that any object in, say, a preference set is some combination of attributes whose vector sum determines its location in the preference order. For example, given a set of alternative grocery stores within the cognitive field of the respondents, one can scale the preferences for all the members of that set. However, people may not see a grocery store as a unitary entity, but rather one composed of a set of attributes. The "percept" of that entity is the product or sum of the attribute magnitudes that underlie that percept. Thus, the whole preference scale is determined by this multidimensional process attached to each object, each pair judged together, or the whole set judged as a unit.

A second aspect of multidimensional scaling concerns those situations in which choices must be made on the basis of a combination of independent attributes. For example, in the selection of an activity site, say, restaurants, the individual must scale several dimensions before a choice may be made. These might include type of food, price, and accessibility. The process by which these dimensions are combined provides a final choice that is of interest.

Basically, there are 2 ways to approach this problem. One is to assume that the behavioral process involves some vector addition of the magnitudes of the basic attributes. This leads to a multidimensional scale development. Several methods have been developed to generate such scales, but the mathematical bases for the scale functions are far from satisfactorily developed. There are inadequate tests of error functions and serious questions about the validity of the scales. Although much methodological development has been done, much more is currently under way. The research under way should lead to rationalizable means of combining several attribute dimensions into 1 scalar measure.

An alternative approach to the multidimensional scaling operation is to assume a hierarchical decision model of human choice behavior. Basically, the idea is that people do not combine attributes into a single scale, but rather scale attributes of importance independently. They then evaluate or scale the objects among which choice is to be made on each attribute scale sequentially. In essence, people scale attributes and then compare objects on each attribute ordered from highest to lowest importance. An alternative rated high on the most important attribute is then evaluated on the second most important attribute. If it is rated low on the highest important attribute, it is rejected from further consideration. Objects forming a common set are thus scaled in hierarchical fashion on subjectively important attributes. And this rating may be on a simple pass-fail basis. This kind of a model of decision behavior leads to a fairly simple analytical process for people and one that is easily learned. In this scheme, unidimensional scaling procedures are sufficient. So far, no tests of such a model in transportation or elsewhere have been carried out, nor has the mathematical form of such a model been fully developed.

To summarize this discussion, the following points may be made.

1. Observed choice behavior is the product of the evaluation of the alternatives in terms of subjective needs, attitudes, and preferences.
2. This need and preference structure is an inherent characteristic of human behavior that is not determinate directly from observed behavior.
3. The nature of this structure may be inferred by direct measurement of attitudes and preferences toward qualitative or quantitative dimensions of the physical or social environment.
4. The measurement of attitudes and preferences requires a greater concern for measure theory simply because of the indirect relation between overt and covert behavior.
5. Within this context, a variety of techniques, both unidimensional and multidimensional, have been developed to provide reliable measures of attitudes and preferences.
6. The caveat is that the objects used, real or symbolic, to evoke or tap the psychological domain in scale may have no direct relation to that domain.

In sum, the measurement of attitudes and preferences is a well-developed area. To determine the perceptions of people toward social systems seems perfectly feasible.

To expect those perceptions to be determinant of choice behavior as long as choice exists is further reasonable. As far as transportation is concerned, trip generation, distribution, and mode split represent the output of a behavioral process. Because the elements making up this process are determinate and potentially as measurable as travel time, cost, and distance, they appear to offer a more valid approach to the prediction of travel demand and distribution than surrogate measures. There are 2 major problems that inhere in using behavioral measures in this way: People learn so that their attitudes and preference structure change over time, and correspondence between items used to evoke response and the underlying domain from which the responses emerge is not necessarily direct. Consequently, a demand estimate generated in this fashion will have only limited life and will have reasonably large components of unexplained variance. In the end, behavioral measures offer a means of predicting demand and identifying those factors that would cause demand to change. There is no way to do the latter today except by trial and error. This alone justifies investment in the development of more comprehensive measures of attitudes and preferences.

REFERENCES

1. Bock, R. D. and Jones, L. V. The Measurement and Prediction of Judgment and Choice. Holden-Day, San Francisco, 1968.
2. Bowlby, S. R. Spatial Variation in Consumer's Information Level. Transportation Center, Northwestern Univ., Res. Rept., 1972.
3. Comrey, A. L. A Proposed Method for Absolute Ratio Scaling. Psychometrika, 1950.
4. Edwards, A. L. Techniques of Attitude Scale Construction. Appleton, New York, 1957.
5. Ekman, G. Two Generalized Ratio Scaling Methods. Jour. of Psychology, Vol. 45, 1958, pp. 287-295.
6. Ekman, G. Direct Method of Multi-Dimensional Ratio Scaling. Psychometrika, Vol. 28, 1963, pp. 33-41.
7. Golob, T. F., et al. An Analysis of Consumer Preferences for a Public Transportation System. Transportation Research, Vol. 6, 1971.
8. Green, P. E., and Carmone, F. S. Multi-Dimensional Scaling and Related Techniques in Marketing Analysis. Allyn and Bacon, Boston, 1970.
9. Guilford, J. P. Psychometric Methods. McGraw-Hill, New York, 1954.
10. Lancaster, K. J. A New Approach to Consumer Theory. In The Demand for Travel: Theory and Measurement (Quandt, R. E., ed.), Heath, Lexington, Mass., 1968.
11. Michaels, R. M. Attitudes of Drivers Toward Alternative Highways and Their Relation to Route Choice. Highway Research Record 122, 1966, pp. 50-74.
12. Michaels, R. M., and Watson, P. L. Social and Psychological Factors in Urban Transport Mode Choice. Transportation Center, Northwestern Univ., Res. Rept., 1971.
13. Reichman, S., and Stopher, P. R. Disaggregate Stochastic Models of Travel-Mode Choice. Highway Research Record 369, 1970, pp. 13-23.
14. Pfanzangl, J. Theory of Measurement. Wiley, New York, 1970.
15. Stevens, S. S. A Metric for Social Consensus. Science, Vol. 15, 1966, pp. 530-541.
16. Summers, G. F., ed. Attitude Measurement. Rand McNally, Chicago, 1970.
17. Torgerson, W. S. Theory and Methods of Scaling. Wiley, New York, 1958.
18. Wright, L. W. Behavioral Model for Transportation Planning. Transportation Center, Northwestern Univ., Res. Rept., 1972.

Assessment of Preferences and Perceptions Toward Attributes of Transportation Alternatives

Thomas F. Golob and Ricardo Dobson, General Motors Research Laboratories

This paper integrates psychological measurement and economic utility theories to derive an approach for enhancing the understanding of decision-making behavior with respect to transportation-related alternatives. Examples of theoretical formulations, empirical tests, and data collection procedures are selected from a body of transportation research, market research, econometric, and psychometric literature. The research and theoretical activities of diverse disciplines appear to be compatible with a general schema, which is proposed for the prediction of transportation-related decisions. The schema is centered on the description of transportation-related alternatives in terms of multiple characteristics or attributes. The choice of an individual decision-maker or class of decision-makers is assumed to be mediated by preferences and perceptions toward this attribute set. This schema is also used to indicate how new models may be developed to produce more valid predictions than are currently available from existing models.

One objective of urban transportation research is to improve the usefulness of analytical models that are employed to predict transportation-related decisions of individuals and families that are faced with changes in travel means and opportunities. Accelerated efforts in the specification and testing of so-called disaggregate behavioral models have characterized much of the recent new work toward this objective. This paper identifies some of the issues deemed important to the development of a class of such disaggregate behavioral models described along the lines of 2 propositions. First, the models should be founded on theories and tested on hypotheses directly describing the decision-making behavior of individuals. Second, the models should be defined with respect to at least some subjective data, such as stated preferences and perceptions.

Judgments are not expressed here on the ultimate usefulness of this class of models to the urban transportation planning community and its immediate clients. Such judgments will be deferred until appropriate comparisons of alternative models can be performed with respect to particular generic types of transportation decisions (e.g., modal choice, automobile ownership, or residential location). The approach is to present a variety of theories and related methods of data collection and statistical processing. These models are contrasted in terms of their application to the explanation of phenomena of urban transportation behavior. Selected empirical test results are summarized. Portions of a survey that was designed and implemented to gather data for testing various models describing decisions regarding proposed new systems of arterial transportation are used to illustrate some data collection techniques (28).

GENERAL SCHEMATIC REPRESENTATION

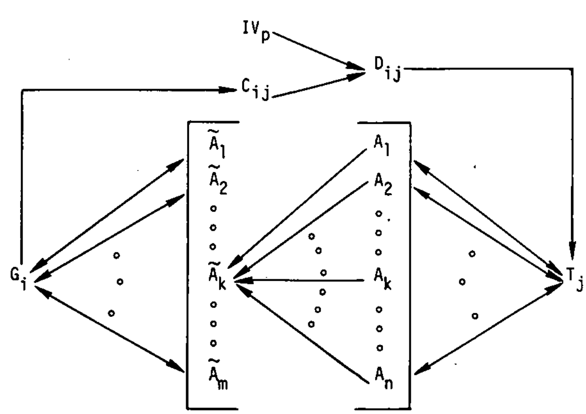
A general schematic representation has been formulated as a common basis on which to contrast various models in terms of their basic analytical structure and underlying assumptions. The set of models discussed in this paper was selected from the total of those documented in the literature of the fields of psychology, market research, and economics. The authors reviewed a variety of models familiar to them and their colleagues. Models were judged primarily as to their anticipated potential for generating insights into individuals' transportation decision-making and for advancing the development of new models of transportation along the lines of the 2 propositions outlined in the introduction.

The most complete form of the general schema is shown in Figure 1. In this form, rather complex multiple relations are specified among the schema elements defined below. In later sections of this paper, various classes of modules are introduced for discussion by identifying the particular simplifications of the complete schema that are considered to characterize the class. These simplifications are created from the complete form by compressing certain multiple relations into single relations or even by specifying identity relations.

The complete form of the schema (Fig. 1) shows an individual or group of individuals, denoted by G_i, as making a decision with respect to a set of transportation alternatives, T_j. The realization of this decision by G_i toward T_j is designated by D_{ij}. As one example, D_{ij} might be defined as the selection from set T_j of a mode of travel by individual G_i (the choice to make a trip to a particular destination at a particular time having previously been made). Choices by G_i with respect to T_j are differentiated from decisions because there are intervening, and perhaps random, variables, IV_p, that may block the translation of the choice directly into action. These choices, shown as C_{ij}, are mediated by the relation of G_i to a set of subjective relations that are in turn related to the transportation alternatives. The attribute arrays are designated by the bracketed grouping of the A_k and $\tilde{A}_k$ variables. The A_k represent those attributes described from a priori considerations; the $\tilde{A}_k$ represent those attributes derived from a set of judgments expressed by the G_i respondents. The objective of any model applied within the schema context should be to predict the D_{ij} of G_i as closely as possible.

The schema is specifically designed for subjective data, and the G_i-attribute and attribute-T_j relations are assumed to be based on cognitive and affective data and theories for those data. Furthermore, it is designed to allow for aggregation and segmentation with regard to the G_i or T_j sets or both. For example, G_i may be differentiated into groups of individuals that are important for policy considerations, or it may be differentiated into groups that are formed according to observed homogeneity in G_i-attribute relations. Likewise, T_j may be differentiated into groups of transportation opportunities and means confronting the decision-makers. Establishment of such T_j groups is somewhat analogous to the specification of separable activities in economic utility theory models of individual travel behavior.

Figure 1. General schema for predicting transportation-related decisions.



Although the general schema permits multiple G_i-attribute and attribute-T_j relations, it does not require multiple relations. Therefore, both unidimensional and multidimensional scaling approaches may be compared within its framework. However, general psychometric and statistical models may be used in their stead because the schema is not a scaling model. It is not strictly necessary that the number of G_i-attribute relations be equal to the number of attribute-T_j relations. Moreover, the form of the $\tilde{A}_k \leftarrow A_k$ interrelations is open to many variations. Indeed, the availability of these many modeling options allows the comparison of diverse psychological, market, economic, and transportation research models within the common framework of the general schema. Each specific model can supply the functional relations among the schema elements necessary for concrete application to the description and prediction of transportation behavior.

Models are presented in this report in a typology defined with respect to a central focus of the general schema—the linkages between C_{ij} and T_j through the set of mediating attributes. First, the univariate class of models is discussed. Next, multivariate models exhibiting assumed attribute independencies are presented. Finally, multivariate models exhibiting assumed attribute interdependencies are presented also in 2 subclasses: those based on structuring selective intercorrelations (econometric models) and those based on structuring the full complement of intercorrelations. As a preface to these discussions, the following section deals with the important relations between behavioral models employing subjective, cognitive, and affective data and the concepts of economic utility theory. This theory holds the potential of improving the ties between models of individuals' decision-making and general consumer demand theory.

Relation to the Economic Concepts of Utility

The basic assumption of the economic utility theory approach to travel demand is that decision-makers evaluate the alternate actions available to them in terms of the individual preferences as applied to their perceptions of the nature of all the relevant alternatives. If these preferences are transitive and continuous, then there exists a decision vector function whose ordering of alternatives reflects preferences by the decision-maker. This function has been labeled a utility function by microeconomists. A vast literature deals with utility theory hypotheses, their geneses and ramifications. Quirk and Saposnik (82) give a relatively modern treatment and identification of basic references. Ferguson (35) gives a historical treatment. The brief introduction to the subject contained here focuses on the adaptation of the theory to the modeling of transportation decision-making behavior in terms of the subjective data of preferences and perceptions from individuals and within the context of the general schematic representation outlined above.

Individual utility functions are usually postulated to be monotone increasing and concave (i.e., to display, at some point, diminishing returns in satisfaction that the individual obtains from a given activity). The assumption of rational choice can then be defined in utility terms: That set of actions is chosen by the individual for which his utility is maximum. This definition does not preclude a possible distribution of selected choices for an individual faced with repetitive situations, for it is admissible (and indeed practicable) to have random components of perception and preference within utility specifications in a manner consistent with the underlying hypotheses of scaling methods. Such random components of utility are often introduced as foundations for aggregation (i.e., repeated choices by "similar" individuals), and such usage is again deemed consistent with judgmental theories in psychology. [Luce and Raiffa (65) give a discussion of more purely stochastic utility, which is not discussed here.]

Utility theory links preferences and perceptions toward a class of alternative activities (here urban transportation opportunities and means) to the mainstream of microeconomic consumer theory: the concept of markets of demand and supply and subsidiary notions such as welfare theory and cost-benefit evaluation (e.g., consumer surplus). For the simplest case, consider the set $(x_1, x_2, \ldots, x_n)$ of non-negative levels of a set of transportation-related activities. Then,

$$u = u(x_1, x_2, \ldots, x_n) \tag{1}$$

represents the utility (satisfaction) to an individual gained from those activity levels. If u is differentiable, the necessary conditions for an optimum are

$$u_j = 0 \text{ when } x_j > 0; \; j = 1, 2, \ldots, n \tag{2}$$

and

$$u_j \leq 0 \text{ when } x_j = 0; \text{ some } j = 1, 2, \ldots, n \tag{3}$$

where u_j represents the partial derivative of u with respect to the activity level x_j.

Since u has been specified as concave and increasing for all x_j, these conditions are both necessary and sufficient for a maximum, and if u is strictly concave and increasing the solutions are unique. [Beckmann et al. (14) and Debreu (27) give a detailed development of these principles.]

Another approach, common in consumer demand theory, is to postulate the individual maximization of utility as being subject to one or more constraints. As an example of a single, binding constraint, consider the restrictions of a money budget.

$$\sum_{j=0}^{n} p_j x_j \leq y \tag{4}$$

where

$$p_j \geq 0; \; j = 0, 1, \ldots, n \tag{5}$$

are the costs of the activities, and

$$y \geq 0 \tag{6}$$

represents the expenditure budget or income. Here x_o denotes all activities other than those of direct interest (all other consumption), and, without restriction,

$$p_0 = 1 \tag{7}$$

The necessary and sufficient conditions for utility maximization then become (assuming that the equality sign holds in constraint Eq. 4)

$$-u_o p_j + u_j = 0; \; j = 1, 2, \ldots, n \tag{8}$$

Thus, at the implied equilibrium, the marginal utilities of all activities must be proportional to their prices. Moreover, differentiation of the budget equation (Eq. 4) yields the following propositions that help to define markets:

$$\sum_{j=0}^{n} p_j \frac{dx_j}{dy} = 1 \tag{9}$$

The demand for at least 1 activity must decrease with an increase in a price p_i.

Recently, the utility theory framework has been employed by a number of researchers to provide a behavioral framework for the explanation of travel demand phenomena (e.g., trip distribution) that had been previously described only in terms of probabilistic or metaphysical processes. Although these studies have concentrated almost exclusively on the use of objective, aggregate data, they collectively form a secure basis on which to develop models outlined in this paper. Golob and Beckmann (41), Beckmann (10), and Charles River Associates (19) specified rather general theories of (integrated) trip generation, distribution, and mode and route choice. Golob et al. (42) and Gustafson (47) performed empirical tests of utility hypotheses as applied to individuals' trip distribution decisions, and Niedercorn and Bechdolt (73), Beckmann and Golob (11), and Hansen (51) provided methodological derivations of trip distribution formulas (e.g., those obtained from gravity and entropy-maximizing models) commonly employed in transportation planning studies. Beckmann et al. (12) extended the utility approach to the description of automobile ownership decisions.

It is necessary to select specific functional forms for individuals' utility, and in almost all the cases referenced above the specific forms were selected from the generic class of utility functions that can be called separable and additive (57).

$$u = \sum_{j=0}^{n} \phi_j(x_j) \tag{10}$$

A sufficient condition for such a utility function u to be monotone increasing and concave is for all ϕ_j to be monotone increasing and concave.

If the ϕ_j are twice differentiable, a necessary and sufficient condition for utility maximization under a binding constraint is

$$-p_j \phi_0'(y - \sum_{i=1}^{n} p_i x_i) + \phi_j'(x_j) = 0; \; j = 1, 2, \ldots, n \tag{11}$$

where ϕ_j' denotes the first derivative of ϕ_j with respect to x_j. Consequently, the marginal utility of x_j must equal p_j times the marginal utility of the reference activity 0. In particular, the ratio of 2 marginal utilities must be equal to the ratio of their expenditure rates.

$$[\phi_j'(x_j)]/[\phi_i'(x_i)] = p_j/p_i; \; j, i = 1, 2, \ldots, n \tag{12}$$

It is contended that the inclusion of variables representing individuals' perceptions and preferences in utility theory models of travel behavior is the most direct way of tying these variables directly to decision-making behavior. Since the essence of the utility theory approach can be considered an analytical description of personal evaluations of perceived alternatives within a preference structure, assessments of individuals' attitudes toward decision situations in terms of the perceived costs and benefits involved can be used as determinant variables and as parameters in the descriptions. On a general consumer demand scope, the merging of preferences and perceptions into utility methodology has characterized a not insubstantial portion of modern microeconomic thought. This is generally classified under the heading of subjective value theory, and the basic utility concepts summarized above remain relevant to these subjective models.

The specification of decision alternatives in terms of attributes, as in the general schema described in the preceding section, is consistent with the (new) general consumer theory of attribute-defined goods. This theory defines the objects on which individuals' utility or satisfaction is based as the attributes of a good or activity, as opposed to the goods or activities themselves. It was initially advanced by Lancaster (62) and was initially adapted to the transportation demand case by Quandt and Baumol (81) and later, in a different form, by Wallace (111). Reports of specific modal-choice applications of attribute utility from general consumer demand theory to trip-making behavior can be traced through the works of Mathur (68), Allen (1), and Niedercorn and Bechdolt (73, 74, 75).

Final evaluations of the usefulness of the utility concepts within the subjective realm will have to wait for the development and testing of models that differ in many aspects from those outlined above. These models may emerge from an integration of classical economic utility concepts and psychometric scaling procedures for the assessment of preferences and perceptions. Some of these scaling procedures are discussed in this report. The general schematic representation is designed to facilitate the comparison of alternate techniques for predicting decisions about transportation-related options.

UNIVARIATE MODELS

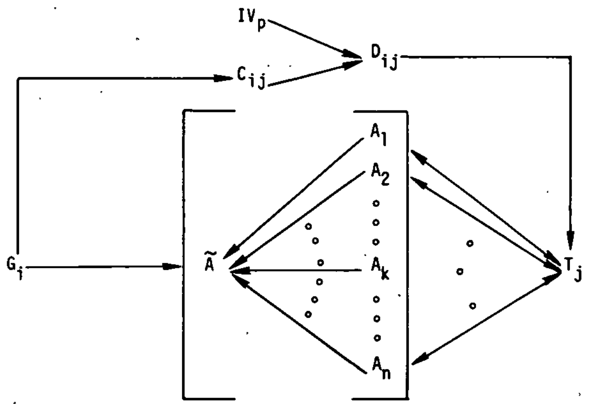
Univariate scaling and statistical approaches assume only one $\tilde{A}$ within the context of the general schematic representations. This single $\tilde{A}$ constitutes the sole scale or variable of interest. The entities, which are positioned on the scale or evaluated with respect to the variable being studied, are designated by the set of A's; these entities may be either elements of the set T_j or attributes that are presumably relevant to the elements of T_j. Figure 2a shows a reduced form of the general schema for univariate models. When the A's represent attributes, then there is only one link between G_i and the mediating set of entities, but there are multiple links between the latter set and T_j. On the other hand, when the A's represent members of the T_j set, then there are multiple links between G_i and the mediating entity set, but there is only a single link between the latter set and T_j (Fig. 2b). These generic relations will be expanded on with examples in the remainder of the section.

The work of Thurstone and Chave (106) illustrates a classic application of the law of comparative judgment on the measurement of attitudes toward religion. The theory underlying this scaling method is available in a variety of primary and secondary sources (46, 105, 107). More recently, Golob, Canty, Gustafson, and Vitt (42) measured preferences for attributes of an evolutionary transportation concept, the demand-responsive jitney, via Thurstone's law of comparative judgment. A sample section from their paired comparison questionnaire is shown in Figure 3. These investigators derived $\tilde{A}$'s, which revealed the subjective relations among the attributes, for the total sample of 786 respondents and also for special subgroups, such as elderly, low-income, and youth. This procedure of segmenting G_i was used by Gustafson and Navin (48) in a systematic replication of the Golob et al. study.

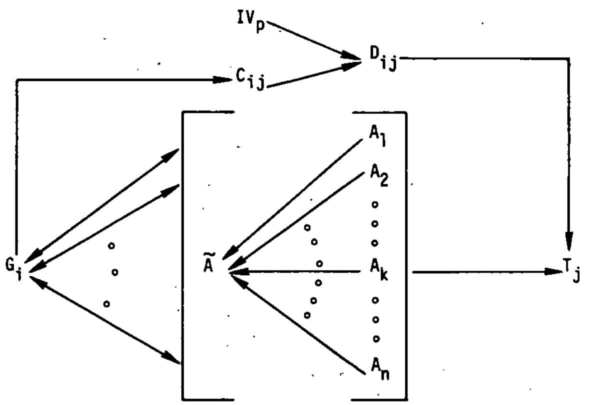
The indirect scaling methods of Thurstone can be contrasted to the direct scaling procedures of Stevens and others (99, 100, 101, 102, 103). Although both classes of techniques position attributes or T_j alternatives along a single continuum, or $\tilde{A}$, numerals are directly assigned to entities by respondents with the latter procedures; numerals are assigned to entities as a joint function of respondent judgments and model assumptions with indirect scaling. The resulting $\tilde{A}$ is more precisely defined when direct scaling is done to a ratio rule than when a Thurstone scale is used. Shinn (97) applied Stevens' ratio scaling to the problem of generating an urban transportation demand model. He was able to reveal unique sensitivities to travel time and cost for making a trip as a function of mode. In addition to segmenting T_j alternatives, he was able to identify unique $\tilde{A}$'s for different parts of G_i. Stevens (101) cited Indow's research that compared Thurstone and ratio scales of preference for wrist watches and then showed how judged fair price for the watches was a power function of the ratio preference scale values for them. Indow's research not only developed an $\tilde{A}$ but also related $\tilde{A}$ to something approximating C_{ij} within the context of the general schema.

When direct scaling is implemented according to an equal-interval or category rule, then the resulting $\tilde{A}$ is determined up to a scale factor and an additive constant. Thurstone scales are determined subject to the same constraints. A method of collecting category judgments is shown in Figure 4. It shows how importance ratings may be collected for attributes of a transportation system (28). Sellin and Wolfgang (88) scaled the seriousness of crimes by category and ratio direct scaling procedures. The $\tilde{A}$'s generated by the alternative procedures had the usual concave relation to each other (103). Ryan, Nedwek, and Beimborn (87) used category rating scales to assess community attitudes toward transportation services; through multivariate contingency tables, category judgments were related to socioeconomic and demographic characteristics of the respondents.

Figure 2. Schematic representations for univariate models.



(a) A set members are attributes.



(b) A set members are transportation-related alternatives.

Figure 3. Questionnaire format for collecting paired-comparison judgments about transportation-related alternatives.

GROUP C

This set of decisions deals with the interior design and structure of the vehicle that might be used in a new transportation system. For example, some of the choices will involve the amount of light, air, heat and sound around you in the vehicle, the exit and entry ways and several more.

Again, select your choice by circling the letter A or B, whichever is appropriate.

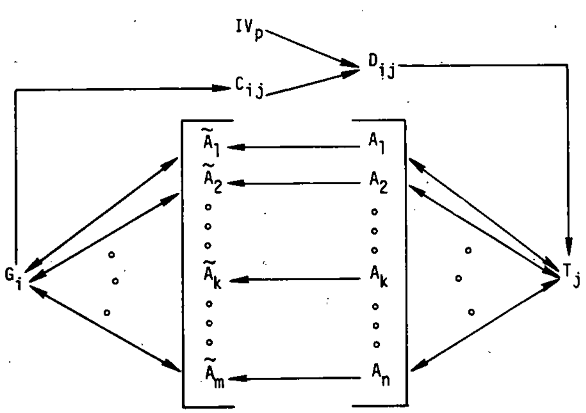
1. A. Ability to adjust the amount of light, air, heat and sound around you in the vehicle.
   or
   B. Easier entry and exit from the vehicle.

2. A. Easier entry and exit from the vehicl
   or
   B. Lower fare for passengers.

Figure 4. Questionnaire format for collecting category judgments about transportation system attributes.

Thinking about when I would use Public Transportation for longer trips and where I might go—This Feature Is This Important to Me:	Extremely Important	Very Important	Somewhat Important	Neither Important Nor Unimportant	Somewhat Unimportant	Very Unimportant	Extremely Unimportant
Having a short time waiting for a vehicle	7	6	5	4	3	2	1
Having short travel times . .	7	6	5	4	3	2	1
Having low fares	7	6	5	4	3	2	1
Having a comfortable ride in a quiet vehicle	7	6	5	4	3	2	1
Having a driver instead of a completely automatic system	7	6	5	4	3	2	1
Having my own private section in the vehicle . . .	7	6	5	4	3	2	1
Being able to get where I want to go on time	7	6	5	4	3	2	1
Being safe from harm by others and from vehicle accidents	7	6	5	4	3	2	1
Having room for strollers or	7	6	5	4	3	2	1

Figure 5. Schematic representation for models that assume attribute independence.



Another procedure for generating a single $\tilde{A}$ follows from the unfolding theory of Coombs (24). This theory allows for the derivation of a scale for the attributes or T_j alternatives; the scale also contains ideal respondent points. Ideal respondent points correspond to those positions on the scale that are more preferred by a respondent. One advantage of unfolding theory over previous scaling techniques is that it assumes respondent judgments are accurate only up to their order, but it derives a scale that is approximately interval in nature. However, the difficulty associated with implementing the theory has presumably discouraged its widespread application. The theoretical appeal of unfolding theory offers ground for its continued investigation in major scaling efforts. Previous applications of unfolding theory include the research of Runkel (86) and Coombs and Pruitt (25).

MODELS WITH ASSUMED ATTRIBUTE INDEPENDENCE

The first major class of multiple attribute models to be discussed are those models with assumed attribute independencies. Making this assumption is equivalent to selecting the mediating attribute set on an a priori basis, for use of attribute intercorrelations in the combining or weeding of variables is precluded (whenever data-derived attribute sets are employed, the multivariate model is classified with the models presented in the following section of this paper). Two subclasses of models with assumed attribute independencies are presented. Both subclasses of models can exhibit multiple G_i - ($\tilde{A} \leftarrow A$) and ($\tilde{A} \leftarrow A$) - T_j relations; however, both also have identity relations between A_k and $\tilde{A}_k$. The schematic representation for these subclasses is shown in Figure 5.

A logical starting point for the discussion of aggregate models is Rosenberg's cognitive summation model of attitude. The hypothesis specified by Rosenberg (84) is

$$\hat{C}_{ij} = \sum_{k=1}^{m} P_{ijk} V_{ik} \tag{13}$$

where

$\hat{C}_{ij}$ = affect aroused in individual i by object j;
P_{ijk} = perceived potency or perceived instrumentality of object j for achieving or blocking the value k for individual i;
V_{ik} = rated value importance of the k th value to individual i; and
m = the number of salient values.

In the adoption of this model to the explanation of transportation decision-making behavior, a correspondence can be developed between Rosenberg's affect, $\hat{C}_{ij}$, and choice by G_i, C_{ij}, and the (postulated) orthogonal space of the m values can be mapped into the (assumed) orthogonal space of the n attributes through development of a single parameter. Howard and Sheth (58) have accomplished these extensions in the context of general consumer buying behavior. In terms of the general schema, P_{ijk} and V_{ik} represent mediating set-T_j and G_i-mediating set relations respectively, and the summed products of P_{ijk} and V_{ik} represent an estimate of the degree of choice (C_{ij}) for alternative T_j by individual G_i. Rosenberg chose to focus on the affective component of attitude, which was then described in terms of the postulated attitudinal cognitive structure. This approach to the theory of attitude is similar to that of Peak (79), and it characterizes, with some modifications, much of the psychological and consumer theory work on attitude structures judged as being directly relevant to travel demand modeling. Golob (40) provides an extensive discussion of this and alternative theories of attitude.

Employing data on the ranking of value item statements and chi-square tests of association, Rosenberg reported the successful testing of the above hypotheses and also the successful testing of hypotheses relating overall affect of each of perceived instrumentality and value importance taken alone. However, as Howard and Sheth (58) point out, a number of procedural and methodological problems prevented Rosenberg from establishing convincing comparisons among the differences in explanatory power of his 3 hypotheses.

Fishbein (36) and Anderson and Fishbein (3) presented a 2-component cognitive theory of attitude in which the variables were defined as follows:

$$\hat{C}_{ij} = \sum_{k=1}^{n} B_{ijk} a_{ik} \tag{14}$$

where

$\hat{C}_{ij}$ = individual i's attitude toward object j;
B_{ijk} = strength of the belief k held by individual i about object j;
a_{ik} = evaluative aspect of B_{ijk}; and
n = number of salient beliefs.

Fishbein and his associates noted that, although evaluative beliefs represent only one type of belief, they make up that particular subset of beliefs that is related to an individual's attitude toward an object. For evaluative beliefs, the object is considered to be perceived as an instrument that can satisfy the evaluator's goals and objectives (i.e., block or aid the attainment of various valued states), and the attributes of the object are considered to be perceived as goal-satisfying properties (93). The extensions of this model to decision-making behavior are similar to those characterizing the Rosenberg model. In terms of the general schema, both models have identical relations.

This cognitive summation theory of attitude organization and change was proposed as an extension to the cognitive consistency theories in which attitude is viewed as a weighted average of belief scores (which were measured usually through the semantic differential scales discussed in the preceding section). Consistency theories were advanced by Osgood and Tannenbaum (77) and Osgood et al. (76) under the label of the congruity principle, by Heider (54) under the label of balance theory, and by Anderson (4). The evidence from comparative tests of the 2 approaches, as provided by Fishbein and Hunter (38) and Anderson and Fishbein (3), argues in favor of summation, primarily because of the discovered significant contribution to attitude of the set size, n.

Market researchers soon applied the cognitive summation model, with few modifications, to consumer buying behavior (9, 49, 50). This work was consistent with the definition by Kotler (59) of a product as "a bundle of physical, service and symbolic particulars expected to yield satisfactions or benefits to the buyer" (see the discussion of Lancaster's attribute utility theory in an earlier section). Attitude was approached as a unidimensional expression of the degree of favorableness toward a product, and Sheth (92) observed that the general consensus in the field was that attitude is "an affect-type construct in which buyer's likes and dislikes of a brand or product class are abstracted." However, Sheth and his associates scrutinized the major assumptions built into the cognitive summation models. Sheth (95) listed 4 questions concerning the models: Are 2 factors necessary for the calculation of attitude scores? Why employ a multiplicative combination of these 2 factors? Why aggregate over all salient beliefs (i.e., object attributes) to a single value? Should such summation be performed before or after factor multiplication?

The second subclass of models with assumed attribute independencies estimate indirectly the G_i-mediating set relations instead of collecting them from judgments from the respondents. Sheth (92) introduced a multiple regression approach for the explanation of attitude in terms of the n separate belief scores. Using semantic differential scale data obtained from a longitudinal consumer panel, he obtained (multiple) correlations between separate scores and overall attitudes toward a brand (as measured by a single rating score) that were significantly higher than (simple) correlations between single aggregated belief scores and the overall attitudes.

There is at present little disagreement in the market research area concerning the superiority of the indirect model over the direct one, and additional evidence as to improvements in explanatory power have been supplied by Sheth (93, 95) and Alpert (2). A major advantage of the direct model is that it enables the identification of the relative contributions of the beliefs about or attributes of the object toward formation of consumers' attitude, which is, of course, important information in promotional planning and new product development. A wide variety of statistical estimation procedures can be used to obtain this information from various survey data sources. Among such efforts are the regression approaches of Sheth (92, 93), Cohen and Houston (22), and Alpert (2) and the discriminant analysis approach of Banks (8), Perry (80), and Cohen and Ahtola (21).

Another approach of a slightly different nature is the ideal point model advanced by Lehmann (63):

$$\hat{C}_{ij} = \sum_{k=1}^{n} V_{ik} \left| P_{ijk} - I_{ik} \right|^{r} \tag{15}$$

where $\hat{C}_{ij}$, P_{ijk}, and n are defined as in Eq. 13 (84), I_{ik} represents individual i's ideal point for attribute k, and r is an integer defining the distance metric. This model is strongly related to the psychometricians' ideal point multidimensional scaling research discussed in the next section. Although success in predictive ability has been reported (63), some operational problems have been experienced, such as respondents' revealed inability to conceptualize ideal point values (15). As one interesting variation to the above, Einhorn and Gonedes (34) tested a model in which the discrepancy between an object's value and the ideal point is an exponentially increasing function.

With respect to the issue of whether 2 measurements on A_k are necessary for the determination of $\hat{A}_k$ (i.e., whether both evaluative belief and importance are needed), there is contradictory evidence. Arguing for a single measurement per attribute, Howard and Sheth (58) reanalyzed the tables of Rosenberg (84) and tentatively concluded that his value importance terms actually suppressed the correlation between attitude and perceived instrumentality in the model. Moreover, Sheth and Talarzyk (96), Lutz and Howard (67), and Sheth (93) each uncovered additional information (determined through multiple regression, canonical correlation analysis, and multiple-set canonical analysis respectively) that the attribute (or value) importance measure, as reported by respondents through direct questioning with the use of semantic differential scales, adds nothing to the explanation of overall attitude accomplished by the data from the semantic differential scales of beliefs (or perceived instrumentalities). On the other side of the coin, Hansen (50), in tests of a model describing the difference in attitudes between 2 alternatives, proposed

$$\hat{C}_{i1} - \hat{C}_{i2} = \sum_{k=1}^{n} V_{ik} \left(P_{i1k} - P_{i2k} \right) \tag{16}$$

where the variables are defined as in Eq. 13 (84), found the value importance terms contributed significantly to the variance explanation.

Most analysts responsible for development of these multivariate models (37) did not substantially differentiate between affect and behavioral intention (i.e., an individual's intention to react in a certain way, given his attitude toward an object), although Fishbein introduced a concept of social normative beliefs to help account for institutional and social constraints. Dulany (31, 32), in his theory of propositional control, explicitly incorporated these constraints by specifying behavioral intention as a function of attitude, beliefs (weighted by their reinforcing values), and social and institutional pressures (weighted by their strengths). This approach is similar to the distinction drawn by Rokeach (83) between attitudes toward an object and attitudes toward a situation and, together with the related work of McGuire (72), forms a basis for much of the consumer theory work in the field.

Dulany made no distinction, however, between behavioral intention and behavior. This was accomplished by Howard and Sheth (58) and Sheth (93). They specified actual behavior as a function of behavioral intention and nonpredictable (often random) situational factors (i.e., the intervening variables, IV_p, in the general schema). Such factors might be the availability of a brand or the sudden introduction of a new product. Multiple regression tests performed by these researchers have confirmed the hypothesis that evaluative beliefs (and possibly value importances) are most strongly related to affect, next to behavioral intention, and least to behavior in the brand purchase context.

Conjoint measurement models are similar to previous ones in this section in that they assume that a criterion variable can be predicted as a function of manifold attributes or entities. In the initial additive conjoint model (66), it was further assumed that the judgments can be rescaled so that the $\tilde{A}$'s are independent of each other and their sum is a monotonic function of the criterion variable. Figure 6 shows one page of a response booklet that can be used to collect data appropriate for this model; notice the judgments are rankings instead of ratings, unlike other data collection formats for previous models in this section. Green and Rao (45) discussed and illustrated various applications of conjoint measurement to general marketing problems, and Davidson (26) applied the technique to predict demand for short take-off and landing (STOL) craft. His analyses showed that the model produced excellent descriptions of existing multimodal intercity transportation shares, and it generated reasonable predictions for shares adjustments when the STOL craft was added to the T_j set. At the time his report was completed, STOL service had not commenced, and he was therefore unable to confirm the veracity of his predictions.

All the models discussed in this section can be disaggregated with respect to G_i. To achieve this end requires only the segmenting of the sample in a manner similar to that of Golob et al. (42) or that of Gustafson and Navin (48). Other means of segmenting G_i may be based on the G_i - ($\tilde{A} \leftarrow A$) or ($\tilde{A} \leftarrow A$) - T_j relations. Fixed and maximally effective procedures for segmenting G_i do not appear to be available.

The limited application of indirect, attribute-independent multivariate models to the transportation decision-making context has been characterized by the affect-choice-decision linkage and the focus on the binary choice situation exemplified by Hansen's equation (Eq. 16). Wallace (11) and Golob (39) presented a single-factor approach in which the attribute importances are estimated through fitting the model to reported existing choice. A page of their questionnaire used to collect attribute satisfaction ratings for the respondent's first-choice mode of traveling to work is shown in Figure 7; a repeat of the semantic differential scales for the same attributes for the reported second-choice mode then secures the necessary information for forming the (P_{i1k} - P_{i2k}) differences. Both linear and nonlinear estimation techniques were employed in this study, but considerations identical to those below led this work into the realm of covariance models discussed in the next section.

Although these multivariate statistical studies serve to validate particular postulates concerning relations between cognition, affect, and conation, all reveal rather poor connectivities between attribute-level attitude and actual behavior in the consumer context. This performance, together with an insecurity traceable to the assumption of attribute independencies and the consequent reliance on a priori judgments of attribute sets, has led researchers to the more general, albeit complex, set of covariance models presented in the following section of this paper.

MODELS WITH ASSUMED ATTRIBUTE INTERDEPENDENCE

This section treats 2 classes of models that are capable of making predictions about transportation-related decisions as a function of underlying subjective relations. These models are different from those in the section on univariate models because multiple $\tilde{A}$'s are permitted, and they are different from those in the preceding section because identity functions are not presumed between the A's and $\tilde{A}$'s. Although one class of

Figure 6. Questionnaire format for collecting respondent-ranked preferences about various levels of 2 attributes.

Here are 12 different types of transportation you could choose (described in terms of how long you would have to wait for a vehicle and how much the one-way fare would be). Each type of transportation would take you to the same place.

You would have to wait this long for the vehicle to arrive after you get to the transit station.

And your one-way fare would be:	Not At All	5 minutes	15 minutes
15¢			
75¢			
$1.25			
$3.00			

Figure 7. Questionnaire format for collecting data for single-factor approaches.

Below is a list of phrases some people use to describe their trip to work. For each phrase, rate your overall HOME TO WORK trip by placing a check mark ☑ in the box along the scale at that point which best describes your SATISFACTION with that aspect of the overall trip. If a phrase does not apply, check the box marked "Not Applicable" (N.A.)

COMFORT IN VEHICLE *(See Footnote) — N.A.
EXCELLENT ☐☐☐☐☐☐☐ POOR ☐

DEPENDABILITY OF ON-TIME ARRIVAL — N.A.
EXCELLENT ☐☐☐☐☐☐☐ POOR ☐

PROTECTION FROM WEATHER WHILE WAITING — N.A.
EXCELLENT ☐☐☐☐☐☐☐ POOR ☐

FREQUENCY OF VEHICLE DEPARTURE TIMES — N.A.
EXCELLENT ☐☐☐☐☐☐☐ POOR ☐

PLEASANTNESS OF TRIP — N.A.
EXCELLENT ☐☐☐☐☐☐☐ POOR ☐

ATTRACTIVENESS OF VEHICLE *(See Footnote) — N.A.
EXCELLENT ☐☐☐☐☐☐☐ POOR ☐

NOISE IN VEHICLE *(See Footnote) — N.A.
COMPLETELY ACCEPTABLE ☐☐☐☐☐☐☐ HIGHLY UNSATISFACTORY ☐

CHANCE OF ACCIDENTS — N.A.
COMPLETELY ACCEPTABLE ☐☐☐☐☐☐☐ HIGHLY UNSATISFACTORY ☐

EXPOSURE TO UNDESIRABLE BEHAVIOR OF OTHERS — N.A.
COMPLETELY ACCEPTABLE ☐☐☐☐☐☐☐ HIGHLY UNSATISFACTORY ☐

TRAFFIC — N.A.
COMPLETELY ACCEPTABLE ☐☐☐☐☐☐☐ HIGHLY UNSATISFACTORY ☐

BODILY CROWDING — N.A.
COMPLETELY ACCEPTABLE ☐☐☐☐☐☐☐ HIGHLY UNSATISFACTORY ☐

OUT OF POCKET COST OF TRIP — N.A.
...ETELY ... ...LY UNS...

models discussed in this section makes prior assumptions about the nature of the relations between A's and $\tilde{A}$'s, the other class derives these relations from respondent judgments. Some attention is also devoted to models whose sole purpose is to uncover the structure of subjective relations.

The first approach considered for the structuring of the interrelations between the attributes involves the specification of certain (endogenous) attributes as explicit functions of sets of other attributes. These selected interattribute relations are generally known as supply-side equations. The basic postulates are those of demand and supply equilibrium from microeconomic theory (i.e., the observed levels of the attributes are generated through simultaneous demand and supply processes).

To develop this argument more fully, we consider the A vector of n attributes, which were found to mediate the choice of T_j by G_i, as a monotone mapping of the n utilities (satisfactions) to G_i expected to be obtained from provision of these attributes within the activity T_j. (For an exposition of the concepts of utility underlying this model, see the section on relations to economic concepts of utility.) The overall utility to G_i from pursuit of activity alternative T_j is then related to the individual attributes in 2 ways: (a) through the manner in which the utilities are combined within G_i's preference structure (e.g., via weighted summation in the model of linear additive utility discussed in the preceding section of this paper) and (b) through the manner in which the attributes are related in the process that provides for the actual existence of the activity (i.e., its supply).

As a hypothetical example, assume that the 6-component vector of attribute ratings $(A_1, A_2, \ldots, A_6)$ is used to describe the T_j alternative facing G_i. This is shown in terms of the general schema (Fig. 8) and can be represented in general functional terms.

$$C_{ij} = f(A_1, A_2, A_3, A_4, A_5, A_6) \tag{17}$$

However, the supply process dictates that 2 of the attributes, $\tilde{A}_3$ and $\tilde{A}_4$, are endogenous and can be expressed as functions g and h respectively of 4 of the exogenous attributes.

$$\begin{aligned} \tilde{A}_3 &= g(A_3, A_4, A_5) \\ \tilde{A}_4 &= h(A_5, A_6) \end{aligned} \tag{18}$$

Thus, C_{ij} can be expressed in terms of combinations of the 4 endogenous attributes only. This is shown diagrammatically in Figure 8. Failure to account for the 2 supply-side relations would result statistically in a biased and inconsistent estimate of the contributions of $A_1, A_2, \ldots, A_6$ for the description of C_{ij} in Eq. 17. A number of econometric procedures are available for developing statistical inference from a set of simultaneous equations such as that defined by the functions of f, g, and h above. Theil (104, chap. 10) gives a discussion of these procedures.

The foremost application of the simultaneous equation approach to the explanation of transportation behavior in terms of choice-mediating attributes is in a research project reported by Sherret (90) and later by Sherret and Wallace (91). The attribute levels, A_k, employed in their model were the satisfactions reported by respondents for each attribute with regard to 2 entities, the respondents' first- and second-choice modes for their reported usual journeys to work. The instrument used for collecting the (first-choice mode) attribute ratings is shown in Figure 7, and the questionnaire used for gathering some objective trip data relevant to the formulation of supply-side equations is shown in Figure 9.

The primary attraction of the simultaneous equation approach involves its power to make full use of prior information in a Bayesian estimation sense: A priori information about the nature of transportation alternatives can be unambiguously incorporated into specific hypotheses that are readily understandable by diverse clients of the research. However, if the supply-side relations are found merely by searching interattribute correlation matrices for high values, or if supply-side equations are found by fitting a large number of equations and choosing those with the maximum coefficients of deter-

Figure 8. Schematic representation for simultaneous equation model from econometric theory.

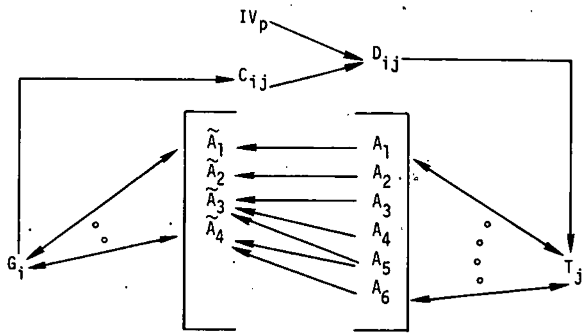


Figure 9. Questionnaire format for collecting objective trip data.

Do you travel to work in a different way when the weather is bad?

☐ **Yes** ☐ **No**

On the first page, you described your USUAL or FIRST-CHOICE way of getting FROM HOME TO WORK. Now consider your ONE NEXT BEST or SECOND-CHOICE way of getting FROM HOME TO WORK which is available to you.

How long does (would) this NEXT BEST way of getting to work take?....................minutes

Check the ONE box below which describes the type of transportation which you use, or could use, to make this second-choice one-way trip FROM HOME TO WORK.

☐ Automobile (driver)	☐ Automobile and Elevated or Subway
☐ Automobile (passenger)	☐ Automobile and Commuter Railroad
☐ Bus or Streetcar	☐ Bus or Streetcar and Elevated or Subway
☐ Elevated or Subway	☐ Commuter Railroad and Bus
☐ Commuter Railroad	☐ Walking ALL the Way
☐ Automobile and Bus or Streetcar	☐ Other (please specify)......................

☐ No second-choice available

If you indicated that you use, or could use as a second-choice, any of the types of public transportation listed above which have SCHEDULED DEPARTURES, what is the normal time between departures for each type you use at the time of day you usually travel TO WORK. Also, what are the ONE-WAY fares?

	Leaves Every	ONE-WAY fares
Bus or Streetcar	......Min.	$.........
Elevated or Subway	......Min.	$.........
Commuter Railroad	......Min.	$.........

If you checked the "Automobile (driver)" box above, how much does it cost you per day to park? $......

In total, how much time do you spend walking to and fr[illegible] vehicles durin[illegible] your *second-choice* [illegible]NE-WA[illegible] [illegible] total m[illegible] mination, then the technique becomes similar to those multivariate statistical methods used to simplify structure (e.g., factor analysis). The validity of the simultaneous equation approach depends critically on the veracity of the analyst's a priori knowledge.

There are at least 2 documented examples of models that interrelate the A's with $\tilde{A}$'s via a posteriori procedures for predicting decisions. Neither example is immediately concerned with the forecasting of transportation-related decisions, but both models may be extended easily to this class of decisions.

Sheth's (94) proposed theory to predict purchase behavior fits very neatly into the framework of the general schema. He defined purchase behavior to be a function of behavior intention and nonpredictable irregularly occurring events, but behavior intention was in turn a function of overall affect, predictable situations, and social factors. Finally, overall affect was conceived to be a function of a set of evaluative beliefs about the members of T_j. Sheth tested his model via canonical analysis (5, 23). The evaluative beliefs correspond to relations between the mediating attribute set ($\tilde{A} \leftarrow A$) and the members of set T_j, and the canonical weights for the evaluative beliefs correspond to the G_i - ($\tilde{A} \leftarrow A$) relations. Behavior intention, which he defined as a function of these two sets of relations and other variables, is analogous to our choice construct, C_{ij}. He also distinguished between the choice to use a mode and the act of using a mode, or what he calls purchase behavior. Lutz and Howard (67), using multiple-set canonical analysis, confirmed Sheth's general findings and constructs.

Wainer and his colleagues (109, 110) successfully implemented a 2-stage theory of senatorial decision-making that fits within the context of the general schema. The first stage used Tucker's 3-mode factor analysis procedure (108) to derive weights that were determined from senatorial voting records on various issues over time. The second stage used the weights from Tucker's procedure to predict voting behavior on a new set of issues. The 3-mode weights correspond to the G_i - ($\tilde{A} \leftarrow A$) relations of the schematic representation. The beta weights from the multiple logit procedure correspond to the ($\tilde{A} \leftarrow A$) relations. Presumably because Wainer used voting roll calls instead of subjective judgments, he failed to draw a distinction between C_{ij} and D_{ij}.

The Sheth and Wainer examples illustrate a range of models that may be compared in the framework of the general schema. Both approaches assume that a decision (i.e., to either purchase a product or vote affirmatively on an issue) is mediated by a set of underlying attributes, which relate to the decision-maker and the entity about which the decision is made. Sheth used the canonical factors from a preselected set of attributes, and Wainer used 3-mode factor analysis to derive latent factors believed to be important in decision-making. The actual functional forms used to relate the underlying attributes to the T_j alternatives were also different. Wainer relied on the nonlinear technique of multiple logit analysis, but Sheth employed the linear transformation technique of canonical analysis.

Factor analytic models have been applied widely in psychology and market research for simplifying the covariance structure of interrelated data sets such as the $\tilde{A} \leftarrow A$ set of the general schema. Extensive texts are available on the theory and application of this class of methods (52, 55), and the most widely used method has been the principal components analysis with varimax rotation of latent factors for interpretation purposes. Because of the availability of reports on the use of factor analytic methods in summarizing individuals' preferences for transportation modal attributes (16, 53, 78, 90), this class of techniques will not be elaborated on in this report. Suffice it to say that this method in essence performs a (simultaneous) regression of each variable on every other variable and attempts to simplify the results by emphasizing the predominant relations. Its use is subject to the well-discussed problems associated with subjective interpretation of results and decisions involving cutoff of the process of extracting eigenvalues (i.e., characteristic roots of the correlation or, less frequently, covariance matrix).

A relatively new class of procedures, multidimensional scaling (MDS) may be used to study the interrelations between A and $\tilde{A}$. The traditional MDS method (107, 116, 117) involved the derivation of a Euclidean space from respondent similarity judgments about attributes or objects.

Multidimensional scaling has attracted considerable attention as a theoretical topic within psychometrics (17, 89, 113) and within the social sciences in general as a numerical analysis technique (44, 85, 98). The primary objective of multidimensional scaling is to derive a geometric space for the row and column elements of a data matrix in which the distances between the points in the space are some function of the entries in the data matrix, and the coordinate matrix for the space is of a lower dimensionality than the data matrix. The positions of points in the derived space have often been subject to interpretation that provides insights about the cognitive processes underlying the judgments recorded in the data matrix. Dobson and Young (30), for example, were able to uncover latent dimensions describing how people perceived a class of form stimuli, and McDermott (69) was able to determine the dimensions of preference for various types of auditory distortion in recorded messages.

Recent developments within MDS by Shepard (89) and others (60, 64, 70, 115) have provided more flexibility in the properties of the data matrix, the nature of information in the data matrix, and the nature of the space that may be derived by what has come to be known as the nonmetric model. The nonmetric model differs from the traditional one primarily in that the judgments are assumed to be only monotonically related to the resulting interpoint distance instead of linearly related to the interpoint distances, as is the case with the traditional model. Aside from facilitating the treatment of incomplete data matrices, the nonmetric model also allowed MDS to consider preference as well as similarity judgments. Kruskal's development of the nonmetric model included a discussion of a wide class of spaces variously known as Minkowski (i.e., generalized Euclidean) spaces, which have the Euclidean space as a special case. The psychological implications of these non-Euclidean spaces have been known at least since the early work of Householder and Landahl (56), but their significance has continued to be discussed by Attneave (7), Torgerson (107), and Arnold (6), among others.

Dobson, Golob, and Gustafson (29) applied 2 MDS models to transportation system preference data collected with a paired comparison technique; these same data were previously analyzed unidimensionally by Golob et al. (42). The vector preference model was based on the Eckart-Young singular decomposition theorem (33), and the nonmetric unfolding preference model was an extension by Kruskal and Carmone (61) of the earlier work of Coombs (25). The vector model was superior to the unfolding model in 2 respects: (a) The vector model solution was related to socioeconomic and demographic characteristics of the respondents, but the unfolding solution was not, and (b) the vector model more neatly accounted for the variance of an earlier Thurstone scaling of the same data. Both MDS models, however, appear to yield valuable insights to the underlying factors governing transit choices. The MDS analysis of the data enhanced the prior unidimensional analysis by recovering most of the variance of the Thurstone scale in addition to some new scales that were independent of the Thurstone scale.

As noted above, though, MDS models were initially designed to scale similarity and not preference data. There appears to be only one prior study that attempted to collect similarity judgments about transit attributes. At this time, only the documentation for the questionnaires is complete (28). Figure 10 shows a questionnaire format that allows a respondent to select k of n - 1 attributes as similar to the n th attribute; each of the n attributes is compared to the remaining n - 1 with this procedure. Subject to appropriate preliminary data processing, the results from such a task may be analyzed by any of the standard MDS computer programs (18, 20, 71, 114, 115). The judgments about the attributes (the A set) will be reduced to some smaller set of perceptually relevant scales (the $\tilde{A}$ set) in either case. These $\tilde{A}$'s and any other output from the models may be used to generate predictions about D_{ij}, which are based at least in part on the perceptual similarity judgments of the respondents.

CONCLUSIONS: DIRECTIONS FOR FUTURE RESEARCH

This paper calls for a merging of econometric and psychometric theories to facilitate the understanding of how individuals make decisions about transportation-related alternatives. Furthermore, the general schematic representation provides a context in which a wide variety of existing and new models of choice for transportation-related alternatives can be compared. A corpus of transportation research, market research,

Figure 10. Questionnaire format for collecting similarity judgments about transportation system attributes.

Please read the feature enclosed in the box at the top of this page. Then read each feature listed below it. If you feel the two features are alike "X" the "yes" box. If you feel the two features are not alike "X" the "no" box. Please "X" either "yes" or "no" for every feature listed below.

Is $\boxed{\text{BEING ABLE TO GET WHERE I WANTED TO GO ON TIME}}$ like:.

	Whether This Is Like the Feature Above:	
Having my own private section in the vehicle	yes ☐	no ☐
Having short travel times	yes ☐	no ☐
Having a short waiting for a vehicle	yes ☐	no ☐
Having low fares	yes ☐	no ☐
Having a comfortable ride in a quiet vehicle	yes ☐	no ☐
Having a driver instead of a completely automatic system .	yes ☐	no ☐
Being safe from harm by others and from vehicle accidents	yes ☐	no ☐
Having room for strollers or wheel chairs	yes ☐	no ☐
Being able to get to many places in the Detroit area using the guideway	yes ☐	no ☐
Having refreshments and newspapers for sale at stations. .	yes ☐	no ☐
Having control of temperature in the vehicle	yes ☐	no ☐

econometric, and psychometric literature has been reviewed to show its relation to the themes.

It is recommended that econometric and psychometric theories be merged because neither is complete with respect to the central problem of this paper. Econometric theory offers a set of very detailed explanations of the role of utility in decision-making, and it also expresses these explanations in a series of mathematically precise functions. Examples of econometric formulations that predict choice behavior as a result of utility maximizing processes are presented. However, the variables that determine utility are psychological in some, if not all, cases, and microeconomic theory does not significantly consider how these variables should be measured.

In this paper, manifold ways to assess psychological variables are mentioned, but there are still many more. The general issue of the measurement of psychological variables is considered by psychometric theory. One major distinction among the models proposed from theory is that between unidimensional and multidimensional scaling procedures; this distinction may be more clearly defined by comparing the section on univariate models and the preceding section. However, the distinction does have a fuzzy boundary; the section on models with assumed attribute independence reveals this matter. The major differences between the classes of models discussed in the last 3 sections are clearly illustrated in their corresponding schematic representations.

There are 2 advantages to the general schema. As mentioned above, it provides a framework in which to compare the multiplicity of existing psychometric models. It also helps to identify a major weakness of these models with respect to the central problem of this paper. Although a great deal of attention is devoted to the structure of subjective relations, the connections between these relations and decision-making are not directly addressed. The general schema clearly defines this issue without selecting a particular functional form as the answer. The preceding section describes alternative procedures for identifying the structural relations and the functional forms for mapping the relations into decision-making.

The directions for future research seem obvious. First, the relative merits of quantifying subjective relations via different procedures need to be evaluated. Psychometric theory is a strong discipline with respect to this problem, but models that develop from other than psychometric theory should not be avoided. Next, alternative functional forms for linking the subjective relations and other variables to decision-making need to be compared. Although economic utility theory is one place from which to derive reasonable functional forms, equally reasonable forms may be collected from other approaches. Through the iterative application of these 2 steps, new classes of models may be formed that generate predictions about and insights into decision-making beyond what is currently available.

REFERENCES

1. Allen, W. B. An Economic Derivation of the "Gravity Law" of Spatial Interaction: A Comment on the Reply. Journal of Regional Science, Vol. 12, 1972, pp. 119-126.
2. Alpert, M. I. Identification of Determinant Attributes: A Comparison of Methods. Journal of Marketing Research, Vol. 8, 1971, pp. 184-191.
3. Anderson, L. R., and Fishbein, M. Prediction of Attitude From the Number, Strength, and Evaluative Aspect of Beliefs About the Attitude Object: A Comparison of Summation and Congruity Theories. Journal of Personality and Social Psychology, Vol. 3, 1965, pp. 437-443.
4. Anderson, N. H. Averaging Versus Adding as a Stimulus Combination Rule in Impression Formation. Journal of Experimental Psychology, Vol. 70, 1965, pp. 394-400.
5. Anderson, T. W. An Introduction to Multivariate Statistical Analysis. Wiley, New York, 1958.
6. Arnold, J. B. A Multidimensional Scaling Study of Semantic Distance. Journal of Experimental Psychology, Vol. 90, 1971, pp. 349-372.
7. Attneave, F. Dimensions of Similarity. American Journal of Psychology, Vol. 63, 1950, pp. 516-556.
8. Banks, S. The Relationship Between Preference and Purchase Brands. Journal of Marketing, Vol. 15, 1950, pp. 145-157.
9. Bass, F. M., and Talarzyk, W. W. A Study of Attitude Theory and Brand Preference. In Marketing Involvement in Society and the Economy (McDonald, P. R., ed.), Fall Conference Proc., American Marketing Association, Chicago, 1969.
10. Beckmann, M. J. The Soft Science of Predicting Traveller Behavior. Transportation Planning and Technology, Vol. 1, 1973, pp. 175-181.
11. Beckmann, M. J., and Golob, T. F. A Critique of Entropy and Gravity in Travel Forecasting. In Traffic Flow and Transportation (Newell, G. F., ed.), Proc. of Fifth International Symposium, American Elsevier, New York, 1972.
12. Beckmann, M. J., Gustafson, R. L., and Golob, T. F. Locational Factors in Automobile Ownership Decisions. Presented at Annual Meeting of the Western Regional Science Association, Monterey, 1973.
13. Beckmann, M. J., Godfrey, M., Golob, T. F., Huber, M., Jones, A., and Whorf, R. Prediction of Demand for New Urban Transportation Systems. Proc. of ORSA/TSS Urban Transportation Workshop, Operations Research Society of America, Baltimore, 1973.
14. Beckmann, M. J., McGuire, C. B., and Winsten, C. B. Studies in the Economics

of Transportation. Yale University Press, New Haven, 1956.
15. Bolger, J. F. How to Evaluate Your Company Image. Journal of Marketing, Vol. 24, 1956, pp. 7-10.
16. Brunner, G. A., et al. User Determined Attributes of Ideal Transportation Systems: An Empirical Study. University of Maryland, College Park, 1966.
17. Carroll, J. D. Individual Differences and Multidimensional Scaling. In Multidimensional Scaling (Shepard, R. N., Romney, A. K., and Nerlove, S. B., eds.), Vol. 1, Seminar Press, New York, 1972.
18. Carroll, J. D., and Chang, J. J. Analysis of Individual Differences in Multidimensional Scaling Via an N-Way Generalization of "Eckart-Young" Decomposition. Psychometrika, Vol. 35, 1970, pp. 283-319.
19. A Disaggregated Behavioral Model of Urban Travel Demand. Charles River Associates, 1972.
20. Cliff, N. The "Idealized Individual" Interpretation of Individual Differences in Multidimensional Scaling. Psychometrika, Vol. 33, 1968, pp. 225-232.
21. Cohen, J. B., and Ahtola, O. T. An Expectance × Value Analysis of the Relationship Between Consumer Attitudes and Behavior. Presented at Annual Meetings of Association for Consumer Research, University of Maryland, 1971.
22. Cohen, J. B., and Houston, M. J. The Structure of Consumer Attitudes: The Use of Attribute Possession and Importance Scores. Presented at Attitude Research and Consumer Behavior Workshop, Urbana-Champaign, Illinois, 1970.
23. Cooley, W. W., and Lohnes, P. R. Multivariate Data Analysis. Wiley, New York, 1971.
24. Coombs, C. H. A Theory of Data. Wiley, New York, 1964.
25. Coombs, C. H., and Pruitt, D. Components of Risk in Decision Making: Probability and Variance Preferences. Journal of Experimental Psychology, Vol. 60. 1960, pp. 265-277.
26. Davidson, J. D. Forecasting Demand for a New Mode of Transportation. Presented at Meeting of Association for Consumer Research, Chicago, 1972.
27. Debreu, G. Theory of Value. Wiley, New York, Cowles Foundation Monograph 17, 1959.
28. Dobson, R. Documentation for the Metro Guideway Home-Interview and Leave-Behind Questionnaires. General Motors Research Laboratories, Warren, Michigan, Publication GMR-1511, 1973.
29. Dobson, R., Golob, T. F., and Gustafson, R. L. Multidimensional Scaling of Consumer Preferences for a Public Transportation System: An Application of Two Approaches. Socio-Economic Planning Sciences, 1974.
30. Dobson, R., and Young, F. W. On the Perception of a Class of Bilaterally Symmetric Forms. Perception and Psychophysics, Vol. 13, 1973, pp. 431-438.
31. Dulany, D. E. The Separable Effects of the Information and Affect Conveyed by a Reinforcer. Presented at Annual Meeting of Psychometric Society, 1964.
32. Dulany, D. E. Awareness, Rules, and Propositional Control: A Confrontation With S-R Behavior Theory. In Verbal Behavior and General Behavior Theory (Dixon, T. R., and Horton, D. L., eds.), Prentice-Hall, Englewood Cliffs, N.J., 1968.
33. Eckart, C., and Young, G. The Approximation of One Matrix by Another of Lower Rank. Psychometrika, Vol. 1, 1936, pp. 211-218.
34. Einhorn, H. J., and Gonedes, N. J. An Exponential Discrepancy Model for Attitude Evaluation. Behavioral Science, Vol. 16, 1971, pp. 152-157.
35. Ferguson, C. E. Microeconomic Theory. Richard D. Irwin, Homewood, Illinois, 1966.
36. Fishbein, M. An Investigation of the Relationships Between Beliefs About an Object and the Attitude Toward That Object. Human Relations, Vol. 16, 1936, pp. 233-240.
37. Fishbein, M. The Relationships Between Beliefs, Attitudes and Behavior. In Cognitive Consistency (Feldman, S., ed.), Academic Press, New York, 1966, p. 199.
38. Fishbein, M., and Hunter, R. Summation Versus Balance in Attitude Organization and Change. Journal of Abnormal and Social Psychology, Vol. 69, 1969, pp. 505-510.
39. Golob, T. F. The Survey of User Choice of Alternate Transportation Models.

High Speed Ground Transportation Journal, Vol. 4, 1970, pp. 103-116.
40. Golob, T. F. Attitudinal Models. HRB Spec. Rept. 143, 1973, pp. 130-147.
41. Golob, T. F., and Beckmann, M. J. A Utility Model for Travel Forecasting. Transportation Science, Vol. 5, 1971, pp. 79-90.
42. Golob, T. F., Canty, E. T., Gustafson, R. L., and Vitt, J. E. An Analysis of Consumer Preferences for a Public Transportation System. Transportation Research, Vol. 6, 1972, pp. 81-102.
43. Golob, T. F., Gustafson, R. L., and Beckmann, M. J. An Economic Utility Approach to Spatial Interaction. Papers of the Regional Science Association, 1974.
44. Green, P. E., and Carmone, F. J. Marketing Research Applications of Nonmetric Scaling Methods. In Multidimensional Scaling (Romney, A. K., Shepard, R. N., and Nerlove, S. B., eds.), Vol. 2, Seminar Press, New York, 1972.
45. Green, P. E., and Rao, V. Conjoint Measurement for Quantifying Judgmental Data. Journal of Marketing Research, Vol. 8, 1971, pp. 355-363.
46. Guilford, J. P. Psychometric Methods. McGraw-Hill, New York, 1954.
47. Gustafson, R. L. An Empirical Study of Factors Influencing Trip Attraction and Trip Generation. Presented at 43rd National Meeting of Operations Research Society of America, Milwaukee, 1973.
48. Gustafson, R. L., and Navin, F. P. D. User Preferences for Dial-A-Bus. HRB Spec. Rept. 136, 1973, pp. 85-93.
49. Hansen, F. An Experimental Test of a Consumer Choice Model. In Marketing and the New Science of Planning (King, R. L., ed.), Fall Conference, American Marketing Association, Chicago, 1968, pp. 393-400.
50. Hansen, F. Consumer Choice Behavior: An Experimental Approach. Journal of Marketing Research, Vol. 6, 1969, pp. 436-443.
51. Hansen, S. Utility, Accessibility and Entropy in Spatial Modelling. The Swedish Journal of Economics, Vol. 74, 1972.
52. Harman, H. H. Modern Factor Analysis. University of Chicago Press, 1967.
53. Hartgen, D. T., and Tanner, G. T. Individual Attitudes and Family Activities: A Behavioral Model of Travel Choice. High Speed Ground Transportation Journal, Vol. 4, 1970, pp. 439-467.
54. Heider, F. The Psychology of Interpersonal Relations. Wiley, New York, 1958.
55. Horst, P. Factor Analysis of Data Matrices. Holt, Rinehart, and Winston, New York, 1965.
56. Householder, A. S., and Landahl, H. D. Mathematical Biophysics of the Central Nervous System. Mathematical Biophysics Monograph 1, 1945.
57. Houthakker, H. S. Revealed Preference and the Utility Function. Economica, Vol. 17, 1950, pp. 159-175.
58. Howard, J. A., and Sheth, J. N. The Theory of Buyer Behavior. Wiley, New York, 1969.
59. Kotler, P. Marketing Management: Analysis, Planning, and Control. Prentice-Hall, Englewood Cliffs, N.J., 1967.
60. Kruskal, J. B. Multidimensional Scaling by Optimizing Goodness of Fit to a Nonmetric Hypothesis. Psychometrika, Vol. 29, 1964, pp. 1-27.
61. Kruskal, J. B., and Carmone, F. J. How to Use M-D-SCAL: A Program to Do Multidimensional Scaling and Multidimensional Unfolding. Bell Telephone Laboratories, Murray Hill, N.J., 1969.
62. Lancaster, K. J. A New Approach to Consumer Theory. Journal of Political Economy, Vol. 14, 1966, pp. 132-157.
63. Lehmann, D. R. Television Show Preference: Application of a Choice Model. Journal of Marketing Research, Vol. 8, 1971, pp. 47-55.
64. Lingoes, J. C. A General Survey of the Guttman-Lingoes Nonmetric Program Series. In Multidimensional Scaling (Shepard, R. N., Romney, A. K., and Nerlove, S. B., eds.), Vol. 1, Seminar Press, New York, 1972.
65. Luce, R. D., and Raiffa, M. Games and Decisions. Wiley, New York, 1957.
66. Luce, R. D., and Tukey, J. W. Simultaneous Conjoint Measurement: A New Type of Fundamental Measurement. Journal of Mathematical Psychology, Vol. 1, 1964, pp. 1-27.

67. Lutz, R. J., and Howard, J. A. Toward a Comprehensive View of the Attitude-Behavior Relationship: The Use of Multiple-Set Canonical Analysis. Proc. American Statistical Association, 1971.
68. Mathur, V. K. An Economic Derivation of the "Gravity Law" of Spatial Interaction: A Comment. Journal of Regional Science, Vol. 10, 1970, pp. 403-405.
69. McDermott, B. J. Multidimensional Analyses of Circuit Quality Judgments. Journal of the Acoustical Society of America, Vol. 45, 1969, pp. 774-781.
70. McGee, V. The Multidimensional Analyses of "Elastic" Distances. British Journal of Mathematical and Statistical Psychology, Vol. 19, 1966, pp. 181-196.
71. McGee, V. Multidimensional Scaling of N Sets of Similarity Measures: A Non-metric Individual Differences Approach. Multivariate Behavioral Research, Vol. 3, 1968, pp. 233-248.
72. McGuire, W. J. The Nature of Attitudes and Attitude Change. In Handbook of Social Psychology (Lindsey, G., and Aronson, E., eds.), Addison-Wesley, Reading, 1968.
73. Niedercorn, J. H., and Bechdolt, B. V. An Economic Derivation of the "Gravity Law" of Spatial Interaction. Journal of Regional Science, Vol. 10, 1969, pp. 407-410.
74. Niedercorn, J. H., and Bechdolt, B. V. An Economic Derivation of the "Gravity Law" of Spatial Interaction: Reply. Journal of Regional Science, Vol. 10, 1970, p. 1106.
75. Niedercorn, J. H., and Bechdolt, B. V. An Economic Derivation of the "Gravity Law" of Spatial Interaction: A Further Reply and a Reformulation. Journal of Regional Science, Vol. 12, 1972, pp. 127-136.
76. Osgood, C. E., Suci, G. J., and Tannenbaum, P. H. The Measurement of Meaning. University of Illinois Press, Urbana, 1957.
77. Osgood, C. E., and Tannenbaum, P. H. The Principle and Congruity in the Prediction of Attitude Change. Psychological Review, Vol. 62, 1955, pp. 42-55.
78. Paine, F., et al. Consumer Conceived Attributes of Transportation: An Attitudinal Study. University of Maryland, College Park, 1967.
79. Peak, H. Attitude and Motivation. In Nebraska Symposium on Motivation (Jones, M., ed.), University of Nebraska Press, Lincoln, 1955.
80. Perry, M. Discriminant Analysis of Relation Between Consumers' Attitudes, Behavior, and Intentions. Journal of Advertising Research, Vol. 9, 1969, pp. 34-40.
81. Quandt, R. E., and Baumol, W. J. The Demand for Abstract Transport Modes: Theory and Measurement. Journal of Regional Science, Vol. 6, 1966, pp. 13-25.
82. Quirk, J., and Saposnik, R. Introduction to General Equilibrium Theory and Welfare Economics. McGraw-Hill, New York, 1968.
83. Rokeach, M. Beliefs, Attitudes, and Values. Jossey-Bass, Inc., San Francisco, 1969.
84. Rosenberg, M. J. Cognitive Structure and Attitudinal Affect. Journal of Abnormal and Social Psychology, Vol. 53, 1956, pp. 367-372.
85. Rosenberg, S., and Sedlak, A. Structural Representations of Perceived Personality Trait Relationships. In Multidimensional Scaling (Romney, A. K., Shepard, R. N., and Nerlove, S. B., eds.), Vol. 2, Seminar Press, New York, 1972.
86. Runkel, P. J. Cognitive Similarity in Facilitating Communication. Sociometry, Vol. 19, 1956, pp. 178-191.
87. Ryan, C. R., Nedwek, B. P., and Beimborn, E. A. An Evaluation of the Feasibility of Social Diagnostic Techniques in the Transportation Planning Process. Highway Research Record 410, 1972, pp. 8-23.
88. Sellin, T., and Wolfgang, M. E. The Measurement of Delinquency. Wiley, New York, 1964.
89. Shepard, R. N. The Analysis of Proximities: Multidimensional Scaling With an Unknown Distance Function I. Psychometrika, Vol. 27, 1962, pp. 125-140.
90. Sherret, A. Structuring an Econometric Model of Mode Choice. Cornell University, PhD dissertation, 1971.
91. Sherret, A., and Wallace, J. P., III. Estimating the Relative Importance of Product Attributes. General Motors Corporation, Detroit, 1972.

92. Sheth, J. N. Attitude as a Function of Evaluative Beliefs. Presented at American Marketing Association Consumer Workshop, Columbus, Ohio, 1969.
93. Sheth, J. N. An Investigation of Relationships Among Evaluative Beliefs, Affect, Behavioral Intention and Behavior. College of Business Administration, Pennsylvania State University, No. 7. in Working Series in Marketing Research, 1970.
94. Sheth, J. N. Canonical Analysis of Attitude-Behavior Relationship. Presented at 18th International Meeting of Institute of Management Sciences, Washington, D.C., 1971.
95. Sheth, J. N. Measurement of Attitude Scores From Beliefs and Importances. College of Commerce and Business Administration, University of Illinois, Faculty Working Paper 50, 1972.
96. Sheth, J. N., and Talarzyk, W. Relative Contribution of Perceived Instrumentality and Value Importance Components in Determining Attitudes. Fall Conference Proc., American Marketing Association, Boston, 1970.
97. Shinn, A. M. Toward a Policy Oriented Urban Transportation Demand Model: A Psychometric Approach to Modal Split. Presented at Urban Regional Information Systems Association, San Francisco, 1972.
98. Stefflre, V. J. Some Applications of Multidimensional Scaling to Social Science Problems. In Multidimensional Scaling (Romney, A. K., Shepard, R. N., and Nerlove, S. B., eds.), Vol. 2, Seminar Press, New York, 1972.
99. Stevens, S. S. The Direct Estimation of Sensory Magnitudes-Loudness. American Journal of Psychology, Vol. 69, 1956, pp. 1-25.
100. Stevens, S. S. On the Psychophysical Law. Psychological Review, Vol. 64, 1957, pp. 153-181.
101. Stevens, S. S. A Metric for the Social Consensus. Science, Vol. 151, 1966, pp. 530-541.
102. Stevens, S. S. On Predicting Exponents for Cross-Modality Matches. Perception and Psychophysics, Vol. 6, 1969, pp. 251-256.
103. Stevens, S. S., and Galanter, E. H. Ratio and Category Scales for a Dozen Perceptual Continua. Journal of Experimental Psychology, Vol. 54, 1957, pp. 377-411.
104. Theil, H. Principles of Econometrics. Wiley, New York, 1971.
105. Thurstone, L. L. Psychophysical Analysis. American Journal of Psychology, Vol. 38, 1927, pp. 268-389.
106. Thurstone, L. L., and Chave, E. J. The Measurement of Attitude. University of Chicago Press, 1929.
107. Torgerson, W. S. Theory and Methods of Scaling. Wiley, New York, 1958.
108. Tucker, L. R. Some Mathematical Notes on Three-Mode Factor Analysis. Psychometrika, Vol. 31, 1966, pp. 279-311.
109. Wainer, H., Gruvaeus, G., and Zill, N., II. Senatorial Decision Making: I. The Determination of Structure. Behavioral Science, Vol. 18, 1973, pp. 7-19.
110. Wainer, H., Zill, N., II, and Gruvaeus, G. Senatorial Decision Making: Prediction. Behavioral Science, Vol. 18, 1973, pp. 20-26.
111. Wallace, J. P. Some Applications of Marketing Research Techniques to the New Mode Demand Forecasting Problem. Presented at Conference on Methods and Concepts of Forecasting Demand for New Transportation Systems, University of Pennsylvania, 1969.
112. Sherret, A., and Wallace, J. P., III. Product Attributes. HRB Spec. Rept. 143, 1973, pp. 146-174.
113. Young, F. W. A Model for Polynomial Conjoint Analysis Algorithms. In Multidimensional Scaling (Shepard, R. N., Romney, A. K., and Nerlove, S. B., eds.), Vol. 1, Seminar Press, New York, 1972.
114. Young, F. W., and Dobson, R. TORSCA-10: A Small-Machine (IBM 1130) FORTRAN-IV Program for Nonmetric Multidimensional Scaling. Behavioral Science, Vol. 17, 1972, p. 325.
115. Young, F. W., and Torgerson, W. S. TORSCA: A FORTRAN IV Program for Shepard-Kruskal Multidimensional Scaling Analysis. Behavioral Science, Vol. 12, 1967, p. 498.

116. Young, G., and Householder, A. S. Discussion of a Set of Points in Terms of Their Mutual Distances. Psychometrika, Vol. 3, 1938, pp. 19-22.
117. Young, G., and Householder, A. S. A Note on Multidimensional Psychophysical Analysis. Psychometrika, Vol. 6, 1941, pp. 332-333.

Conference Paper on Aggregation Problems

Problem of Aggregation in Disaggregate Behavioral Travel Choice Models With Emphasis on Data Requirements

David A. Hensher, Australia Commonwealth Bureau of Roads

A preliminary consideration of the process leading to acts of choice is outlined in terms of the underlying dynamic process that molds the consumer's preference functions. This is designed with 3 main objectives in mind: the role of attitudes in influencing behavior, the directional relation between behavior and attitudes, and the identification of various homogeneous groups of travelers based on various prespecified physical and value-associated criteria and designed to ensure a more meaningful aggregation where within-group variance is minimized and between-group variance is maximized. An important feature of attitude-behavior models is that, being based on psychological principles, they are applicable to more than simply transportation problems. They can, therefore, be applied in some form to all aspects of human behavior (though perhaps with varying success) and so provide a basis for more coordination in governmental decision-making. A consideration of data requirements can emphatically contribute to a greater understanding of the causal connection within and between various acts of travel choice and accordingly lead to improvements in the models themselves via improved perspective in the selection of variables.

In recent years the progress of analytical rigor in modeling travel demand at the level of disaggregate behavioral travel choice has far outpaced the consideration of data requirements compatible with the relative level of sophistication of such models. [Tanner (46) gives an excellent discussion of the various interpretations of disaggregate and behavioral.] It is important to indicate the greater predictive ability of disaggregate stochastic behavioral models (henceforth referred to as behavioral models) tested on existing inappropriate and somewhat uncertain data collected in the past before the development of improved predictive models [for example, the Cook County Highway Department's data used by Warner and Lave (37)]. However, there are now new issues and emphases not evident in data requirements specified at previous points in time.

In addition to recognizing the urgent need for improved data sources, we must establish a number of guidelines to identify the nature of data requirements in terms of the real issues in planning for an improved quality of urban life and to meet the specification and estimation requirements of current and future modeling systems. Both the content (i.e., range) and conceptualization (i.e., structure) of mechanisms used to collect new data must be clearly spelled out. Once the objectives are clarified, then the issue of aggregation in its various guises should be operationally clearer.

This paper confines the discussion of aggregation in behavioral travel choice modeling to specific data needs and possible structural mechanisms suitable to the development of models that display a maximum maintenance of relevant behavioral interactions identified and measured at the level at which primary travel choice decision processes occur. Data requirements are broadly interpreted to entail identification and measurement of the physical and nonphysical attributes of an individual or type of individual, his or her environment, and the interaction within the attribute space and between this space and environment space. The individual as the basic decision unit attempts to maximize some objective function (subjectively defined and not necessarily homogeneous across individuals) subject to household and environmental constraints. That is, relative travel preferences and choices are related to the values and perceptions of individuals for the attributes associated with travel. This approach is operationally better than having the family as the decision-making unit, for identification of a utility function for an individual can be regarded as a relatively less onerous task than the identification of a utility function for a family. Immediate additivity problems associated with interpersonal comparisons occur at the level of the family unit.

BASIC HIERARCHICAL STRUCTURE

The emphasis is on the development of a schema that focuses on the understanding of the decision process leading to action by the user of various transport facilities in time and space. A great deal can be learned in the process of identifying data requirements by referring to the microstructural schemes that originated in the early 1920s with Tolman's cognitive maps (48, pp. 279-361) and in the 1930s with Lewin's topological spaces and valences (30, pp. 197-221) and Lazarsfeld's structural scheme to explain consumer behavior (28, pp. 26-38). These structural models are explanatory and predictive in contrast to the reduced-form models typified by contemporary transport planning submodels, which are noncausal associative models. Explanation is the vital link in the process of essentially improving predictability in the light of any system-sensitive adjustments [e.g., the effect of a fare increase on choice of mode (25)]. There is a need not only to identify and measure the relative influence of the determinants of the status quo but also to identify and measure the sensitivity of parameters from a given point in time and over time. Although time series data are necessary and are being collected by a few researchers or organizations (24), the time-dependent interaction effects will only be acknowledged as another area for data-requirement consideration. The discussion will be confined to cross-sectional issues associated with data needs in behavioral travel choice modeling in accordance with the requirement of desirable spatial aggregation criteria.

The Lazarsfeld approach, which was extended by Nicosia (34), emphasized the study of human conduct in natural settings in an attempt to uncover the structure of action (29, pp. 99-155). Assume that the individual's travel considerations can be represented in terms of 8 basic choices, each influenced and constrained by the traveler and his or her environment. That is, each component of travel choice can be divided into variables internal and external to the traveler. The 8 choices are

1. Whether to make a trip,
2. Single or multiple destinations,
3. Connecting and main modes,
4. Connecting and main routes,
5. Timing of trip,
6. Frequency of trip,
7. Employment location, and
8. Residential location.

Choice in this context is derived from preference in a way that gives the greatest weight to preference eventually (with flexible timing), and this requires that preference be sometimes revealed in immediate choice, sometimes distorted or abandoned (32, pp. 139-143).

In addition to the internal-external division, analysis of action can be expressed in terms of the morphological and analytical approaches. The morphological approach involves the form of a decision process obtained when certain types of variables are considered rather than others (34). Initially, a behavior space is postulated to include the set of all variables necessary and sufficient for understanding the act of travel choice. Successive stages in model building can then be described by the travel choice variables being postulated on the basis of previous empirical evidence or causal hypotheses, their functional relations determined, and their relative role in the decision process assessed.

Existing data sources completely disregard the extent of the behavior space. The result is that variables are postulated as relevant without really having any adequate ex ante empirical support other than that these variables have been shown to be correlatively good predictors in other contemporary studies (no mention of explanation, causality, or behavioral space identification). Transferability is almost certainly a risky game when such second-best approaches are adopted.

Lazarsfeld's paradigm of consumer action (Fig. 1) can be used to develop the general framework for identifying the orientation of data requirements and also as a lead into the specification of a number of major homogeneity criteria on which such consumer travel choices might be based. Aggregation of disaggregate homogeneous groups can be a useful way of modifying the criticisms currently associated with initial aggregation models. The measurement of the relevant variables in the behavior space will also be discussed.

Exposure is defined in terms of external variables such as the characteristics of a mode, a route, or a destination; influence is an exposure to which a causal impact has been imputed; dispositions are essentially the consumers' preferences; and motives are dispositions to which a causal impact has been imputed. The relations between these 4 classes of variables can be traced through. At any point in time, the consumer is in a circumstance that may be described in terms of a set of variables representing geographic (e.g., residential and employment location), social (occupational and class constraints), and other elements external to the individual (such as neighborhood and workplace considerations). The role of these elements can be seen as stimuli that may or may not impinge on the traveler. If they do impinge, they may act either as forces setting the individual's responses in motion or as constraints that bound and hence partially direct these responses.

There are a number of environmental variables to which the consumer is exposed, for example, the visual awareness of the existence of a public transport system. The relation between environmental and exposure variables implies a mechanism by which the environmental variables are (or are not) transformed into exposure variables. This mechanism may include those internal and external variables that assist or constrain the individual's exposure to a certain stimulus. For example, residential location may significantly influence the number, type, and destination of trips that the individual will usually be associated with and thus the spectrum of modes and routes to which he or she will usually be exposed. In addition, dispositions and motives might lead the individual to expose himself or herself only to certain information channels and certain messages. The influence variables are a subset of the exposure variables. Nicosia (34, p. 104) indicates that such variables are singled out as a morphologically relevant group because "an exposure variable may or may not have a psychological meaning for the receiving consumer."

For example, advertising might expose an individual to an alternative form of transport (the transit organizations are attempting to sell their products by marketing them along the lines of private organizations), but not alter any of his or her dispositions toward this alternative facility. At this point, the advertisement of this mode is not a component of the individual's decision process. The relation between exposure and influence variables implies a mechanism by which the former are (or are not) transformed into the latter. This mechanism consists of dispositions and motives (cognitive structures). The stimulus influence is now a relevant component of the decision process and hence becomes internalized as part of the individual's psychological reality. This suggests that data contributing to the explanation of the individual's nonphysical value structure are required in any study of travel choices. The explicit nature of this data requirement will become even clearer when we note that this internalized stimulus relation (externally influenced by the environment broadly interpreted) is tied in with the organization of the individual's cognitive processes (6, pp. 285-287) and structure.

Lazarsfeld identified 2 broad groupings of internal variables: dispositions and motives. Disposition variables are passive nondriving from a dynamic point of view, for example, opinions and beliefs. In contrast, motive variables (encompassing attitudes) drive the individual's behavior toward object goals (travel choices) from a dynamic point of view. More explicitly, the distinguishing feature of motives is that they

Figure 1. Lazarsfeld's paradigm of consumer action.

	Described	Causally Assessed
External	Exposure	Influence
Internal	Disposition	Motive

Figure 2. Questionnaire for collecting data on levels of importance and satisfaction of attributes of modes.

(a) This question is concerned with how you, with respect to any particular method of travel, value the various factors you consider important in the selection of a method of travel to work. Some of these factors are written below. If you wish, write in any other factors that might be important to you in items 5, 6 and 7 below. You have 100 points in total. Allocate points to each factor to indicate how important you consider that factor to be.

		POINTS YOU WOULD ALLOCATE
1.	TIME	
2.	COST	
3.	CONVENIENCE	
4.	COMFORT	
5.		
6.		
7.		
	TOTAL	100 POINTS

(b) Please indicate how satisfactory your usual method of travel is by crossing (x) the scale below (or by placing a cross in a box) to show the degree of satisfaction to you of each feature listed below. Repeat the procedure to indicate your satisfaction with your best available alternative method of travel to work that you can afford.

COMPLETELY SATISFACTORY (place a cross in the box)

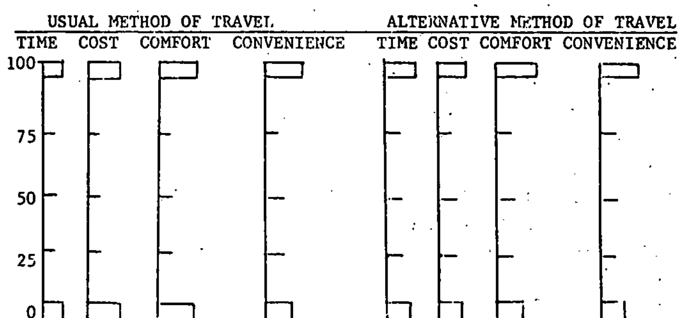
VERY SATISFACTORY Mark between 71 and 99

GENERALLY SATISFACTORY Mark between 51 and 70

GENERALLY UNSATISFACTORY Mark between 31 and 50

VERY UNSATISFACTORY Mark between 1 and 30

COMPLETELY UNSATISFACTORY (place a cross in the box)



appear in the decision process as driving forces that direct the individual toward an act of choice. This frame of reference is seen as a sequence, exposure-influence-disposition-motive, indicating an overall pattern of interaction up to the point of contributing to the explanation of the choice process. However, given the many inherent difficulties in operationalizing this schema, we will concentrate on the motivational level of disaggregation, which can be interpreted to encompass attitudes as driving forces. Attitudes, hence, represent a major determinant of the individual's orientation toward the social and physical environment, including himself or herself. An attitude implies that motives are aroused and action is mobilized to approach or avoid a situation. In the travel choice context, it is becoming clear that the basis of selecting maximum-similarity criteria as a means of suitably aggregating disaggregate behavioral travel choice models must include a level of segmentation related to the individual's decision process that can be identified initially by developing attitudinal indexes.

The homogeneity criterion need not be purely physical. Differences in the values of individuals are an important source of transport discrimination (51, pp. 83-90). An individual who prefers to travel in a second-class train compartment and to be classified as working class might own a very expensive car. A high-paid individual may prefer to run an old car and spend more money in entertaining. The same individual might be involved in a dichotomous value situation because of differing experiences. By segmenting the market on the basis of values, purposes, needs, and attitudes relevant to the product being investigated (i.e., travel as represented by a series of choices), misleading information derived from attempts to divide people solely on physical socioeconomic characteristics might be minimized. This procedure is seen as a complementary mechanism to the physical orientation. Since attitudes are related to motives and hence to the exposure and influence variables in the paradigm of action, the environmental variables (broadly defined to include physical trip characteristics and socioeconomic characteristics of the travelers) must also be considered as constraining influences on attitudes and acts of choice. Physical segmentation is only one of a number of maximum-similarity criteria.

Census and existing area transportation study data contain useful information, but they identify neither the crucial issues of the urban transport demand problem nor those groups whose behavior patterns are still fluid nor the needs, values, and attitudes that influence how these various groups of actual and potential travelers react to system changes. Far too often, recommended transport improvements are directed to all members of the community, but are often only of relevance to a partitioned group within that community. We need to seek out the various groups on a psychological continuum and then recommend improvements that best meet those requirements (including unmet needs) rather than those that conform to planner's deficiency-oriented, model-prediction recommendations based on observed behavior that was influenced by past experience with existing systems.

Value segmentation can be usefully represented along a number of continua just as various socioeconomic characteristics are split (e.g., age groups). A threefold division representing how individuals look at the meaning of value in a mode might be

1. Individuals who travel by a mode for cost reasons;
2. Individuals who want to use the best mode available for their money (the emphasis is on values such as reliability, economy in utilization, speed, and comfort); and
3. Individuals interested in personal enhancement (although the value of a car as a status symbol has declined, the personal satisfaction from owning a fine car has not lessened for this segment of the market).

Attitudinal Schema

In recent years, evidence on price inelasticity (11, 36) has reduced the relative influence of division 1 and increased the relative importance of division 2, product value. The reduced influence of cost has tended to marginally reduce the importance of misperception of money cost but at the same time has reoriented identification and measurement to the previously referenced nonquantifiable abstract summarizers such as comfort, convenience, and reliability. The data requirement in accordance with the second division points to the use of techniques capable of accommodating such nonquantifiables. It is most convenient that attitudinal measurement techniques are admirably suited to this task in addition to being suited to the decision process schema on which the foundations of acts of choice are based.

In the majority of contemporary social psychology textbooks, attitude is defined as a concept containing an affective or liking component, a cognitive or belief component, and a conative or action tendency component. The broad acceptance of this multiple component view has been usefully explained by Fishbein (19, p. 4):

> Two people might feel the same amount of affect toward an object but might behave differently with respect to that object and/or might hold different beliefs about what should be done with respect to that object. Clearly then, since the "action" component is different, these people must have different attitudes. Similarly, two people might be equally favourable toward the object, but they might also have different cognitions about the object. . . .Here again they must have different attitudes.

Despite the theoretician's espousal of the multicomponent view of attitudes, most psychological and marketing research seems to consider only the affective component, a single overall liking index expressed in the form of a linear summation of the perceived instrumentality subcomponent of the evaluative belief model. The basic formulation is

$$\sum_i \sum_j (S^i_{1j} - S^i_{2j}) \tag{1}$$

where S^i_{kj} = degree of satisfaction associated with the k th mode with respect to the i th attribute for the j th individual (k = 1, 2).

In addition to summing evaluative beliefs prior to relating them to affect (overall liking), a number of studies (2, 14, 22, 23) have expressed evaluative beliefs in a way that distinctively retains each belief in the individual's perceptual map by relating the separate attributes to behavior (choice of mode) or to overall liking. The latter is empirically identified as a single satisfaction rating, $(S_{1j} - S_{2j})$.

Several recent studies (2, 22, 23, 35, 39, 42) have introduced a relevance weight. The argument is that an individual's attitude toward a mode is determined by his or her evaluations of a set of beliefs expressed in the general form

$$\sum_i \sum_j I^i_j (S^i_{1j} - S^i_{2j}) \tag{2}$$

where I^i_j = index of the relative importance of the i th attribute for the j th individual with respect to a particular set of circumstances (e.g., the choice of commuter mode).

In addition to the role of importances indicated above, the importance, I, weights are introduced because of the artificial measurement of affect on the satisfaction, S, scales (44, pp. 10-12; 23, pp. 137-141). As stated by Stanley (44, p. 11), "The scaled satisfaction from each (attribute) is equal by construction (Fig. 2) but the corresponding utility scale ranges differ." It is argued that deterministically the correct operational measure of affect or utility is a composite I•S index. In terms of utility measurement, the generalized utility function can be given as

$$du^j = \sum_i (\partial u^i_j / \partial A_i)\, dA_i \tag{3}$$

where

du^j = change in utility of the j th individual,

$\partial u_j^i/\partial A_i$ = change in utility of individual j resulting from a small change in attribute i, and
A_i = i th attribute.

Stanley has shown (44, p. 10) that

$$du^j = \sum_i I_j^i (\partial S_j^i/\partial A_i)\, dA_j \qquad (4)$$

where

I_j^i = positive constant that may differ for each attribute, and
S_j^i = real-valued function over the i th attribute.

The ∂S_j^i are representations of ∂u_j^i except for scale unit. For example, an individual may be completely satisfied with automobile travel time and automobile comfort yet derive less utility from the latter than the former. To make the S scales consistent with the ∂u_j^i scales, the I weights are introduced. The interpretation of this composite utility function is, for example, the traveler derives more utility from present levels of automobile comfort than from automobile travel time because comfort is more important even though he or she is completely satisfied with both.

In completed studies the deterministic summation of the importance weights has been either constrained to unity (23) or unbounded (22, 35). The importance weight must be constrained to unity to provide a measurement unique up to a positive linear transformation since the strength of the attitudinal index approach lies in the ability to compare relative utilities on attributes for each individual. If it is open ended, then the absolute intensity of each variable can be observed but not the relative attribute value intensity. The perceptual importance weight is a way of ensuring this compatibility.

An alternative procedure is to use probabilistic estimation procedures and interpret the estimates of the attitudinal parameters as statistical proxies of the relative importance of attributes in explaining behavior (39, 40). The standardized partial regression coefficients (beta coefficients) have been interpreted as directly assigned importances. The major criticism of this approach is that the beta weight is a statistical weight, a number associated with a given attribute in such a way that some combination of attributes is observed to account for or "explain" behavior of a group of individuals. As such, it is an ex post standardized raw coefficient that is not related in any necessarily predictable way to the utility function of a particular individual but rather performs as an average indicator of likely response of the "typical" sample observation. This assumes that the attribute weights may be attributed to all travelers within the market. It does not perform the scaling function performed by the I weights on an individual basis. Until a mapping test is undertaken to test for invariance between the single statistical beta weight and the distribution of psychological weights, this general area of modeling remains open to debate. An important issue is the extent to which the inclusion of I weights as scale standardizers in the utility function introduces an element of double counting in the probabilistic function where beta weights are obtained. Limited empirical work is generally inconclusive.

It is concluded that the complete utility index unique for each individual should be obtained prior to statistical estimation both to conform with scaling requirements and to increase the influence of causative rather than necessarily correlative relations. Figure 2 gives an example of the type of empirical question designed to elicit the information required for the deterministic formulation (Eq. 2) and its probabilistic equivalent, i.e.,

$$\text{Choice of mode} = f\left[\sum_i \sum_j I_j^i (S_{1j}^i - S_{2j}^i)\right] \qquad (5)$$

Finer divisions into the various components of travel time may also be obtained by the use of the same technique (23, p. 16).

The conative component, $(AT)^i_j$, involving sensitivity testing of individuals' preferences to single and combination changes in attributes influencing acts of choice, is somewhat more difficult to handle, especially when the number of attributes exceeds 3, because the possible combinations of attributes increase by $2^n - 1$. Ackoff (1) selected 3 attributes for automobile users whom he asked to supply information on hypothetical questions as to what conditions must occur in order for them to switch to public transport. He also asked whether combinations of the attributes will make the individual change mode. Multiple answers may exist for 2 reasons:

1. In terms of the individual's utility, a change in A alone or B alone may not be enough to cause a modal switch; and
2. If an individual indicates that a change in B is enough to make him or her switch modes, this implies that AB, BC, and ABC should also be chosen by the individual since all the attributes yield positive utility for the individual.

An interpretation applied to cognition that needs to be separated out for consideration refers to the individual's awareness and knowledge of the existence of the travel circumstances (modes, number of trips, timing) and their associated characteristics. Cognition interpreted as an awareness component of attitudinal measurement is particularly relevant where information and perception are not uniformly distributed among the various relevant determinants of travel choice and among the various groups of individuals. Although behavioral mode choice research has provoked much discussion on the misperception of costs of travel by an alternative mode in contrast to the knowledge of costs of travel on the chosen mode, little evidence is available on the extent of misperception or the degree of awareness of attributes of alternative modes. In general, there is a spectrum of degrees of awareness of attributes that influence travel choice. This must be allowed for somewhere in the planning model. One potentially useful empirical way of identifying the awareness-cognition is shown in Figure 3. This attitudinal component now becomes an additional component in an attitudinal model or index, which might be analytically expressed in a final form as

$$A^i = f \sum_{ij} \left[I^i_j(S^i_{1j} - S^i_{2j}),\ (K^i_{1j} - K^i_{2j}),\ (AT)^i_j \right] \tag{6}$$

where

$I^i_j(S^i_{1j} - S^i_{2j})$ = affective index,
$K^i_{1j} - K^i_{2j}$ = cognitive-awareness index, and
$(AT)^i_j$ = conative index.

In the modal context, A^i could be the choice of mode or a measure of overall attitude. The precise functional form of the model is an issue for further investigation.

Allen (2) cites an example of 9 individuals answering the hypothetical question in the following manner:

	Individual								
Attribute	1	2	3	4	5	6	7	8	9
A	x								
B	x		x	x					
C		x			x				
AB	x		x	x					
AC	x	x	x		x	x	x		
BC	x	x	x	x	x				
ABC	x	x	x	x	x	x	x	x	
None									x

This information can be summarized as follows:

Figure 3. Questionnaire for collecting data on awareness of attributes of travel mode.

How well do you believe you know the time, cost, levels of comfort, convenience of your USUAL method of travel and your best available ALTERNATIVE method of travel for the journey to work?

Answer by crossing (x) on the scale below or placing a cross in a box.

		USUAL METHOD OF TRAVEL				ALTERNATIVE METHOD OF TRAVEL			
		TIME	COST	COMF-ORT	CONVEN-IENCE	TIME	COST	COMF-ORT	CONVEN-IENCE
I know exactly (Place a cross in the box)	100								
I know very well Mark between 71 & 80	80								
I know fairly well Mark between 51 & 70	70								
I have some Knowledge Mark between 31 & 50	50								
I have very limited knowledge Mark between 21 & 30	30								
	20								
I do not know at all (Place a cross in the box)	0								

Figure 4. Questionnaire for collecting data on usage intention.

Do you believe you would change COMPLETELY to public transport (where the automobile might only be used as a connecting transport to your local station) for traveling to work if the following single changes or combinations of changes occured:

	I believe I definitely would change	I believe I probably would change	I believe I probably would NOT change	I believe I definitely would NOT change
(a) Public transport was free (TICK ONE)	( )	( )	( )	( )
(b) Public transport was made more comfortable according to your meaning of comfort given in Q.17 (TICK ONE)	( )	( )	( )	( )
The time spent travelling to work in the train was reduced by:				
(c) 5 minutes (TICK ONE)	( )	( )	( )	( )
(d) 10 minutes (TICK ONE)	( )	( )	( )	( )
(e) 15 minutes (TICK ONE)	( )	( )	( )	( )
(f) Free and more comfortable public transport (TICK ONE)	( )	( )	( )	( )
(m) Free, more comfortable and a 5 minutes reduction in travel by public transport (TICK ONE)	( )	( )	( )	( )
(n) Free, more comfortable and a 10 minutes reduction in travel by public transport (TICK ONE)	( )	( )	( )	( )
(o) Free, more comfortable and a 15 minutes reduction in travel by public transport (TICK ONE)	( )	( )	( )	( )

Attribute	Number of Individuals
A	1
B	3
C	2
AB	3
AC	6
BC	5
ABC	8
None	1

Transit ridership will increase by 1 if A is improved, by 3 if B is improved, and by 2 if C is improved. Thus, if improvements could be implemented with equal ease, B would be implemented first. However, if resources exist to make 2 improvements, A and C should be undertaken and not B. An example of a question designed to elicit this information is given in Figure 4, where the 3 attributes, time, cost, and comfort, are assumed for illustrative purposes to be the most significant determinants of modal choice. The "I believe" approach should be tested against revealed preference data to evaluate reliability. Empirical information on the perceptual meaning of the abstract summarizer "comfort" would also be required in order to use the results of an attitudinal study to suggest various policy options (24). This conceptual framework presented is currently being empirically tested in Australia with information gathered from questionnaires shown in Figures 2, 3, and 4.

So far the attitudinal index has been illustrated in the context of modal choice. However, its powerful generalization permits transference to other (interdependent) choice situations. For example, the frequency-of-trips process may be expressed in the following form:

$$\text{Number of trips per unit of time} = f \sum_i \sum_j \sum_k \left[I^i_{jk} (S^i_{ujk} - S^i_{ajk}),\ (K^i_{ujk} - K^i_{ajk}),\ (AT)^i_{jk} \right] \quad (7)$$

where

$\sum_i \sum_j \sum_k I^i_{jk} (S^i_{ujk} - S^i_{ajk})$ = affective index of summation of the relative importance of the i th factor in influencing the number of trips per unit of time for the k th journey purpose, weighted by the level of satisfaction associated with the present situation, u, with respect to that factor for the k th journey purpose in relation to the degree of satisfaction associated with the i th factor when less (or more) weekly trips, a, for the k th purpose are undertaken;

$(K^i_{ujk} - K^i_{ajk})$ = awareness component defined in terms of the relative level of awareness of the influence of the various factors included in the affective index for the k th journey purpose by the j th individual under present and any indicated new circumstances resultant from change; and

$(AT)^i_{jk}$ = conative component defined in terms of the probability of the i th individual adjusting the number of weekly trips for the k th purpose as a result of a change (reaction tendency) in the i th factor or a combination of i factors.

The degree of nonindependence among the 3 indexes must be assessed before the trichotomous model can be adopted.

ATTITUDES AND BEHAVIOR

Although attitudinal indexes can provide the core data for developing choice models, discrepancies are expected between attitude and behavior because individuals do not always act in accordance with what they believe. Behavior is determined not only by attitudes but also by external factors in the immediate environment (e.g., social, geographical, legal, and economic considerations).

The complete range of data requirements should be extracted from each trip producer if the causal criterion is to be met. All requirements are assumed to be internally measured. Three broad categories of measurement are identified: the psychologically defined measures (e.g., attitudinal and perceptual), the physically defined personal user characteristics, and the physically defined nonpersonal characteristics. Family and traveler behavior might be expressed as a function of the interaction between all the individual's inner determinants, such as temperament, attitudes, or character traits and all the environmental factors as perceived by the individual, i.e., action space. [Action space can be defined as the collection of all urban locations about which the individual has information. It is the subjective utility the individual associates with these locations (27).] With complete knowledge of all but one part of the formula, the variable that is not known can be predicted.

Behavior has a complex relation with its various inner determinants because of the influence of environmental factors (which may be differently perceived by different individuals). Thus, it cannot be used as a measure of inner determinants, and we cannot accurately infer attitudes from behavior unless full knowledge of the effects of environmental determinants is assumed. Furthermore, for the same reasons we cannot expect a direct prediction of overt behavior merely from a knowledge of one determinant, such as a score on an attitude scale. Other inner determinants (including conflicting attitudes) may play a part, but above all we need full knowledge of the effects of the perceived environment. An attitude scale may indicate inclinations toward cheating, but respondents will probably act honestly if they think they will be found out. Behavior is a compromise, a resultant of the interaction of multiple forces. We may conclude, therefore, that the failure to predict a particular action does not mean that the attitude scale is invalid. The scale may well have given valid and accurate measures of a given attitude and correctly described the individual's response tendencies. These may, however, have been offset or nullified by other tendencies that have gone unmeasured and by the individual's perception of the environment at that time, which likewise has not been taken into account.

Attitudes to choice are seen as the guiding rather than the motivating force behind activity. What influence do attitudes have on behavior? Among the more important research findings that are relevant from social psychology are those concerned with cognitive dissonance (18). The dissonance principle (17, p. 13) holds that 2 elements of knowledge "are in dissonant relation if, considering those two alone, the obverse of one element would follow from the other."

It is predicted that all choices result in dissonance to the extent that the alternative not chosen contains positive feasures that make it attractive also, and the alternative chosen contains features that might have caused it to be rejected. Hence, after making a choice, people seek evidence to confirm their decisions and so reduce dissonance. This finding suggests that behavior change may cause attitude change rather than the reverse. This situation has clear implications for data requirements. There is no point in setting out to influence attitudes if they do not influence behavior—but do they?

One prediction from dissonance theory is that, in certain circumstances, dissonance may be reduced by the fitting of behavior to attitudes. We become increasingly dissatisfied with our usual mode or the timing of a usual trip or the frequency of shopping trips. Dissonance theory can assist in the recognition of the dual-directional relation between attitudes and behavior, i.e., attitudes $\rightleftharpoons$ behavior, in a tug-of-war situation. In situations where attitudes and behavior are dissonant, one or the other may change. Hence, the attitudinal focus must be seriously investigated. Although planners may choose to disregard, at some peril, the utility or attitudinal judgments of individuals, it is at least possible and often desirable for them to aim at the maximization of a welfare function that is based on private utilities or attitudes. The case for this would be considerably strengthened if a complete utility theory of traveler behavior (i.e., not just modal-choice behavior) could be developed.

HOMOGENEITY OR MAXIMUM SIMILARITY RATIONALE

The homogeneity rationale entails the selection of groupings of data in which the measure of central tendency is a sufficiently useful indication of a particular group of observations in accordance with the goals of developing demand models. In essence, minimization of variation within a homogeneous group and maximization of variation between homogeneous groups are the procedural rule. (In Australia, traffic zones are defined in terms of aggregates of census collector districts; i.e., areas in which the distances within the district enable a census collector to manually collect census forms with minimum effort. This suggests, however, that information can still be physically collected along existing lines but reshuffled in accordance with various homogeneity criteria to obtain relevant groupings.) The existing zonal demarcation structured on physical geographical rules has been continually criticized on many grounds, especially the existence of within variances often greater than between variances on many important predictors of choice. We are continually emphasizing a systematic approach enabling the planner to select the strategically most important segmentations and then plan around them (for example, the disadvantaged). However, this group can be defined along a number of continua (e.g., poverty scale, nonavailability of alternative mode, handicapped), each requiring separate homogeneity analysis. Given that market segmentation emphasizes the group as the unit of analysis, then variance among groups and not individuals should be the unit of analysis.

The automatic interaction detector (AID) is one multivariate technique suitable for determining those variables considered and categories within them that combine to produce the greatest discrimination in group means by the dependent variable. Data need not be limited to the handling capacity of models but can be as extensive as necessary in accordance with the requirement to explain and predict travel choice. AID offers an efficient method of data reduction and selection of the characteristics related to travel choice. From a large group of possible explanatory variables, AID selects those most useful for statistically explaining the variation in a given explanand by employing a nonsymmetrical branching process. Analysis of variance techniques subdivide the total number of observations into K mutually exclusive types that, for a given K, explain more of the total sum of squares than any other K types. By this procedure, potentially relevant data required are not excluded on the basis of some intuitive criterion. For travel choice analysis, each of these types may be viewed as defining a relatively homogeneous class of travelers with respect to the taxonomy of travel choices.

Input to the AID analysis is a raw data matrix consisting of every respondent's score on the usage level variable and on several independent predictor variables. At the outset of the analysis, there is only 1 group—the total population. The performance of this group on the dependent variable, e.g., usage level, can be represented by a frequency distribution such as that shown in Figure 5, where the horizontal axis represents values of usage level and the vertical axis represents number of respondents. Typically the total population has a high variance about its mean value. When there is so much variation about the mean, to predict what the usage level of any one individual in the group will be is difficult.

The AID program seeks to subdivide the total population into 2 subgroups having significantly different mean values on the dependent variable and much smaller variances about their means (Fig. 5, distributions B and C). If this can be done, then knowing whether a respondent is a member of one of these subgroups will help in predicting more accurately his or her usage level.

In the subdivision, the difference in usage level is considered between all possible 2-way splits on the predictor variables. The predictor variable that is selected depends on a statistical analysis. The procedure is as follows. Suppose one of the variables is age, having 4 different levels. The program will consider every possible 2-way split of this variable: It will divide the population into people in age brackets 1 and 2 versus those in 3 and 4; 1 versus 2, 3, and 4; and finally 4 versus 1, 2, and 3. For each split, the program calculates the mean value and the variance of usage level for each of the subgroups. It then goes on to calculate the significance level of the split. Thus, it uses the explanatory variable to yield subgroups and then evaluates how different these

Figure 5. Population divided by AID into subgroups.

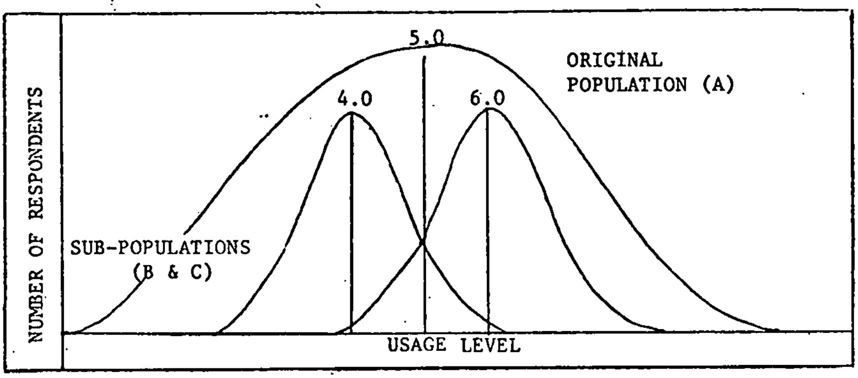
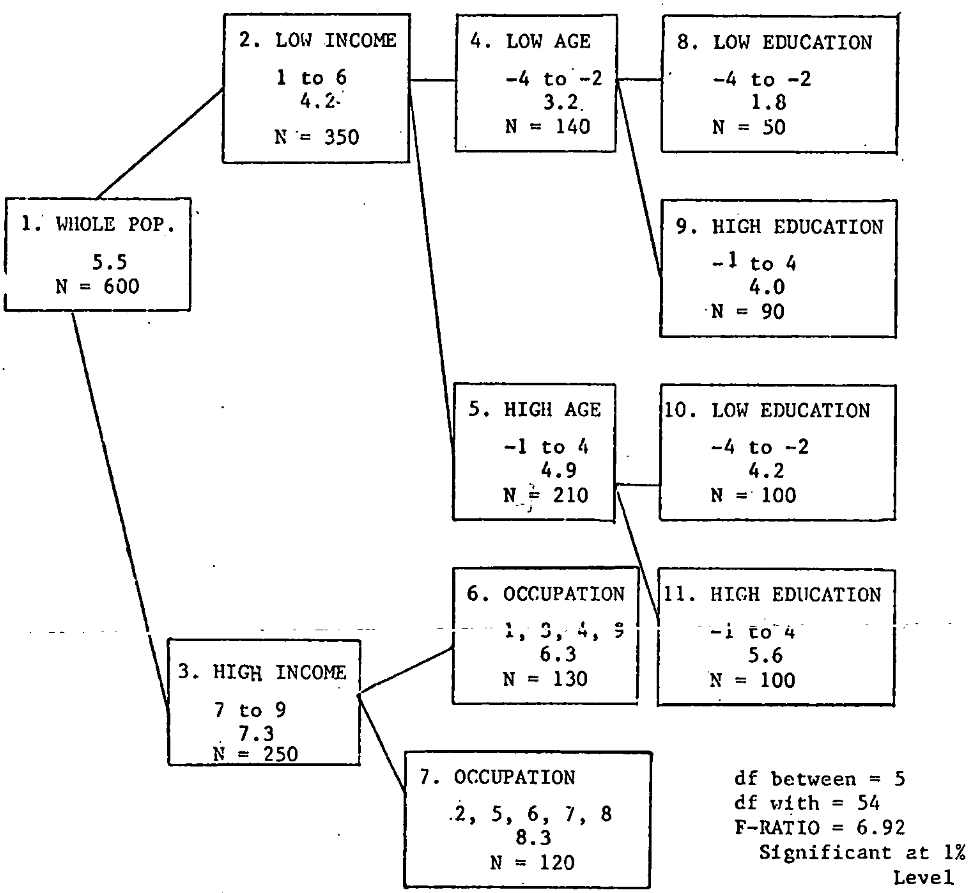


Figure 6. AID tree diagram.



subgroups are with respect to usage level, the dependent variable.

Having done this, the program then considers the next explanatory variable and all its possible 2-way splits. Finally, when all the possible 2-way splits on all the explanatory variables have been considered, the program selects the one explanatory variable and its one 2-way split that yields the best division of the total population. This split is then used to subdivide the original population.

Having thus completed one division of the population, the program treats each subgroup as if it were a base population, and the entire process of searching all the explanatory variables for the most significant split is repeated for each subgroup. Every time a new subdivision of the population is completed, the process repeats itself on the new subgroups until, finally, preset criteria for subdivision are met.

The final result is a tree structure in which every split of the population is shown. The end points of the branches of this tree are the mutually exclusive subgroups or market structures of the total population. These groups all differ significantly in their performance on the dependent variable and are all well defined in terms of the levels of the predictor variables that were used in dividing them from the total population (Fig. 6).

The procedure used by AID has several important consequences. First, because the AID program considers all predictor variables for every split, it allows for detection of interaction effects. Thus, although age might not have proved to supply a significant 2-way split for the original division of the population, it may turn up as an important way to split a subpopulation. Also, the AID analysis, by a process of statistical evaluations, selects only those explanatory variables that are significant to a subdivision of the population. The original data may be on some 30 different variables, but AID may have used only 10 of them to divide up the population into its market structures. Finally, the AID program can operate equally well on classificatory data as on scaled data. It makes no difference if one constructs a split that is long trips versus short trips or a split that actually represents ages 20 to 40 versus ages 40 to 60.

CONCLUSIONS

Appropriate specification of choice in accordance with the processes leading to acts of choice and development of criteria based on maximum-similarity groupings will contribute significantly to the development of disaggregate behavioral models of travel choice capable of aggregation at various levels of regional segmentation devoid of some of the contemporary aggregation problems. Data requirements have been broadly outlined in the context of decision processes. The essential point is that a reasonable proportion of information originally collected in accordance with other data requirements will be more useful in a complementary role with the type of information that will be obtained in accordance with data required to explain and predict travel choices. The formatting of existing transportation study data files in terms of individuals and household records instead of a record of each trip made will enable greater conformity of data with the more relevant behavioral modeling statistical procedures (15, pp. 53-70). In addition, some existing data will become redundant, helping to offset the absolute cost of data acquisition. When consideration is given to the costs and benefits of such improved and relevant data, then the real cost increase might be minimal if not negative.

REFERENCES

1. Ackoff, R. Individual Preferences for Various Means of Transportation. Management Science Center, University of Pennsylvania, Philadelphia, 1965.
2. Allen, W. B., et al. Developing and Testing a Behavioral Modal Split Model. Transportation Studies Center, University of Pennsylvania, Philadelphia, June 1971.
3. Alonso, W. The Quality of Data and the Choice and Design of Predictive Models. HRB Spec. Rept. 97, 1968, pp. 178-192.

4. Arrow, K. J. Utilities, Attitudes, Choices: A Review Note. Econometrica, Vol. 20, No. 1, Jan. 1958.
5. Bailey, D. E. Cluster Analysis and the BCTRY System. Tyron-Bailey Associates, Inc., Boulder, Colorado, 1970.
6. Bayton, J. A. Motivation, Cognition, Learning—Basic Factors in Consumer Behaviour. Journal of Marketing, Vol. 22, Jan. 1958.
7. Beckmann, M. J., Miller, R. L., and Wallace, J. P. Socioeconomic Evaluation of Urban Systems. Presented at Annual Meeting of Operational Research Society of America, May 1968.
8. Bird, M., and Ehrenberg, A. S. C. Intentions-to-Buy and Claimed Brand Usage. Operational Research Quarterly, Vol. 17, 1966.
9. Brown, A., and Deaton, A. Models of Consumer Behaviour: A Survey. Economic Journal, Vol. 82, No. 328, Dec. 1972.
10. Brunner, G. A., Hille, S. J., Nash, A. N., Paine, F. T., Schellenberger, R. G., Smerk, G. M., and Taff, C. A. User Determined Attributes of Ideal Transportation Systems: An Empirical Study. Department of Business Administration, University of Maryland, 1966.
11. Charles River Associates, Inc. Free Transit. Lexington Books Inc., Boston, 1972.
12. A Disaggregate Behavioral Model of Urban Travel Demand. Charles River Associates, Inc., 1972.
13. Craik, K. Transportation and the Person. High Speed Ground Transportation Journal, Vol. 3, 1969.
14. Demetsky, M. J., and Hoel, L. A. Modal Demand: A User Perception Model. Transportation Research, Vol. 6, 1972.
15. Douglas, A. A. Home-Based Trip End Models—A Comparison Between Category Analysis and Regression Analysis Procedures. Transportation, Vol. 2, No. 1, April 1973.
16. Eliot Hurst, M. E. The Structure of Movement and Household Travel Behaviour. Urban Studies, Vol. 6, 1969.
17. Festinger, L. A Theory of Cognitive Dissonance. Row, Peterson, Evanston, Ill., 1957.
18. Festinger, L. Conflict Decision and Dissonance. Stanford University Press, 1964.
19. Fishbein, M. A Consideration of Beliefs, Attitudes and Their Relationships. In Current Studies in Social Psychology (Steiner, I., and Fishbein, M., eds.), Holt, Rinehart and Winston, New York, 1965.
20. Fisher, W. D. On Grouping for Maximum Homogeneity. Journal of American Statistical Association, Vol. 53, Dec. 1958.
21. Golob, T., and Beckmann, M. A Utility Model for Travel Forecasting. Transportation Science, Vol. 4, 1971.
22. Hartgen, D. The Influence of Attitudinal and Situational Variables on Urban Mode Choice. Northwestern University, PhD thesis, March 1973.
23. Hensher, D. A. The Consumer's Choice Function: A Study of Traveller Behaviour and Values. School of Economics, University of New South Wales, PhD thesis, Oct. 1972.
24. Hensher, D. A. Consumer Preferences in Urban Trip-Making. Commonwealth Bureau of Roads, Melbourne, Working Paper 1, Dec. 1972.
25. Hensher, D. A. Valuation of Travel Time: An Alternative Procedure. Presented at Third Australasian Conference of Economists, University of Adelaide, South Australia, May 1973.
26. Hille, S. J. The Role of Attitude Studies in Shaping Corridor Demand. High Speed Ground Transportation Journal, Vol. 5, No. 1, Winter-Spring 1971.
27. Horton, F., and Reynolds, D. R. Action Space Formation: A Behavioral Approach to Predicting Urban Travel Behavior. Highway Research Record 322, 1969.
28. Lazarsfeld, P. F. The Art of Asking Why in Marketing Research. National Marketing Review, Vol. 1, Summer 1935.
29. Lazarsfeld, P. F. Sociological Reflections on Business: Consumers and Managers. In Social Science Research on Business: Product and Potential (Dahl, R. A., Haise, M., and Lazarsfeld, P. F., eds.), Columbia University Press, 1959.

30. Lewin, K. Group Decision and Social Change. In Readings in Social Psychology (Maccoby, E. E., Newcomb, T. M., and Hartley, E. L., eds.), Holt, New York, 1958.
31. Lewin, K. Principles of Topological Psychology. McGraw-Hill, New York, 1966.
32. Majumdar, T. The Measurement of Utility. MacMillan, London, 1950.
33. McQuitty, L. L. Hierarchical Syndrome Analysis. Educational and Psychological Measurement, Vol. 20, No. 2, 1960.
34. Nicosia, F. M. Consumer Decision Processes. Prentice-Hall, Englewood Cliffs, N.J., 1966.
35. Paine, F., et al. Consumer Conceived Attributes of Transportation: An Attitude Study. Department of Business Administration, University of Maryland, 1967.
36. Paterson, J., and Hensher, D. A. Elasticity of Demand for Public Transport. John Paterson Urban Systems Pty. Ltd., Melbourne, 1972.
37. Plummer, A. V., Wilkie, L. G., and Gran, R. F. The Transportation Usage Study. Cook County Highway Department, Chicago, 1957.
38. Rand, W. M. Objective Criteria for the Evaluation of Clustering Methods. Journal of the American Statistical Association, Vol. 66, No. 336, Dec. 1971.
39. Sherrett, A., and Wallace, J. P. Estimating the Relative Importance of Product Attribute. HRB Spec. Rept. 143, 1972.
40. Sheth, J. An Investigation of Relationships Among Evaluative Beliefs, Affect, Behavioral Intention and Behavior. University of Illinois, Urbana, April 1970.
41. Sibson, R. Order Invariant Methods for Data Analysis. Journal of the Royal Statistical Society, Series B, Vol. 34, No. 3, 1972.
42. Sommers, A. N. Towards a Theory of Traveler Mode Choice. High Speed Ground Transportation Journal, Vol. 4, No. 1, Jan. 1970.
43. Sommers, A. N. Expanding a Non-Demographic Factor Modal Split Model. Transportation Science, Vol. 4, No. 1, Feb. 1971.
44. Stanley, J. K. A Cardinal Utility Framework for Project Evaluation. Department of Economics, University of Southampton, Discussion Paper 7305, March 1973.
45. Straus, P., and Peterson, G. L. Public Acceptance of an Attitudinal Transit Questionnaire. Traffic Quarterly, Vol. 26, No. 2, April 1972.
46. Tanner, G. Behavioral Models: Extent of Their Compatability With the Transportation Planning Process. New York State Department of Transportation, 1972.
47. Tobin, J. On the Predictive Value of Consumer Intentions and Attitudes. Review of Economics and Statistics, Vol. 41, No. 1, Feb. 1959.
48. Tolman, E. C. A Psychological Model. In Towards a General Theory of Action (Parsons, T., and Shils, E., eds.), Harvard University Press, Cambridge, Mass., 1951.
49. Watson, P. L. System Service Requirements, Other Than Travel Times and Costs, to Be Included in the Models. Transportation Center, Northwestern University, 1973.
50. Wootton, H. J. New Lines of Development for Transportation Models. Urban Traffic Model Research, PTRC, London, 1970.
51. Yankelovich, D. New Criteria for Market Segmentation. Harvard Business Review, Vol. 42, 1964.

Conference Papers on Policy Issues

Common Economics of Travel Time Value

Thomas E. Lisco, Illinois Department of Transportation

Time, like money and other economic goods, has value only because people value it. The value of time is determined not by the amount of work required in its production but by its scarcity. Because people have limited amounts of time available to them, they allocate their time carefully among activities so as to maximize overall utility and satisfaction.

As an economic good, the only unique quality of time is that it cannot explicitly be bought or sold in the marketplace. Each person has the same number of hours to consume each day, and all that an individual can do is determine the activity content of his or her time.

The fixed-quantity aspect of time and the fact that it cannot be bought or sold cause many difficulties in the understanding and application of time value. This is particularly true in the field of transportation where travel time is a critical input to travel decisions and where travel time value is a crucial element in evaluating potential transportation projects.

These problems have risen in several areas. First, problems have been evident in the understanding of the concept of travel time value itself. Considerable discussion, for instance, has centered on whether time can have value since it is never sold and whether its value should be monetized or considered as part of the gross national product. Similarly, there have been questions as to whether travel time "savings" is a sensible notion given that time passes at a uniform rate and cannot be kept for use in a future period. Other conceptual questions have had to do with the relation between average and marginal time value and the value of small amounts of travel time.

The second major area of difficulty has been in the actual derivation of travel time values. Because market values for time per se cannot be established, means must be used to implicitly determine "shadow prices" or values for time. This is usually done by analyzing people's choices of travel modes, routes, or destinations where the alternatives have differing time and cost attributes. Here vexing problems have had to do with variations in travel time values and with the difficulties associated with attempting to measure a "pure" opportunity cost of time. Also, there have been continuing questions of data and approach.

Finally, there have been numerous difficulties in the application of travel time value to travel demand forecasting and to transportation evaluation. In part, these difficulties have been direct results of travel time value concept and measurement problems. To a large degree, however, they have had to do with the inability of standard models and procedures used to properly address travel time value questions.

With this background of problems in travel time value, it would appear appropriate to see whether standard concepts and procedures of economic analysis can offer directions for consistent and appropriate handling of the time value question in transportation. For this reason, a simple neoclassical economic analysis of transportation demand is presented in which time is considered as a cost of travel. This is followed by an examination of contemporary issues of time value concept and measurement in light of standard economic analysis procedures and the travel demand-time cost relations. Finally, some questions of travel demand forecasting and transportation evaluation are discussed, and proposals are made regarding appropriate directions of approach.

TIME, COST, AND TRAVEL DEMAND

In standard neoclassical economic analysis, the relation between the price of a good and the quantity purchased is usually depicted as shown in Figure 1. For every price P there is a quantity of goods Q that will be purchased. The locus of points showing the differing quantities of the good that will be bought with varying prices is called the demand curve for the good. Clearly, as shown in the figure, as the price of the good falls, more of it will be bought.

The price quantity diagram shown in Figure 1 is also used to demonstrate the relation between the price of the good, the total amount of money spent on it, and the benefits accruing to purchasers as a result of changes in price. At price P_o, an amount of the good Q_o will be bought yielding a total sales volume of P_oQ_o equal to the area of the rectangle OP_oAQ_o. Similarly, if the price is P_1, Q_1 of the good will be bought at a price of P_1Q_1, which is equal to the area of the rectangle OP_1BQ_1. The net benefit to consumers of lowering the price of the good from P_o to P_1 is equal to the change in price $P_o - P_1$ times Q_o plus half the change in price times $Q_1 - Q_o$. This is equal to the area of the rectangle P_oACP plus the area of the triangle ABC.

An almost exact analogy to the traditional price-quantity analysis presented above can be developed for a good whose demand is related to time rather than to money cost or to both time and money. Figure 2 shows this relation for a transportation good whose demand is solely related to the amount of time involved in accomplishing a given travel purpose.

Just as before, the amount of transportation purchased is determined by the cost—now the cost in elapsed time necessary to accomplish a particular trip: the more the time cost, the less the transportation demanded. Also, just as before, the total travel time demanded when T_o time is required to accomplish a trip is T_oQ_o, which is equal to

Figure 1. Price-quantity relation in standard economic demand analysis.

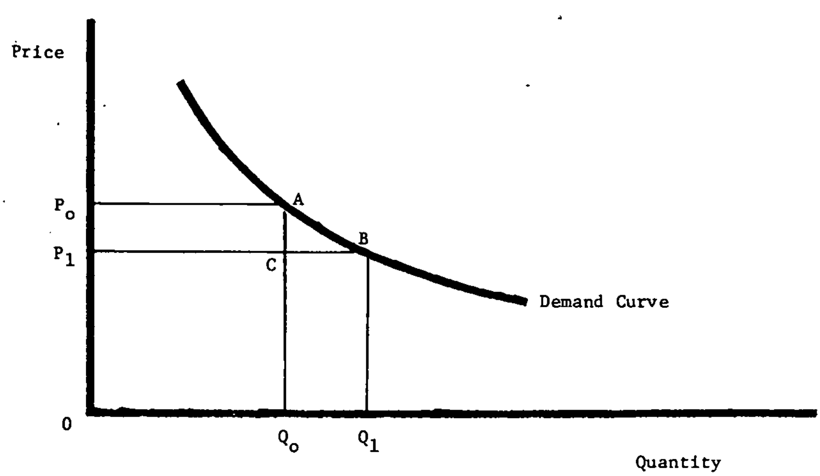
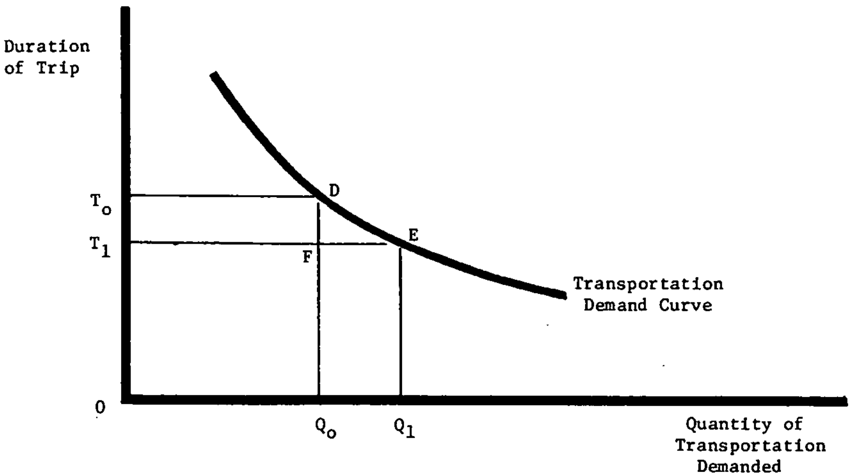


Figure 2. Transportation demand related to time necessary to accomplish travel.



the area of the rectangle T_oDQ_oO. If T_1 time is necessary to accomplish a trip, then the total travel time for trips is T_1Q_1 or the area of the rectangle T_1EQ_1O. The benefits of reducing the amount of time necessary to accomplish a trip from T_o to T_1 are calculated as T_o - T_1 times Q_o plus half T_o - T_1 times Q_1 - Q_o. Again, this is equal to the area of the rectangle T_oDFT_1 plus the area of the triangle DEF. All the way through, the analysis is the same as before, except that costs and benefits are calculated in terms of time rather than in terms of money.

A number of observations having strong implications regarding various conceptual and measurement problems of time value may be made from the above analyses.

1. In both analyses, the results bear no necessary relation to what time or money may or may not have been paid for any components of the good by the supplier. The only relevant considerations are the time and money prices at which the goods are sold and the amounts of goods sold at those prices.

2. Questions of savings are in essence unrelated to each of the analyses. The relevant consideration in each case is that at given time or money prices certain time or money resources are used to purchase the respective goods. The time or money resources that may be reserved for other purposes do not enter into the calculations.

3. In the first situation analyzed in which goods are purchased with money, the analysis cannot be performed—and in fact the purchases of the goods cannot be made—unless a monetary price is set for the goods. Presumably in this case various inputs of different sorts constitute each good, but unless these inputs are added together in terms of a common measure of value, a consistent basis for pricing and value based on input costs cannot exist.

Similarly in the case where time resources alone are being expended for transportation, a total time cost needs to be set for each unit of the good before one can determine how much one wishes to use from one's time budget to purchase that good. Here, however, the cost and benefit analyses in fact become more complicated because various subtime units of the transportation good may have different activity contents and thus different values. To the extent that transportation time is not homogeneous in value, the total time costs and benefits shown in Figure 2 will not necessarily reflect total value. The only way that this problem can be avoided is either to define a "master" time unit and relate time subunits to it in terms of fractions of its value or alternatively to simply relate the values of the various time subunits to money and operate consistently with a monetary base.

Further, if both time and money elements are involved in the demand for a transportation good (as is typically the case), then the only way that the cost and benefit analyses can be made possible is if both the time and the nontime units are monetized. As with the rest of economics, the only way available of comparing apples and oranges is through comparing their price.

4. In both the time cost and monetary cost examples given above, the analyses are basically marginal value calculations based on the price rather than total value calculations. It is true that certain amounts of the good in each case would have been bought at higher time or money prices had those prices been charged. But the relevant value for the total amount of each good is the actual price of the sales contract rather than what the good might have been worth in a consumer surplus sense to the average person who bought it.

5. The benefits received from a price reduction in each case accrue to the people who would have bought the good at the original price in the full amount of the savings in price times the amount that they would have originally bought. To the marginal users of the good—those who would buy it at the lowered price but not at the original price—the benefit is the new amount bought times half the lowering of the price. This, of course, also applies to extra amounts bought by people originally buying the good beyond what they would have bought at the original price.

6. The calculated benefits in both analyses are directly related to the degree to which the money or time price is lowered. In neither case is there a threshold below which benefits cannot be considered to exist. The benefit of the smallest price drop is calculated in exactly the same way as the largest. This result derives from one of the basic continuity assumptions of economics.

7. The benefits received through the lowering of price bear no necessary relation to particular values placed by consumers on individual components of goods. Similarly, the cost and benefit calculations bear no necessary relation to socioeconomic characteristics of individuals buying the goods or to the uses to which the goods are put. Clearly, these are all relevant factors influencing how much of the goods the individuals may choose to purchase. But again, the critical question is solely the degree to which people are or are not willing to buy the goods at the given prices.

8. Finally, the cost and benefit calculations bear no necessary relation to what the buyers perceive themselves to be getting. To the extent that the purchasers may misperceive what is available and at what price, then buying activities may be altered. But nonetheless, the amounts, costs, and benefits are dependent on what people actually buy at the prices they actually pay rather than on what they may think they are paying for what they may think they are getting.

SOME CONCEPTUAL PROBLEMS IN TRAVEL TIME VALUE

The above analyses and observations about them may be applied to various conceptual problems in travel time value. In this section a number of conceptual problems are discussed and the results of the previous section are applied as appropriate.

Time as a Valued Good

The previous section showed that, from the point of view of standard tools of economic analysis, travel time may be treated just as any other good valued by people. The analysis procedures are identical and analytical results parallel. The analysis showed that, to the extent that people do value travel time, they will purchase higher money price travel options involving less time. As the time cost of a given trip is higher, people will buy it less. Similarly, the analysis showed that lessening the time costs of travel has benefits that may be calculated in the same way as those for any other good if the time values are known.

To balance the theoretical discussion, immense amounts of evidence have demonstrated repeatedly and strongly not only that people do value their time but also that they value it highly. Casual reasoning, for instance, would lead one to conclude that much of the success of the automobile and aviation industries has been a direct result of their travel time cost attributes. Similarly, empirical studies of all types of travel situations have universally shown substantial time values. This has been true of travel for all purposes for which measurements have been made, and it has applied from the shortest trips (walking from parking meters) to the longest (intercontinental travel). Depending on the exact situations and alternative activity contents of travel time, travel time values have been found to vary from 15 to 20 percent of the wage rate of the travelers to several times the wage rate.

The fact that time itself cannot be bought or sold is not relevant to the value that people put on it. All that the impossibility of selling time does is to constrain people to exercise their time values through internal time allocations rather than through time sales and purchases. In this regard, the expenditure of time is similar to the expenditure of productive activity within the household. In neither case is there a sale of a good although in each case the good has value.

Also, the fact that time allocation is within people and not among people is irrelevant with regard to whether time value should be included in the gross national product. From a practical point of view, too little is known about empirical time values to allow sensible inclusion of time values in the GNP. On the other hand, the fact that time value is not included in the GNP is not an argument against recognizing the value of time. To try to so argue is in essence pitting an empirical economic phenomenon against an arbitrarily defined measure. If the GNP is intended to measure all utility value experienced by society, then clearly leaving out time value is incorrect. However, if the purpose is simply to measure the value of the goods and services produced for purchase in the economy, then time value should be left out. Ultimately, the GNP question is definitional rather than substantive.

Monetizing Time Value

Given that time does have value, analysis requirements dictate that its value must in effect be monetized. This is true whether considered from the point of view of travel prediction or transportation project evaluation. In either case, monetizing or its equivalent must be done simply to make measures and values comparable over different inputs to travel. Only if effects of different inputs are put into common terms, can their impacts and values be compared and, as appropriate, added together to gain a complete picture.

From the point of view of travel demand estimation, travel times must be entered into the prediction procedure along with costs and other factors determining traveler behavior because time is a prime variable affecting what people do. If time is left out, the results must of necessity be wrong because in fact people will be acting in response to a major factor not included in the prediction procedure. But putting both times and costs in the prediction procedure does in effect put a monetary value or multiple monetary values on time. This is because the effects of time in the procedure may be compared directly with those of costs, thus establishing conversion factors and consequently determining monetary values of time.

In transportation project evaluation, explicit monetizing of travel time value is a necessity if true returns to investment are to be calculated. Since people do value time and since their time values are prime determinants of how they value potential transportation facilities, their time values must be used in project evaluation. Otherwise the evaluation will be incomplete because real benefits are ignored with the effect that real returns to investment are understated. Monetary measures of time value returns to investment must be used in any cost-benefit or rate of return analysis because returns must be measured in the same terms as costs.

Clearly, whether the returns will ever be gained through marketplace transactions is irrelevant. Society needs to be able to measure the total time and other returns to public transportation investment whether that investment is directly paid for through user charges or otherwise. Private transportation system investors do so automatically because they know that both time and other benefits can be charged for with direct private return.

In recent years, different groups have argued that cost-effectiveness analysis can be substituted for cost-benefit analysis. In such analysis, degrees of achievement of various objectives are compared with costs, but with no monetary returns explicitly measured. Thus the need for monetizing time value is theoretically eliminated.

When alternatives are evaluated through cost-effectiveness analysis, however, monetary comparisons are made implicitly if not explicitly. Also, the final decisions will reflect the implicit values that are used. As an example, people may not wish to put a value on life, but by safety improvements decided on or not decided on, obviously, values for life are implicitly used.

Analysis would appear to be better served if the analyst knows what the values are and uses them explicitly rather than not directly using them and then later finding out, perhaps sadly, the implicit values actually used in reaching investment decisions. Through explicit use of monetary values, prior information is maximized rather than circumscribed as is done in cost-effectiveness analysis. Also, if explicit monetary values are used, the temptation to ignore in public investment the hard financial criteria by which private investments are evaluated is greatly diminished.

Marginal, Average, and Total Values of Time Savings

The preceding 2 sections largely covered the essential elements relating to the concept of time savings and the relations of marginal, average, and total time values. As indicated earlier, the notion of time savings is a misnomer, for, indeed, time cannot be saved. But time can be reallocated, and it is the reallocation of time that has value and that is typically described as saving of time. It is this time value that is involved in transportation investments, and it is this value that is relevant to prediction of traveler behavior and evaluation of transportation projects.

As shown in the preceding section, the analysis of transportation options is basically marginal analysis. All of the options will change the transportation system at the margin from what it was to a new marginally different state. The value of time savings in such an investment is then the full value of the time reallocations for persons already previously making the trips affected, to the full extent of the time reallocation on each of the trips. For newly induced trips, the value is half the value of time savings between the old and the new trip options times the amount of newly induced travel.

In this analysis the marginal value of time is the relevant factor because all persons gain the same ability to reallocate time at the margin. In effect, marginal value is equal to average value because people are considered to value items at the price they actually pay rather than at the price they might be willing to pay for lesser amounts. Finally, total value as measured by the area under the transportation demand curve does not enter into the calculation because total value of the old situation is subtracted from total value of the new leaving as a benefit only the marginal value of the marginal change. This value as shown in the preceding section can be calculated without knowing anything about the shape of the demand curve except in the immediate area of the marginal change.

Value of Small Amounts of Time

If time is to be treated as every other economic good, the value of time per unit of time should essentially be constant regardless of the length of the trip being considered. Similarly, the value of time savings as a rate should be approximately constant whether a large amount of time or a small amount of time is involved.

The first statement is equivalent to the analogous statement for money that a 10-cent savings is worth 10 cents whether on a $1 item or on a $100 item. The analogy of the second statement for money is that 30 cents is worth 3 times what 10 cents is worth. These are both basic tenets of economics and essential to consistency in analysis. Given that time is an economic good, there is no a priori reason for it to be treated differently and for different amounts of it to be accorded different values just because more or less time is involved or because it is being applied to longer or shorter trips.

The available empirical evidence would tend to support the notion of basically constant values of time as a function of amounts of time and different time-length trips. Time value measures per hour for trips ranging from the shortest to the longest have all fallen within limited ranges. To the extent that major differences have occurred, these differences have plainly been in the values of the activity contents of alternative uses of travel times. Thus, walking time has empirically demonstrated a high disutility value per time unit, while time sitting in a comfortable vehicle has shown relatively low disutility value. Obviously, the value is less for small time savings than for large, but at an hourly rate no empirical evidence has clearly indicated larger values for larger amounts of time on longer trips or shorter. Similarly, available evidence has not indicated either greater or lesser values per unit of time for small amounts of time. To the degree that evidence does exist, it appears to indicate that, in the absence of different activity contents for travel times, time values per unit of time are roughly constant as a function of trip length and time savings.

SOME PROBLEMS IN TRAVEL TIME VALUE DETERMINATION

The nature of travel time as a good not explicitly bought or sold has necessitated the use of indirect methods in determining its value. The method primarily used has been to compare travel alternatives with different time and cost attributes and to measure the differential effects of times and costs in affecting people's routes, travel modes, or destinations. Through comparing the effects of different times and costs on choices made, time values have implicitly been derived for the choices analyzed. Most generally these analyses have been based on interview data on actual decisions in real previous situations, given the times and costs of the alternatives as perceived by the people interviewed or as measured by the analysts. In certain cases, people have been asked what they would do if certain travel time and cost options were available to them.

A second method has been used to a much lesser degree to approach the question of travel time value. In this method, attempts have been made to measure time value through determining the potential or real productivity of working time reallocated from traveling. These analyses have revolved about questions of wage rate, overhead, and abilities of firms to recapture in actual productivity the travel time savings of employees requiring smaller amounts of time for necessary travel while on the job.

Both of these methods of determining time value have had problems. In the first, there have been major questions relating to variability of time value and the relation to pure opportunity cost of time. A second major issue has been whether traveler perceived or objectively determined data should be used in measuring either people's actions or their potential actions in response to given travel alternatives. A third issue is the considerable ambiguity and uncertainty regarding the degree to which the alternative productive use of time method is valid or invalid in measuring travel time value. In this section these issues are taken up in order.

Time Value Variability and Pure Opportunity Cost of Time

As increasing numbers of travel time value studies have been performed, many analysts have expressed concern over the relatively wide ranges in empirically measured travel time values determined from the various travel situations analyzed. Studies yielding values ranging from perhaps 20 percent of the wage rate to 2 or 3 times the wage rate have raised question regarding the degree to which calculated time values could be used with validity and confidence in predictions of traveler behavior and transportation cost-benefit analyses.

The assumption has been made by many that the root of the problem lies in the fact that in each situation analyzed the activity contents of the competing options—sometimes described as comfort and convenience factors—have always differed so that in no case could pure opportunity cost values of time be measured. Always the calculated value of time was a measure of the utility or disutility of traveling in situation A as opposed to the utility or disutility of traveling in situation B. Because situations A and B by definition could not be the same, any measurement of time value necessarily mixed in values of other differences between situation A and situation B. The thought, therefore, has been that, if somehow activity content differences between A and B could be eliminated, a pure opportunity cost value of time could be calculated. This, presumably, would be more stable and reliable and thus could be used with more validity in predictions of traveler behavior and evaluations of the benefits of potential transportation projects.

This line of reasoning, however, neglects the fact that transportation projects are not built independent of activity contents. Each new transportation project involves an activity content that differs by given values from the activity contents of the options previously available. And, crucially, it is the values of those activity content differences that are relevant to traveler behavior and benefits in the specific situations analyzed. As pointed out earlier, only alternative uses of time and not time per se can be bought or sold. Thus it is the value of alternative uses of time that is relevant rather than that of the pure opportunity cost of the time itself.

But it is the values of the alternative uses of times that the studies all measure. In each case the time value of situation A is compared with that of situation B. Exactly what is desired! All that is necessary in any new situation is to find the results of previous situations similar to it and to apply them directly. And, of course, there are usually close analogies in existing situations to those of proposed new ones.

When existing studies of time value are viewed in this light, the problem of wide variability of calculated values largely disappears. It should naturally be expected that widely differing situations should have widely differing time values and similar situations, similar values. In fact, this is what is typically seen in empirical analyses. In parking studies, for instance, consistently high values are derived, reflecting the high disutility value of walking as opposed to driving in a car. These values vary according to location: relatively higher disutility values for walking from parking in seamy downtown fringe neighborhoods and lower values for walking from parking in more attractive suburban areas. Similarly, disutility time values are higher for shopping trips where packages must be carried than for work trips where walking is unencumbered.

In other situations, such as free-toll driving choices, the time values calculated are more moderate, reflecting the general comparability of comfort and convenience and the fact that alternative uses of time—which for both travel and the alternative are presumably not disagreeable—are at issue rather than the disagreeability of one travel alternative as opposed to another.

Finally, in some situations such as Sunday afternoon drives in the country and boat cruises, calculated travel time values can be negative reflecting the positive utility of spending time in those types of travel.

What the above implies is that if a suburban commuter parking lot is to be built, values for prediction and evaluation should be used that come from the analysis of commuter parking behavior in suburban commuter parking situations. Similarly, if a new expressway is to be built that makes use of arterial streets unnecessary for certain travel, time values should be used that derive from analyses of situations where people had choices between freeways and arterial streets. Third, if a new rapid transit line is proposed as an alternative to driving for some and to taking the bus for others, the values that should be used for prediction and evaluation should be respectively for the affected populations: those derived from automobile-rapid transit choice studies and from bus-rapid transit studies. The list of examples could be extended.

In all cases values from comparable situations should be used; and in fact these values are empirically found to be remarkably similar, consistent, and stable. Also, in all cases the pure opportunity cost of time, while perhaps an interesting academic notion, is for practical purposes an irrelevant concern.

Objectively Determined Versus Perceived Data

In any standard economic analysis, the relevant factor is always how much money is spent for how much of a good. It is not a matter of concern how much the buyer thinks he is spending on what he thinks he is buying. This latter concern is a concern rather of the marketing and advertising industries. In these industries the assumption is that the consumer either is unaware of the attributes of the products or can be persuaded to buy them by being convinced that the products are something that they are not. Clearly, if the consumer can be made to misperceive either how much he is getting or how much it is costing him, the seller can gain real benefits by selling less for more.

In light of the above it is appropriate that time value questions be treated according to purpose. If basic prediction and cost-benefit questions are at issue for particular transportation options, the analysis should be based on peoples' actual market behavior and the data used should describe objectively and accurately the situations facing them. Alternatively, if the objective is to investigate consumer psychology or misperception of real situations, analyses using perceived data may be very fruitful. Presumably, such analyses can be used to identify where people are misperceiving situations so that advertising can give people more realistic understanding of the options and thus the capability of making more informed rational choices.

Regardless, it is inappropriate to use perceived data for deriving real time values. This is because, to the extent that consumers do misperceive, they will always misperceive in favor of the options that they choose. This has the direct effect in empirical studies using perceived times and costs of raising calculated values of time above what people are actually spending on time allocation. Even though the population on the average may not be biased in perceiving the times and costs of the competing alternatives, the people misperceiving in favor of alternative A will be biased toward use of alternative A and those misperceiving in favor of alternative B will be biased toward the use of alternative B. The end result is that both users of A and of B will think they are saving more time at less cost than they actually are, with resultant overestimates of time value.

Alternative Productive Uses of Time

The alternative productive use method of valuing travel time is the most powerful method of doing so in that time reallocations are directly and explicitly related to the monetary value of production gains through time savings. If a wage rate is paid for a worker's time and the amount of time necessary for travel is reduced, a direct production gain should be evident in proportion to the wage rate and the amount of travel time eliminated. Presumably, one can measure this gain through looking at actual production as related to travel time. Otherwise, if there is a responsive labor market, the wage rate should be an adequate proxy for productivity gains.

Nonetheless, to require demonstrated productivity gains to verify time value imposes a requirement on time value determination that is beyond that for any other good. In standard economic analyses, if a producer buys a good for use in the production process, the value of that good is determined simply by the price paid for it rather than by an analysis of whether in fact the producer was able to gain that full value in production output. Similarly, many goods are final products rather than intermediate products in a production process. The fact that they will not be sold again does not mean that they have no value. Universally, the value is determined by the sale price rather than by the reuse price.

A further problem is introduced when a productivity analysis yields different results from travel behavior analysis of persons working on the job. If productivity results are used in prediction and evaluation, and people behave differently from what their productivity returns would indicate, to that extent the productivity predictions of use will be incorrect. Similarly, there is a conflict between the secondary returns to the employer and the immediate returns to the traveler.

In this situation it seems clear that the prime determinant again in prediction and evaluation is the immediate use of the facility: the amount of actual use at the given price. If there is a differential between the implicit behavioral values of travelers and the returns to their employers, that is a problem of resource allocation in the labor market. It is not immediately relevant to prediction of use and evaluation of benefits for transportation facilities. Empirically, wage rates and productivity gains may well closely relate to behavioral values from employee travel. But if there is a difference, it is the latter and not the former that prevails in economic analysis.

SOME APPROPRIATE DIRECTIONS FOR TRAVEL TIME VALUE DETERMINATION AND APPLICATION

The previous sections should have made it clear that increased understanding of empirical traveler behavior and values is greatly needed in all aspects of transportation. This understanding is needed in all the typical transportation choice situations that exist or are proposed and for all segments of trips. It is needed to understand the behavior of all segments of the population. Also, it is needed to cover not only choices between alternatives but induced travel as well. Further, it is needed to apply to marketing as well as to basic demand questions. Finally, the basis of knowledge for applications needs to span the entire range from knowledge of traveler behavior and values involved in individual transportation projects and portions of projects to application in regional and intercity transportation planning. All of this knowledge is necessary if we are to adequately address the prediction and evaluation questions of transportation related to time value.

The earlier sections should also have made it clear that this necessity for knowledge requires that a great deal of empirical analysis be done to cover the various situations of application. Each type of application situation can be expected to have its own aspects of behavior and accompanying values. However, within specific types of applications, the actual behavior and values are stable and consistent. Thus, if the empirical analyses relating to the different types of situations of application are done, then the behavior and value relations found can be applied to similar but new situations with confidence in their validity and accuracy.

General Modeling Approach

Past studies of traveler behavior and time values have yielded a number of lessons regarding the appropriate nature of approach to such analysis. Analysis based primarily on revealed preference studies of what people actually do in responding to the real travel alternatives that confront them can give suitable and reliable indications of travel behavior for transportation prediction and investment evaluation questions. A second empirical finding has been that, even so, the art of analyzing traveler behavior and values is a fairly imprecise one. In any investigation of a specific situation, only a few strong variables can be shown to affect behavior, and the specific terms in which their effects may take place are not always the same from one type of situation to another or from one variable to another. Further, complicated formulations from detailed theory are rarely testable in practice. Finally, although various forms of the different major variables may all be perfectly satisfactory for prediction and evaluation purposes, the statistical model should conform to the form of the effect of the variable specification used; otherwise, major errors in prediction and evaluation may result.

From these generalized observations, a number of lessons for modeling approach may be stated.

1. In gathering data for meaningful behavioral analysis, one should not only find out what people actually do in transportation choice situations but also measure carefully and objectively the major salient characteristics of those choices.
2. In initial analysis, the gross relations between major variables and the travel phenomenon being analyzed should first be determined. For this purpose, simple graph-

ical analysis is usually most fruitful. It will indicate not only which variables are strong and important but also what the specification relation is between their form and the choice phenomenon being analyzed.

3. When more complex and multivariate analyses are performed, the statistical forms used should correspond to the forms of the effects of the variables. In some cases, the relations will be such that linear regression is an appropriate specification. In others, nonlinear regression of one form or another may be appropriate. The statistical methods used should be carefully fitted to the phenomenon and the data rather than the reverse.

4. In multivariate analysis, only a few major variables should ideally be used. Other minor effect variables will certainly be operating, but, given the accuracy of modeling human behavior, their effect can rarely be measured. The measurement of minor variable effects ultimately will not matter greatly, and the coefficients of estimation must almost necessarily be wrong.

5. Since variable forms themselves are less important than the specification of their effects, to design variable forms to suit the problem and the audience for the analysis is appropriate. In practice, this means having simple models that do not have complex mathematical forms and use a few strong, usually policy, variables that are straightforward and easily understandable both in themselves and in their effects on results.

Urban Systems Modeling

One of the major characteristics of urban systems modeling, such as that represented by the traditional set of urban transportation planning travel demand models, is that the relations involved are many times as crude as those that may be developed from analyzing individual traveler behavior. Therefore, from the point of view of accuracy and validity of results, more than the most gross average representations of traveler behavior and values in simulations must generally be used at the level of regional modeling.

Frequently, however, analysts are asked to predict the effects of very detailed small changes through use of the regional models. To actually fit the regional models to make them responsive to all small variables is impossible, and to try to do so makes little sense. Rather, the effects of minor variables can be built into the regional model sets through simply inserting the results of appropriate individual behavioral models and fitting the regional models by use of calibration constants. By so doing, one can make realistic estimates of the effects of regionally minor variables without experiencing impossible problems of regional variable calibration.

Final Note on Marketing Analysis

Because of the inexact basic nature of the behavioral modeling techniques used in revealed preference studies, it seems unlikely that such studies will be the most fruitful avenues for measuring the effects of the somewhat less elemental variables, such as comfort and advertising, affecting transportation use. The sensitivity of the analysis is simply too small to reliably estimate the effects of such input variables.

Since these variables are typically marginal in nature, it seems appropriate to use an explicitly marginal rather than share analysis technique to analyze their effects. Basically, this means analyzing situations where changes are made in the comfort, advertising, or other marginal factors and relating the changes in the factors to the changes in the market demand.

Such techniques should probably be fruitful also in investigation of the psychology of travelers. If specific input changes are related to specific demand changes, the effects of psychological factors can probably be reliably estimated.

REFERENCES

1. Becker, G. S. A Theory of the Allocation of Time. Economic Journal, Vol. 75, Sept. 1965, p. 299.
2. Time Research Notes. Gt. Brit. Ministry of Transport.
3. Davies, A. L., and Rogers, K. G. Modal Choice and the Value of Time. Local Government Operational Research Unit, London, 1973.
4. de Donnea, F. X. The Determinants of Transport Mode Choice in Dutch Cities. Rotterdam Univ. Press, Louvain, Belgium, 1971.
5. Ergün, G. Development of a Downtown Parking Model. Highway Research Record 369, 1971, pp. 118-134.
6. Gronau, R. The Value of Time in Passenger Transportation: The Demand for Air Travel. Columbia Univ. Press, National Bureau of Economic Research Occasional Paper 109, 1970.
7. Gronau, R. The Value of Time and Transportation Choice: An Economic Approach. Paper prepared for HRB Task Force on Value of Travel Time, 1973.
8. Harrison, A. J., and Quamby, D. A. The Value of Time in Transport Planning: A Review. Gt. Brit. Ministry of Transport, London, 1969.
9. Hensher, D. A. The Consumer Choice Function: A Study of Traveler Behavior and Values. Univ. of New South Wales, PhD dissertation, 1972.
10. Hensher, D. A. Review of Studies Leading to Existing Values of Travel Time. Paper prepared for HRB Task Force on Value of Travel Time, 1973.
11. Lee, N., and Dalvi, M. Q. Variations in the Value of Travel Time. The Manchester School, 1959, pp. 213-236.
12. Lisco, T. E. Demand Analysis for Sub-Regional Mass Transportation Operations and Investment Decisions. Office of Research and Development, Illinois Department of Transportation, Chicago, Technical Papers and Notes Series 1, 1971.
13. Lisco, T. E. The Value of Commuter's Travel Time: A Study in Urban Transportation. Univ. of Chicago, PhD thesis, 1967.
14. Mansfield, N. W., ed. Papers and Proceedings of a Conference on Research Into the Value of Time. Gt. Brit. Department of the Environment, London, 1970.
15. Rassam, P. R., Ellis, R. H., and Bennett, J. C. The n-Dimensional Logit Model: Development and Application. Highway Research Record 369, 1971, pp. 135-147.
16. Reichman, S. Subjective Time Savings in Interurban Travel: An Empirical Study. Highway Research Record 446, 1973, pp. 21-27.
17. Reichman, S. Conceptual Problems in the Evaluation of Travel Time. Paper prepared for HRB Task Force on Value of Travel Time, 1973.
18. Sajovec, J., and Tahir, N. Disaggregate Behavioral Mode Choice Models for Feeder Bus Access to Transit Stations. Northwestern Univ., master's thesis, 1973.
19. Southward Transit Area Coordination Study. W. C. Gilman Co., Chicago, 1970, pp. 153-157.
20. Stopher, P. R., and Lisco, T. E. Modelling Travel Demand: A Disaggregate Behavioral Approach—Issues and Applications. Proc., Transportation Research Forum, New Orleans, 1970.
21. Stopher, P. R. Applications of the Value of Travel Time to Economic Evaluation of Transport Investment Alternatives. Paper prepared for HRB Task Force on Value of Travel Time, 1973.
22. Stopher, P. R. Derivation of Values of Time From Travel Demand Models. Paper prepared for HRB Task Force on Value of Travel Time, 1973.
23. Stopher, P. R., and Reichman, S. Application of Value of Travel Time to Travel Demand Estimation. Paper prepared for HRB Task Force on Value of Travel Time, 1973.
24. Tahir, N. Feeder Buses as an Alternative to Commuter Parking: An Analysis of Economic Trade-offs. Office of Research and Development, Illinois Department of Transportation, Chicago, Technical Papers and Notes Series 15, 1974.
25. Thomas, T. C. Value of Time for Commuting Motorists. Highway Research Record 245, 1968, pp. 17-35.
26. Watson, P. L. Problems Associated With Time and Cost Data Used in Travel

Choice Modeling and Valuation of Time. Highway Research Record 369, 1971, pp. 148-158.
27. Wigner, M. F. Disaggregated Modal Choice Models of Downtown Trips in the Chicago Region. Highway Research Record 446, 1973, pp. 49-65.

Disaggregate Travel Demand Models for Special Context Planning: A Dissenting View

David T. Hartgen, New York State Department of Transportation; and
Martin Wachs, University of California, Los Angeles

This paper addresses the applicability of disaggregate travel demand models to the problems of special context planning. The paper investigates the nature of demand forecasting in special contexts and the degree to which disaggregate techniques meet prespecified modeling requirements. It is not based on a careful search of the literature for examples of the use of disaggregate travel demand models in special context planning. The findings are that disaggregate procedures have certain advantages over conventional techniques for special context planning but fall short of being true advances in demand modeling. This is because they are in reality not materially different in structure from conventional aggregate procedures, contain the same basic limitations as these methods, and do not extract the behavioral process underlying travel choices in special context planning any better than do conventional methods. The paper concludes that disaggregate modeling techniques appear to have their greatest value in structuring the analyst's approach to demand estimation and facilitating the calibration of demand models with small data bases. For these reasons they should continue to be explored as useful tools, but not to the exclusion of other research into the behavioral phenomena underlying special context planning.

Considerable discussion and interest have recently centered on the development of disaggregate behavioral travel demand models and their capabilities compared to conventional techniques. The stated advantages of these procedures are (a) a presumed closer approximation to individual choice processes because of the way in which individual data are treated in model construction and (b) more efficient use of data in model calibration. A central assumption made by the proponents of such models is that disaggregate techniques are by their nature more "behavioral" than conventional procedures and, therefore, are to be preferred in planning applications. Given the importance of such an assumption to the potential application of these tools, its validity should be examined in some detail.

A considerable number of disaggregate models have been developed to date and have mostly been applied to mode and route choice. In this context, disaggregate refers particularly to a group of models and procedures characterized by

1. Use of calibration techniques in which each individual observation is treated as a separate point rather than aggregated spatially, temporally, or demographically; and
2. Use of specific mathematical functional forms.

Of the numerous functional forms [general requirements are that the function be constrained over the 0 to 1 interval and be S-shaped (8)], the logistic curve (1, 2, 3, 4, 5, 7, 8, 9), the closely related discriminant function (5, 7, 10, 11, 12, 13, 14), and the probit function (5, 7, 8, 9, 15, 16, 17, 18) have been the most frequently used. In the logistic function, the probability that an individual will choose a given alternate from a binary set is described as

$$P_A = \frac{e^{G(x)}}{1 + e^{G(x)}}$$

where

P_A = probability of choosing alternative A, and
$G(x)$ = (assumed) linear combination of the attributes of A and other alternatives and also the characteristics of the chooser.

In the probit form, the model takes the shape of the cumulative normal curve

$$P_A = \frac{1}{2\pi} \int_{-\infty}^{G(x)} e^{-\frac{1}{2}u^2} du$$

Calibration has been achieved by least squares methods (1, 5, 20), but the usual procedure is maximum likelihood for probit functions and the discriminant criterion for the discriminant function. In most cases, the decision variables have been descriptors of system performance (e.g., travel time and cost) and socioeconomic descriptors of the traveler (e.g., income, automobiles owned, trip purpose). Some applications (5, 6) have used attitudinal variables in combination with socioeconomic descriptors. A number of multinomial extensions of these procedures have also been developed (2, 3, 4, 8).

That these models are disaggregate in their treatment of observations in calibration cannot be disputed; whether they are also behavioral is open to considerable question. In the context of travel demand analysis, to say that a model is behavioral means (to the authors) that

1. The model contains descriptors of those variables (system, socioeconomic, situational, and motivational) that actually cause the phenomenon being studied to occur (in other words, the model reflects a causal and not just a correlative process);
2. The structure of the model reflects the choice process of behaving units, both the chooser himself and other related decisions influencing his choice; and
3. Model calibration is based on a sample of observations for one behaving unit or a group of behaving units that are assumed (or, better, can be shown) to operate with a similar decision structure.

A central point in this paper is that the disaggregate techniques are not really that at all, but merely refined calibration methods that fall far short of a genuine advance in demand modeling methodology. To develop this point, we need to examine the nature of aggregation in demand models and clearly indicate just what a demand modeling process involves. From that we can specify whether these attributes of disaggregate procedures are in fact unique and whether they adequately meet the needs of special context planning.

AGGREGATION IN TRAVEL DEMAND MODELS

Types of Aggregation

In general, the purpose of travel demand modeling is to forecast—to predict within appropriate limits—the magnitude of travel demand (i.e., person trips or vehicle trips in an interval) expected to use a given alternative mode, route, or time period. This process involves 2 fundamental steps:

1. The construction of a model or forecasting device from a sample of observations of behaving units and the variables influencing them and

2. The application of the model to a (generally) larger set of behaving units to yield an estimate of probable behavior.

In the first step, the forecasting mechanism is developed by describing the characteristics of the behaving unit, the alternatives relevant to the choice, and the nature of the function relating choice to these descriptors. The parameters of the model are then developed empirically from the data sample through a process called calibration; they are interpreted as "best fit" coefficients rather than as representing the importance of the descriptors in any single individual's choice process. The key assumption of such a process, when data are obtained from a cross-sectional sample of observations, is that the observations grouped together for calibration all share similar decision processes (or, at least, processes similar enough for modeling purposes).

In the second step, the numerical values of the variables in the model are assumed at constant, revised, or forecast levels. Model coefficients are generally assumed to be constant, as are the model's functional form and the structural relations among variables. The forecast (i.e., the number of units projected to behave or be affected in a certain manner) is developed by applying the model with forecast variables to a large aggregate group of units, again assumed to be homogeneous with respect to the applicability of the model. This aggregate group itself may be forecast as well. In this step a crucial assumption is that the cross-sectional relation expressed by the model will hold over time. Up to this point we have merely described this process in its general form and have said nothing specific about the form of the model, its variables, or method of calibration. In transportation planning practice, 2 fundamentally different forms of aggregation are generally introduced into this process:

1. Aggregation of individual observations, spatially (e.g., zone or tract), temporally (e.g., peak hour or day), demographically (e.g., income level, trip purpose); and
2. Aggregation of information within each observation, as with travel time (5-minute travel time increments), income class codes, or components of trip travel segments.

At the analyst's discretion, each form of aggregation can also occur prior to or after calibration of the model, often both. Thus, we have 4 separate types of aggregation to contend with in building demand models:

1. Aggregation of observations, precalibration;
2. Aggregation of observations, postcalibration;
3. Aggregation of information, precalibration; and
4. Aggregation of information, postcalibration.

We are now ready to draw the distinction between disaggregate travel demand models and conventional procedures in common use today. In conventional demand models, observations are aggregated spatially, temporally, or demographically prior to calibration of the model, which is fitted to aggregate estimates such as work trip rates per zone. In a forecasting mode, the model is applied to an aggregate number of similar (again spatially, temporally, or demographically defined) units to yield an estimate of activity or behavior.

In addition, information is also aggregated within each individual observation in the process of data collection. Data on items such as income, age, and occupations are all coded to finite levels; travel times between zone pairs are measured from zone centroids; trip segments are sometimes aggregated into in-vehicle and out-of-vehicle components. In each such case, some detail concerning the nature of the individual trip record and the traveler is lost. Similar losses occur when variables similarly aggregated are used in the subsequent application of the model to a group of behaving units to yield the forecast.

In disaggregate demand models, on the other hand, data are not aggregated over observations prior to calibration. Each separate observation is treated as a unique point; calibration consists of estimating the parameters of the model from these separate points.

However, there the difference ends. The use of disaggregate models, once calibrated, is similar to that of aggregate models: The model is also applied to an aggregate (assumed homogeneous with respect to the behavioral process) set of units to yield the forecast. Information may also be aggregated within each observation, as with conventional procedures, in model development and application. In other words, currently constructed disaggregate travel demand models differ from aggregate demand models only in the first form of aggregation: Observations are not aggregated prior to model calibration. The terms aggregate and disaggregate, then, apply only to the treatment of observation prior to calibration; other aspects of aggregation are not included in the dichotomy.

Our main point in the above discussion is that disaggregate travel demand forecasting techniques differ from conventional methods in only 2 basic ways:

1. Treatment of individual observations in model calibration and the use of associated calibration techniques (maximum likelihood, discriminant criterion); and
2. Use of specific mathematical functional forms [even this distinction can easily be lost, as Stopher (1) demonstrates].

On the other hand, these procedures have in common with conventional techniques a number of characteristics:

1. Aggregation of information within observations before calibration;
2. Use of similar variables as descriptors of the behaving unit and the characteristics of alternatives (these variables have traditionally consisted of system performance descriptors, as opposed to the quality of service, and socioeconomic descriptors of the trip, person, and household, as opposed to descriptors of the decision-making process within households);
3. Combination of these variables into similar decision functions, usually expressed as a simple linear combination of attributes;
4. Aggregation of behaving units spatially, temporally, or demographically or all of these for application of the model in forecasting;
5. Development of basically correlative relations, as opposed to causal relations, between observed behavior and independent variables; and
6. Model development from basically similar data bases consisting of individual trip records merged with selected system descriptors.

The differences highlighted above are essentially mechanical in nature and pertain to the method of calibration and functional form of the model. The similarities are essentially structural in nature and pertain to the philosophy of travel demand forecasting. For this reason, we see little fundamental difference between aggregate and disaggregate demand forecasting techniques now employed and no difference suggesting a significant advance in demand modeling capability or in understanding travel behavior.

Are Disaggregate Techniques Really Different?

The above argument suggests that the claim that disaggregate models are by their nature more representative of individual decisions than are aggregate models seems open to considerable question. Disaggregate models are simply calibrated in a different manner—often to specific functional forms, often by the use of the same data in a different way. One may easily construct both aggregate and disaggregate models from the same data base and use the same basic functional form in curve fitting. The fact that one procedure uses individual observations to construct the model and the other uses aggregations of observations does not necessarily make the former more representative of individual behavior than the latter. Both procedures, after all, result in just one model describing the behavior of all individuals in the sample. Both methods of demand forecasting develop basically correlative relations between observed travel behavior (i.e., choices) and sets of system performance (e.g., travel time and cost) and socioeconomic (e.g., income, automobile ownership, trip purpose) variables. Both methods have operated on similar data bases, consisting of individual trip records merged with system characteristics, measured in perceptual or engineering terms. Both methods have generally assumed the choice criterion G(x) to be some combination of socioeconomic and system variables, the coefficient of each variable representing its relative statistical strength. And both methods are traditionally applied to aggregate groups of travelers, who are assumed to be homogeneous with respect to their choice processes, in forecasting demand in a planning context.

We need to begin immediately to separate the idea of disaggregate from that of behavioral. The two are not interchangeable; it does not follow that disaggregate models are behavioral or that aggregate models are not. A critical review of the structure of both disaggregate and conventional demand models constructed to date (and we include here market-share Luce models, abstract mode models, and economic demand models) suggests that (a) virtually all of these models are equally behavioral because of their structural similarities and (b) all of these models are equally inadequate extractors of the behavioral processes causing travel-related choices. Clearly, we have few, if any, examples of behavioral models developed to date for transport planning, disaggregate or otherwise. In addition, to date disaggregate techniques have been carried into forecasting (as opposed to a calibration medium) only rarely (20).

DISAGGREGATE TECHNIQUES IN SPECIAL CONTEXT PLANNING

If disaggregate techniques are not structurally different from conventional procedures, what, then, is their applicability to special context planning? Do their characteristics facilitate or restrict special context planning?

Special Contexts

Transportation planning encompasses a number of special problems that are not easily treated under general urban systems and corridor planning methodologies, both administrative and technical. These include the following.

1. Subarea and subcorridor contexts characterized as point locations in urban space. Examples are industrial parks and universities, urban renewal and development sites, CBDs, and neighborhoods. Transportation problems related to such areas can be described as (a) developmental activities that impact the surrounding transportation system (e.g., a proposed shopping center overloads a local street system), (b) changes in nearby transportation service or travel demand or both generated elsewhere that impact the site (e.g., a new expressway overloads streets of a residential area), and (c) provision of transportation services to particular client groups at the site.
2. Point-to-point and corridor-level contexts characterized by specific origin-destination flows. Examples are suburban-CBD commuter movements and CBD-airport flows. Transportation issues generally involve (a) provision of service to particular client groups (commuters, shoppers) or (b) unique activity site-residential site flows (from a Model Cities area to jobsites).
3. Areawide context characterized by regionwide impacts of service. Examples include (a) certain new technology applications such as PRT or dial-a-bus and (b) special service provision to geographically dispersed clients, such as the handicapped or elderly.
4. Options focusing on demand changes, such as staggered work hours, pricing and tolls, and automobile-free zones.

To the extent that planning in such situations requires special forecasting and evaluation techniques, we treat them below as special planning contexts, recognizing that the line between that planning and broader systems and corridor planning is often blurred.

Planning for special contexts is an important aspect of transportation planning and is receiving increasing emphasis in transportation analysis. In long-range urban transportation planning, problems have been traditionally addressed at the system scale. Analysis at this level involves the structuring and analysis of integrated systems plans for urban areas. Emphasis in evaluation has been on user and nonuser benefits and costs and the probable impacts of proposed facilities on the social, economic, and physical environment. System planning has often been approached (in practice) as a sequence of generalized corridor or sector plans, in which urban areas are broken up into sectors and each is studied separately. Some 250 long-range transportation planning efforts are now under way in nearly all major urban areas. Most of these have published a long-range plan and are moving into reanalysis and reevaluation of their initial assumptions and forecasts. As transportation planning evolves into the continuing phase, increasing emphasis is being placed on smaller scale planning at the corridor and project levels and on special context planning. But the nature of special context planning differs significantly from corridor and system planning in several respects.

1. Scale—Special problems often encompass 1 corridor, 1 point-to-point movement, or limited and fairly well-defined spatial areas.
2. Homogeneity—In some special problems (e.g., universities, CBDs) the population of interest is relatively more homogeneous than the urban population at large, particularly with respect to socioeconomic characteristics. There is little evidence, however, that such homogeneity of characteristics implies a similar homogeneity of the behavioral process that members of this group use in making transport choices (19).
3. Relevant variables—Special context problems often deal with behavioral processes that are quite different from those of larger contexts and that have different influencing variables. An example is the provision of transit service to the elderly.
4. Nature of improvements—Transportation proposals in special contexts often relate to improvements in service, are generally short-range in nature, and usually involve little capital construction or other massive investments. Transport improvements are often qualitative and bear on the comfort, convenience, and reliability of the service provided to the client group rather than on its performance characteristics.
5. Impact—Studies at this scale tend to focus on the impacts of the transportation proposals on client groups as opposed to the estimation of total travel demand. The definition and delineation of the client group itself are, of course, components of this process.

These differences suggest that many of the planning tools (particularly demand forecasting and evaluation) developed for system planning are not adequate for special context planning. It remains to be demonstrated, however, whether disaggregate procedures are any better.

We are now in a position to compare conventional and disaggregate techniques with reference to appropriate criteria for demand modeling in special context planning.

Planning Horizon

Most special context studies have a planning horizon of less than 10 years (new technologies planning is perhaps a notable exception), and thus long-range forecasts of demand are not warranted. To some extent, extensive analysis of transportation and land use feedbacks is unwarranted; travel demand modeling can often be limited to route, mode, and destination choices, unless accessibility is expected to substantially increase.

Both aggregate and disaggregate techniques can easily be developed for component models (e.g., modal split) without the necessity to include completed feedbacks. Most applications of disaggregate models to date have dealt with problems of calibration and have not been extended into a planning context. Both short- and long-range forecasts can be made with these procedures, but their use seems to be more appropriate in short-term forecasting because of the small scale of typical applications. Thus, disaggregate procedures appear to be superior on this criterion.

Extraction of Behavior

Ideally, the design of demand models should be based on the relation thought to exist between traveler behavior and socioeconomic and service variables. Obviously those variables most relevant to the choice should be accounted for. The analyst should resist the temptation to opt for a model based only on easily measured performance variables when it is apparent that significant qualitative factors also influence the choice process. This is particularly true in special contexts where behavioral processes and the variables influencing them are likely to be very different from those of the general population.

Although aggregate techniques have traditionally not been particularly behavioral in nature, they can be made so by the inclusion of relevant variables and more faithful representation of individual choice processes. Consider the problem of forecasting demand for reduced fares for the elderly. In studying such a problem, we should not be concerned as much whether we use an aggregate or a disaggregate procedure as whether we extract and adequately measure those parameters, such as cost, availability of service, special routings to appropriate destinations, factors in boarding and alighting from the vehicle, and time of day, that influence the clients' behavior. Such variables are not well represented in any current or proposed models, disaggregate or otherwise, in spite of the fact that survey research has shown them to be important determinants of behavior.

Method of Forecasting Demand

The nature of the demand forecast itself is different in many special contexts. In systems planning we are concerned with total demand, as influenced by general system and activity parameters; in special contexts we are concerned more with components of demand for subgroups and the sensitivity of this demand to changes in various system parameters, both performance and qualitative.

The primary advantage of disaggregate techniques here is that their use of certain functional forms facilitates computation of elasticities. Certain aggregate models (e.g., abstract mode formulations) also have this property. But this characteristic is wasted if the model does not contain those variables relevant to the choice. Considerable study, for instance, has been put into the estimation by the use of disaggregate models of cost and time elasticities; if this work were extended to other variables for special contexts, the application of disaggregate procedures in such contexts could easily be demonstrated.

The accuracy of disaggregate models compared to conventional techniques is unknown. Some limited evidence (mainly the experience of model builders) suggests that disaggregated models can be better calibrated to an existing data base than a conventional model can, sample size and heterogeneity being equal. How much of this advantage is subsequently lost in external application or in the use of disaggregate models in model chains is not known. Too little is now known of the magnitude of relative error propagated through travel demand models, either aggregate or disaggregate. Nevertheless, it seems clear that the content of variables used in these models will have a greater influence on their accuracy than the level of aggregation or its place in the modeling process.

Data Base

Ideally, one should be able to develop demand models from as small a data base as possible for efficiency in data collection. As much as is feasible, the method should represent or approximate the choice process of travel decision-making units (household or persons) rather than aggregate groups of units. The method must, of course, be applicable to larger population groups to yield the forecast.

Clearly, no one data collection method or procedure is applicable to the problems of all special problems. The particular context and its relevant dimensions (space, time, socioeconomic) should determine the nature of the data, the amount, and the level of aggregation. In general, special context planning appears to require fewer individual observations for analysis than does urban area systems planning. However, the detail of information obtained in each interview is typically greater than when data sets are intended for general system planning. Additional information often obtained includes traveler perceptions of the attributes of alternative modes, routes, or destinations, reasons for the choices, opinions toward proposed transportation improvements, and willingness to pay for them. Data for sampling special contexts are typically at the household or person level. For some contexts, a sampling "universe" is available for the particular client group (e.g., business in the CBD, university students); in other contexts (e.g., the elderly or handicapped), universe definition may be a serious problem.

A clear advantage of disaggregate models is the small sample sizes necessary to calibrate them. Evidence to date shows that they can be easily calibrated with samples of 500 to 1,000 records (5, 6, 20, 21), at least in the binary cases. Further, the use of specific functional forms permits the analyst to better extract the mathematical properties of the model (such as elasticity and behavior at the limits) and apply these to the particular context. This characteristic is applicable, of course, to aggregate models fitted to the same functional forms.

Operation

Demand models should, if possible, possess certain attributes to facilitate their use in practice. Among these are internal consistency and sensible structure, ease of calibration, strong theoretical base, efficiency, and parsimony with respect to input and output. Most important, the technique should be simple to understand and operate and produce relevant output in timely fashion. In special context planning, for instance, the need for computerization is open to question. Although forecasting devices (models) can be developed and calibrated with computerized procedures, the use of these models in special context planning may not require—indeed warrant—computerization. Most problems (innovative technologies at the urban scale are a possible exception) involve only a few point-to-point movements and rely heavily on secondary published data, aggregated spatially, as the population base against which models are applied. Models developed should be capable of being applied to such data bases and, most important, should be capable of producing easy-to-understand output in a timely fashion.

A distinct disadvantage of disaggregate techniques (as now employed) is their reliance on complicated statistical fitting procedures for calibration. The analyst derives few benefits from these calibration methods (particularly in forecasting) as opposed to hand-fitting or table look-up calibration methods. Although least squares fitting routines are widely available to transportation planning agencies, maximum likelihood procedures necessary for disaggregate calibration and analysis are not widely known or used, particularly for multichoice models. To the extent that the use of disaggregate procedures is tied to the availability of such tools, the widespread application of these methods in real planning contexts (as opposed to research environments) must remain limited. To the authors' knowledge, few planning agencies have constructed such models and used them in an on-line demand forecasting context [Allen (16) and Winger (20) present exceptions].

Generalization to Other Contexts

Demand estimation methods should be applicable (within similar situations) to other cases and to ranges of variables not now existing. To the extent that the forecast involves new technology applications, care should be taken to include appropriate descriptor variables in data collection, lest rough surrogates be required to extend the model's range.

It is perhaps unreasonable to insist that just one model (or, for that matter, several models) be applicable to different kinds of special contexts. Yet within a particular context group (e.g., university studies) it seems equally unreasonable to insist that separate and distinct methods be developed for each separate case study. Although the basic factors influencing demand and their interrelations are probably not dissimilar from one case to the next, analysts are often unsure of this structure. Given the state of our knowledge, a policy of experimentation and varied studies appears more appropriate than concerted striving for the model appropriate to a given context.

It does not appear that disaggregate techniques per se are more easily generalized in other planning contexts than are conventional procedures. This capability depends not on a model's mechanical attributes such as the method of calibration of specific functional form but on (a) the degree to which the behavioral phenomena involved in those contexts are similar and are driven by the same underlying factors and (b) the extent to which the model (aggregate or disaggregate) extracts the key elements of that phenomena. These procedures do no better than conventional methods in extracting traveler decision processes or describing individual choice behavior. They have been calibrated on precisely the same transportation system descriptors and socioeconomic variables as conventional techniques.

Summary

We have compared disaggregate techniques with aggregate procedures for use in special context planning. Disaggregate procedures appear superior with respect to (a) application to shorter planning horizons, (b) interpretation of demand sensitivity with respect to system variables, and (c) use of small-sample data bases. Aggregate techniques appear easier to calibrate with currently available procedures. The 2 procedures appear about equal with respect to extraction of behavior, incorporation of relevant variables, accuracy, required detail of individual data records, and generalization to other contexts.

DIRECTIONS FOR RESEARCH

We have suggested that the idea that disaggregate techniques are markedly different (structurally) from conventional procedures should be viewed with considerable skepticism. Similarly, although disaggregate techniques possess certain advantages over conventional procudures for special context planning, they should not be seen as panaceas for demand forecasting in these problem areas. Before we can be confident of these tools, we need considerably more research and experience with their properties and applications to demand forecasting in general and to special contexts in particular. The following extensions of current work would be particularly valuable.

1. Extend the range and type of variables included in current disaggregate models, with particular emphasis on qualitative attributes of alternative transportation choices as perceived by potential users and on psychological and hidden attributes of potential users. This work is essential if we are to better understand travel choice processes and is particularly important with respect to studies of special groups.
2. Demonstrate the applicability of disaggregate techniques and incorporate such variables in actual planning contexts. We suffer from an appalling lack of experience with disaggregate procedures in real planning problems. Virtually all of the work in disaggregate techniques to date has concentrated on problems of model form and calibration (i.e., the first stage in demand forecasting), whereas almost no applications of these procedures in actual planning problems exist. Thus, what the relative merits of disaggregate techniques are compared to conventional procedures is a hypothetical question. The time has come to consolidate the gains made in recent years in disaggregate model theory so that further research may benefit from the experience gained from application of the current state of the art.
3. Extend research in travel behavior. The most basic research needs are the structure of individual choice processes. Specifically, we need to know much more

about phenomena such as (a) nontransportation factors influencing choice, particularly pretrip family decision and allocation structures; (b) time-sequencing of travel patterns, i.e., how these patterns are decided on and interrelated to satisfy person and household needs; (c) the process by which travelers perceive the attributes of alternative destinations, modes, and routes and the degree to which these attributes influence choices; (d) traveler evaluation mechanism, i.e., how certain attributes are filtered, selected, scaled, weighted and combined, or traded off in making choices; (e) effects of memory, learning, expectation, and habit on travel choice processes; (f) effects of external information sources on these processes; and (g) effects of weather, traffic accidents, and other random variables on choices and attribute perception.

Clearly, disaggregate modeling by itself cannot address these topics, although it may prove useful as a tool in studying such travel phenomena. Hence we are not calling for more research into disaggregate techniques per se but are suggesting a reorientation of current research. Perhaps the greatest disadvantage of the use of disaggregate models as forecasting tools in special contexts is that current interest in these techniques seems to have blunted and misdirected badly needed research in other topics. We seem to be in danger of attributing to the disaggregate approach to modeling a host of characteristics that appear to make it ideal for evolving transportation planning needs; in reality, it is just an additional tool and no more. The authors grant the advantages of such techniques in calibration, particularly with small sample surveys; but the analyst should not treat disaggregate models as panaceas or, for that matter, as an improvement over current techniques for special context planning.

REFERENCES

1. Stopher, P. R. A Probability Model of Travel Mode Choice for the Work Journey. Highway Research Record 283, 1969, pp. 57-65.
2. Rassam, P. R., Ellis, R. H., and Bennett, J. C. The n-Dimensional Logit Model: Development and Application. Highway Research Record 369, 1971, pp. 135-147.
3. Stopher, P. R. A Multinomial Extension of the Binary Logit Model. 1969, unpublished.
4. Thiel, H. A Multinomial Extension of the Linear Logit Model. International Economic Review, Vol. 10, No. 3, 1969, pp. 251-259.
5. Hartgen, D. T. The Influence of Attitudinal and Situational Variables on Urban Mode Choice. New York State Department of Transportation, Albany, Preliminary Research Rept. 41, 1973.
6. Allen, W. B., et al. Developing and Testing a Behavioral Modal Split Model. Transportation Studies Center, Univ. of Pennsylvania, 1971.
7. Talvitie, A. P. Comparison of Probabilistic Modal-Choice Models: Estimation Methods and System Inputs. Highway Research Record 392, 1972, pp. 111-120.
8. A Disaggregated Behavioral Model of Urban Travel Demand. Charles River Associates, Inc., 1972.
9. Demetsky, M. J. Behavioral Approaches to Modal Demand Modeling. Carnegie-Mellon Univ., Pittsburgh, 1972.
10. Bock, F. C. Factors Influencing Modal Trip Assignment. National Cooperative Highway Research Program Rept. 57, 1968.
11. Joseph, J. A. A Discriminant Analysis Approach to Modal Split. U.S. Dept. of Commerce, Northeast Corridor Transportation Project, Washington, D.C., Technical Paper 7, 1967.
12. Warner, S. Stochastic Choice of Mode in Urban Travel: A Study in Binary Choice. Northwestern Univ. Press, Evanston, Ill., 1962.
13. McGillivray, R. G. Demand and Choice Models of Modal Split. Journal of Transport Economics and Policy, Vol. 4, No. 2, 1970.
14. Quarmby, D. A. Choice of Travel Mode for the Journey to Work: Some Findings. Journal of Transport Economics and Policy, Vol. 1, No. 3, 1967.

15. Lave, C. A. A Behavioral Approach to Modal Split Forecasting. Transportation Research, Vol. 3, No. 2, 1969.
16. Ergün, G. Development of a Downtown Parking Model. Highway Research Record 369, 1971, pp. 118-134.
17. Hoel, L. A., and Demetsky, M. J. Behavioral Considerations in Modal Split Analysis. Operations Research Society of America, Washington, D.C., 1970.
18. Lisco, T. E. The Value of Commuters' Travel Time. Univ. of Chicago, PhD dissertation, 1967.
19. Sommers, A. N. Toward a Theory of Traveler Mode Choice. High Speed Ground Transportation Journal, Vol. 4, No. 1, 1970.
20. Wigner, M. F. Disaggregate Modal-Choice Models for Downtown Trips in the Chicago Region. Highway Research Record 446, 1973, pp. 49-65.
21. Watson, P. L. Predictions of Intercity Modal Choice From Disaggregate, Behavioral, Stochastic Models. Highway Research Record 446, 1973, pp. 28-35.

Conference Papers on Structure of Disaggregate Models

Multidimensional Choice Models: Alternative Structures of Travel Demand Models

Moshe E. Ben-Akiva and Frank S. Koppelman,
Massachusetts Institute of Technology

Extensive research in travel demand in recent years has been based on theories of individual choice. These choice theories assume a selection from a finite set of mutually exclusive and collectively exhaustive alternatives. We assume that, with qualitative or discrete alternatives, probabilistic behavior explains observations of different choices for the same set of observed independent variables. Such choice theories have been developed in the context of unidimensional choice situations. A consumer was assumed to select an alternative i out of a set of alternative choices A. If the set A includes the alternative choices of a single commodity, then the choice probability, P(i:A), is the choice analog of a demand function for a given commodity. A consumer is faced with a multidimensional choice situation in determining a consumption pattern. (The term multiple choice refers to a choice from a set of more than 2 alternatives. A choice from 2 alternatives is termed binary choice. The term multidimensional choice is used for a set of related choices, each of which can be either multiple or binary.) For example, a consumer who is selecting a residence location within the metropolitan area is choosing also among alternatives such as housing types and automobile ownership levels.

The total number of choices that a consumer makes is very large. The assumptions of a "utility tree," or a separable utility function, and negligible income effects permit the independent modeling of demand for a subset of commodities. That is, the demand functions for a subset of commodities are independent of the prices of all other commodities. [The notion of separability was introduced by Leontief (4). Separable utility functions have been developed by Muth (9) and Strotz (11, 12).]

We assume here that mobility and travel choices are such an independent branch or subset of the consumer's utility function. Choices within this subset are interdependent. This subset may be treated as a block recursive system. That is, the first block consists of the mobility choices, and the second block consists of the travel choices (assuming the mobility choices as fixed). Travel choices with respect to different trip purpose categories can also be considered independently of each other. Thus, we can model separately the set of mobility choices and the sets of travel choices for different trip purposes (assuming that mobility choices are predetermined). Yet, each of the above sets of choices represents a multidimensional choice situation.

The purpose of this paper is to extend the choice theories from unidimensional to multidimensional choice situations. In a multidimensional choice situation different assumptions about the dependencies among choices result in models with different structures. The alternative structures are identified, and their applicability to travel demand models is discussed.

PROBABILISTIC CHOICE THEORY

Choice theories are reviewed in other reports (1, 2, 3, 5, 6). The consumer is visualized as selecting the alternative that maximizes utility. The probabilistic behavior mechanism is a result of the assumption that the utilities of the alternatives are not certain, but rather random variables determined by a specific distribution.

If the utility of alternative i to consumer t is denoted as U_{it}, the choice probability of alternative i is

$$P(i{:}A_t) = \text{prob}\,[U_{it} \geq U_{jt}, \forall j \in A_t] \tag{1}$$

where A_t is the set of alternative choices available to consumer t. The utilities are essentially indirect utility functions, which are defined in theory as the maximum level of utility for given prices and income. In other words, the utility U_{it} is a function of the variables that characterize alternative i, denoted as X_i, and of the socioeconomic variables describing consumer t, denoted as S_t. Thus, we can write

$$U_{it} = U_i\,(X_i,\ S_t) \tag{2}$$

The set of alternatives A_t is mutually exclusive and exhaustive such that one and only one alternative is chosen. The deterministic equivalent of this theory is simply a comparison of all alternatives available and the selection of the alternative with the highest utility.

The mathematical form of the choice model is determined from the assumption about the distribution of the utility values.

DEPENDENCIES AMONG CHOICES

To simplify the discussion we will rely on an example of 2 choices. We consider a consumer who is making a trip for a given trip purpose, say, shopping, and is faced with the choices of destination d and mode of travel m. We distinguish between 2 types of dependencies among choices: dependency in the structural sense and dependency of the sets of alternative choices in a physical sense.

Dependency in the structural sense arises from substitution and complementary relations among choices and different choices being made with respect to the same final commodity, i.e., the utilities from different choices are not independent. For example, the choices of automobile ownership level and residence location are dependent on each other because a downtown location could be a substitute for a high automobile ownership level. The utility from an alternative location will therefore depend on the chosen car ownership level and vice versa.

The choices of mode and destination are made with respect to the same final commodity—a trip. Some of the attributes of a mode, such as travel time by bus, will be different for different destinations. Therefore, mode m to destination d is a different alternative from the same mode to destination $d'(d' \neq d)$. Similarly, some of the attributes of destination d depend on the chosen mode. Therefore, destination d reached by mode m is a different alternative from the same destination reached by mode m' $(m' \neq m)$. In other words, the utility from an alternative mode is dependent on the destination and vice versa.

Thus, the dependency among travel choices can be attributed to the commonality of the attributes. In other words, some attributes of a trip are specific to all travel choices. For example, the travel cost for shopping at a certain frequency depends on attributes such as where one shops and what mode one uses. Similarly, the travel cost of shopping at a given destination depends on how often one shops and what mode one uses. Therefore, a traveler can trade off among choices. For example, one can shop frequently at a nearby grocery store or less frequently at a distant shopping center.

The dependency, or the causality, can be assumed either in 1 direction (e.g., the utility from a mode depends on the chosen destination but the utility from an alternative destination is independent of the chosen mode) or in 2 directions (e.g., the utility from an alternative mode depends on the chosen destination and the utility from an alternative destination depends on the chosen mode). It is realistic to assume that all travel choices are interdependent. However, we consider here also alternative assumptions that result in models with different structures, as will be shown in the following sections.

If the choices of mode and destination depend on each other, then the set of alternative modes is different for different destinations and the set of alternative destinations is different for different modes. We denote the set of alternative modes for a given destination as M_d and the set of alternative destinations for a given mode as D_m.

In addition, the set of alternative modes can be physically dependent on the chosen destination and vice versa. For example, a bus service may be available to 1 destination but not to the other. Therefore, the sets of alternative modes M_d can have different numbers of alternatives for different destinations.

If 2 choices are independent, then their alternative sets will also be independent. If the choice of mode and destination is assumed to be independent, we denote the set of alternative modes as M and the set of alternative destinations as D.

OVERALL SET OF ALTERNATIVES

The consumer can be viewed as selecting an alternative destination and mode combination dm from an overall set of alternatives DM that include all possible destination and mode combinations. For example, if the number of alternative modes available to every destination is identical and equal to M and the number of alternative destinations is D, then the total number of alternatives in the overall set will be $D \times M$.

The overall set of alternatives DM can be partitioned according to modes or according to destinations. If we partition according to destination, then we can write the overall set of alternatives as follows:

$$DM = [M_1, M_2, \ldots, M_d, \ldots, M_D] \tag{3}$$

In this scheme we denote the set of destinations used for partitioning as D. Partitioning according to modes, we write

$$DM = [D_1, D_2, \ldots, D_m, \ldots, D_M] \tag{4}$$

The set of modes used for partitioning is denoted as M. If the alternative sets are independent, then

$$\begin{aligned} M_d &= M, \ \forall d \epsilon D \\ D_m &= D, \ \forall m \epsilon M \end{aligned} \tag{5}$$

ALTERNATIVE STRUCTURES

If we assume that the choices are independent, then we can write the following structural choice probabilities (the probabilities that have direct behavioral interpretation and are originally written to describe a structure are called structural probabilities):

$$\begin{aligned} P(d{:}D) &= \text{prob } [U_d \geq U_{d'}', \ \forall d' \epsilon D] \\ P(m{:}M) &= \text{prob } [U_m \geq U_{m'}', \ \forall m' \epsilon M] \end{aligned} \tag{6}$$

where U_d and U_m are the utilities from destination d and mode m respectively. In essence, the independence assumption implies an additive utility function:

$$U_{dm} = U_d + U_m \tag{7}$$

In words, the total utility from a destination and mode combination is equal to the utility from the destination plus the utility from the mode. Since the choices are independent, we can write the joint probability of d and m as follows:

$$P(d,\ m{:}DM) = P(d{:}D) \cdot P(m{:}M) \tag{8}$$

The structure that represents independent choices, or an independent structure, consists of marginal probabilities of the different choices.

If the choices of mode and destination are dependent on each other, then we can write the following conditional choice probabilities:

$$\begin{aligned} P(d{:}D_m) &= \text{prob}[U_{d|m} \geq U_{d'|m}, \forall d' \epsilon D_m] \\ P(m{:}M_d) &= \text{prob}[U_{m|d} \geq U_{m'|d}, \forall m' \epsilon M_d] \end{aligned} \tag{9}$$

where $U_{d|m}$ is the utility from destination d given that mode m is chosen and $U_{m|d}$ is the utility from mode m given that destination d is chosen. The conditional probability $P(d{:}D_m)$ is the choice probability of destination d given that mode m is chosen, and similarly $P(m{:}M_d)$ is the choice probability of mode m given that destination d is chosen.

For forecasting, however, the 2 conditional probabilities are insufficient information to compute the joint probability of destination and mode. In this case, as opposed to independent choices, the joint probability is not a product of 2 marginal probabilities since $P(m{:}M_d)$ is functionally dependent on d, i.e., $P(m{:}M_d) \neq P(m{:}M)$. If we had $P(m{:}M)$, then the joint probability is equal to its product with $P(d{:}D_m)$. However, to model the marginal probability, $P(m{:}M)$, we need to identify a utility function for an alternative mode that is independent of what destination is actually chosen. Therefore, for such a simultaneous structure, in which the choice of destination depends on the choice of mode and vice versa, we must model explicitly the joint probability $P(d, m{:}DM)$. Given the joint probability, we can derive the marginal probabilities and the structural probabilities as follows:

$$\begin{aligned} P(m{:}M) &= \sum_{d \epsilon D_m} P(d, m{:}DM) \\ P(d{:}D) &= \sum_{m \epsilon M_d} P(d, m{:}DM) \\ P(d{:}D_m) &= \frac{P(d, m{:}DM)}{P(m{:}M)} \\ P(m{:}M_d) &= \frac{P(d, m{:}DM)}{P(d{:}D)} \end{aligned} \tag{10}$$

A dependency that goes only in 1 direction results in a recursive structure. If we assume that the choice of destination is independent of what mode is actually chosen and that the choice of mode is dependent on the chosen destination, we write the following probabilities:

$$\begin{aligned} P(d{:}D) &= \text{prob}[U_d \geq U_{d'}, \forall d' \epsilon D] \\ P(m{:}M_d) &= \text{prob}[U_{m|d} \geq U_{m'|d}, \forall m' \epsilon M_d] \end{aligned} \tag{11}$$

This recursive structure implies the following additive utility function:

$$U_{dm} = U_d + U_{m|d} \tag{12}$$

The utility for a destination and mode combination is equal to a utility from the destination plus a utility from the mode that is dependent on the destination. In a recursive structure, the joint probability is the product of the structural probabilities.

Since we assume in this recursive structure that $P(m{:}M_d) \neq P(m{:}M)$, it is possible to derive from the joint probability a conditional $P(d{:}D_m)$ that is not equal to $P(d{:}D)$. However, this conditional probability is not causal but simply a mathematical relation derived from the model with no behavioral interpretation.

A recursive structure represents a hierarchical conditional decision structure. It is a common practice to replace a complex decision with a large number of alternatives by a recursive structure. The decision is decomposed into stages by successive partitions of the overall set of alternatives. Luce (5) noted that different partitions give different results. Therefore, a recursive structure can be viewed either as a simplifying assumption (this will require a sensitivity analysis of the partitioning scheme to determine how the results are affected) or as truly representing a sequential, or conditional, decision-making process.

SEPARABILITY OF CHOICES

Implicit in the discussion of the alternative structures was a separability-of-choices assumption. The conditional choice probability of mode given a destination was written as $P(m{:}M_d)$. This implies that the choice of m given d is independent of alternative modes to all other destinations $d'(d' \neq d)$, and is dependent only on the alternative modes for the given destination.

This is a reasonable assumption. It is required in order to be able to model choices separately. If we model directly a joint probability and assume a simultaneous dependency, then it appears that this assumption is not necessary. However, the interpretation of the derived conditional probabilities will not be the same as the one used here. It was also impossible to find an example of a model that does not make this assumption.

If we partition the set DM according to destinations, we can write the joint probability as follows:

$$P(d, m{:}DM) = P(m{:}M_d) \cdot P(d{:}D) \tag{13}$$

This equation is similar to the way in which Luce and Suppes (6) described the choice axiom,

$$P(i{:}A) = P(i{:}B) \cdot P(B{:}A) \tag{14}$$

for $i \in B \subset A$. The subset B corresponds to the subset of alternative modes to a given destination. However, the choice axiom is more general than the separability-of-choices assumption. It applies to any partitions of A to nonoverlapping subsets B. The separability-of-choices assumption applies only to partitions according to choices.

There is some similarity between the concept of functional separability and the separability-of-choices assumption. Functional separability is based on the idea that the marginal rate of substitution among a set of variables is independent of other variables. Separability of choices implies that a conditional probability for a given choice depends only on a part of the total utility function. The choice of mode given a destination is assumed to be dependent on $U_{m|d}$, which is the part of the utility function that for a given d varies across modes.

Hence, a separability assumption implies that, from the utility function for a destination and mode combination U_{dm}, we can identify the utility from a mode given a chosen destination $U_{m|d}$ and the utility from a destination given a chosen mode $U_{d|m}$. Clearly, their sum is not equal to U_{dm}. The separability assumption in an independent structure implies the additive utility function of Eq. 7. The separability assumption in a recursive structure where m depends on d implies the additive utility of Eq. 12.

ESTIMATION OF ALTERNATIVE STRUCTURES

It is possible to estimate directly the conditional probabilities or to derive their estimates from the estimated joint probability. [Estimating the joint probability and then deriving the conditional probabilities are analogous to the method of indirect least squares (7).] If the purpose of the analysis is to make only conditional predictions of one choice, given that all other choices remain constant, then the conditional probabilities are all that is needed and one can estimate them directly. However, the coefficient estimates of the conditional probabilities will not necessarily be equal whether they were estimated directly or indirectly through the estimation of the joint probability.

It appears that, if estimated through the joint probability, the coefficient estimates of the conditional probabilities can gain in statistical efficiency and can be less sensitive to specification errors. (Specification errors are the consequences of an incorrect set of explanatory variables or incorrect mathematical form or both.) The basis for this statement is the possibility of incorporating restrictions across conditional probabilities and thereby using more information to estimate some coefficients in the estimation of the joint probability. As an example, consider the simultaneous structure of destination choice and mode choice described previously. It is possible that $U_{d|m}$ and $U_{m|d}$ have common coefficients. By directly estimating U_{dm} we constrain them to be equal and we use simultaneously all the information from the choice among alternative modes as well as from the choice among alternative destinations. If we directly estimate $U_{d|m}$ we can only use information on alternative destinations for the chosen mode, i.e., the alternatives in D_m. If we directly estimate $U_{m|d}$ we can only use information on alternative modes for the chosen destination, i.e., the alternatives in M_d. In estimating U_{dm} we use information on all the alternatives in the overall set DM.

Only under very restrictive conditions will direct estimates of, say, $U_{m|d}$ result in the same coefficient estimates as indirect estimation through U_{dm}. This happens when the alternatives in DM that are not in M_d do not provide additional information to that obtained from M_d alone. In other words, this happens when the variability of modal attributes for destinations $d'(d' \neq d)$ is the same as that for the chosen destination d. The exact conditions that have to be fulfilled by the data for this to occur depend on the exact specification of the choice model. However, knowledge of the exact condition seems to be unimportant because as a practical matter it never occurs. Furthermore, even if it occurs there is no reason not to estimate U_{dm} if it can only be more efficient and it is needed for forecasting anyway.

In a recursive probabilistic structure, there is no reason to estimate directly the joint probability. Therefore, it could be estimated in its structural form, as it was done (3).

A simultaneous structure could also be estimated as a recursive structure as follows: (a) estimate one conditional, say $P(m:M_d)$; (b) derive from the analytical form of the joint probability the marginal $P(d:D)$; and (c) estimate the marginal with the coefficients that are included in $P(m:M_d)$ constrained to their estimates from $P(m:M_d)$. This estimation procedure is suggested only when for some reason the direct estimation of the joint probability is computationally difficult.

MODELING THE TRAVEL CHOICES

The preceding discussion indicates that the appropriate structure for the travel choices is a simultaneous one. In the remainder of this paper we discuss alternative structures of travel demand models in more detail.

A trip taken for a specific purpose is characterized by its origin, destination, time of day, mode of travel, and route. We are interested in predicting the volume of trips V_{idhmr} from origin i to destination d during time of day h by mode m via route r. From the point of view of the individual trip-maker or the household, we consider the probability of a trip instead of a quantity or volume of trips. A trip decision consists of several choices: choice of trip frequency f (e.g., how often to go shopping), choice of destination d (e.g., where to shop), choice of time of day h (e.g., when to go), choice of mode m, and choice of route r. Hence, for an individual traveler, we are interested in predicting the joint probability:

$$P(f, d, h, m, r : FDHMR_t) \tag{15}$$

where t denotes an individual or a household in origin i and $FDHMR_t$ is the overall set of alternative trips that consists of all possible combinations of frequencies, destinations, modes, times of day, and routes available to individual t. (The choice of residence location is assumed as given. Travel demand models assume that mobility decisions are fixed.) The alternatives in this set are exhaustive and mutually exclusive. The individual t is always selecting one and only one alternative from this set. (In the following sections a notation for different subsets of FDMHR is used. This notation follows the same logic that was used to define subsets of DM and is, therefore, not explained in the text.)

For simplicity, we will write the probabilities in the remainder of this paper without denoting the set of alternatives. We write the above probability (Eq. 15) as

$$P_t(f, d, h, m, r) \tag{16}$$

A conditional probability previously denoted as $P(m:M_d)$ will now be written as $P(m/d)$. The joint probability previously written as $P(d, m:DM)$ will now be written as $P(d,m)$.

On the disaggregate level, the travel demand function for a given trip purpose predicts the joint probability $P_t(f, d, h, m, r)$. On the aggregate level, the demand function predicts the volume V_{idhmr}. In either case, we have a complex product—a trip—with an enormous number of substitutes. Microeconomic consumer theory tells us that a demand function expresses the quantity of a product demanded as a function of its price, the prices of related commodities (substitutes and complements), and income. The complexities stem from the large number of relevant prices (i.e., price and many price-like attributes) for all the alternative trips.

ALTERNATIVE STRUCTURES OF TRAVEL DEMAND MODELS

With no further assumption, the travel demand model predicts the probability $P(f, d, m, h, r)$, or the volume V_{idmhr}, as a function of the attributes of all the alternative combinations of fdmhr. (For additional simplicity, we drop the subscript t in writing the probabilities in this section.) We denote the explanatory variables as X^1_{fdmhr}, X^2_{fdmhr}, $\ldots$, X^k_{fdmhr}, $\ldots$, X^K_{fdmhr}, or as a vector X_{fdmhr}. (The explanatory variables include all the levels of service, the spatial opportunities, and the socioeconomic variables. The socioeconomic variables are specific to an individual and not to a trip alternative. However, we assume here that they are introduced into the model as having alternative specific values.) Hence, we can write the travel demand model as follows:

$$P(f, d, m, h, r) = F[X_{fdmhr}, \forall fdmhr \in FDMHR] \tag{17}$$

where $[X_{fdmhr}, \forall fdmhr \in FDMHR]$ is a vector that includes all the variables X for all relevant combinations of the subscripts f, d, m, h, and r, and F is the demand function. Alternatively, we can write the utility function for an alternative trip as

$$U_{fdmhr} = U(X_{fdmhr}) \tag{18}$$

Clearly, this results in a very complex demand model. Without further assumptions, for a simultaneous structure this is the type of travel demand model that must be calibrated.

If, however, we make some assumptions about the travel decision-making process we can divide the overall travel demand function into several less complex functions, each including only a subset of all the explanatory variables. That is, under some assumptions we can formulate the travel demand function as a recursive or as an independent structure.

The first assumption that is required is the separability-of-choices assumption that was described earlier and is usually made also with respect to a simultaneous model. The separability assumption with respect to a certain choice says that the conditional probability of this choice given other choices is a function of only a specific subset of the explanatory variables, as depicted in the following example for route choice:

$$\begin{aligned} U_{r|fdmh} &= U^r(X_{fdmhr}) \\ P(r|f,d,m,h) &= F^r[X_{fdmhr}, \forall r \in R_{fdmh}] \end{aligned} \tag{19}$$

In words, the conditional probability of choosing a route given other choices is a function only of the explanatory variables for all routes for given fdmh. If we considered only 2 choices, say, mode and destination, then the separability assumption with respect to mode choice says that the conditional probabilities of choosing a mode given a destination is a function of the variables for all modes but for only 1 specific destination. For this example we write

$$\begin{aligned} P(d,m) &= F^{dm}[X_{dm}, \forall dm \in DM] \\ U_{dm} &= U(X_{dm}) \\ P(d|m) &= F^d[X_{dm}, \forall d \in D_m] \\ U_{d|m} &= U^d(X_{dm}) \\ P(m|d) &= F^m[X_{dm}, \forall m \in M_d] \\ U_{m|d} &= U^m(X_{dm}) \end{aligned} \tag{20}$$

If we calculate the marginal probabilities P(d) and P(m), they will be a function of the vector $[X_{dm}, \forall dm \in DM]$.

An independent structure is possible only if the set of attributes is separable. That is,

$$[X_{fdmhr}] = [X_f,\ X_d,\ X_m,\ X_h,\ X_r] \tag{21}$$

where we can identify only attributes that vary only across a single choice. The independent utility function can be written as

$$U_{fdmhr} = U^f(X_f) + U^d(X_d) + U^m(X_m) + U^h(X_h) + U^r(X_r) \tag{22}$$

The independent travel demand model can be written as

$$\begin{aligned} P(f) &= F^f[X_f, \forall f \in F] \\ P(d) &= F^d[X_d, \forall d \in D] \\ P(m) &= F^m[X_m, \forall m \in M] \\ P(h) &= F^h[X_h, \forall h \in H] \\ P(r) &= F^r[X_r, \forall r \in R] \end{aligned} \tag{23}$$

and

$$P(f,d,m,h,r) = P(f) \cdot P(d) \cdot P(m) \cdot P(h) \cdot P(r) \tag{24}$$

Clearly, this is an unrealistic structure for a travel demand model.

A recursive structure requires the assumption of a sequential decision-making process or a hierarchy of conditional decisions. The sequence is expressed in a recursive travel demand model in 2 ways. The first is the manner in which the set of all trip alternatives is partitioned. In a recursive model of mode and destination choices where mode choice is conditional on the chosen destination, the set of all alternative combinations of mode and destination is partitioned according to destination. The second way is the composition of explanatory variables. For the same example, the problem is how to include in a model of the marginal probability of destination choice the variables, such as travel time and fare, that are defined by destination and mode. The way this is handled is to construct a composite variable that combines the above variable across modes to create a variable that is specific only to a destination. Consider for example the following recursive structure:

$$\begin{aligned} U_{fdmhr} &= U_f + U_{d|f} + U_{m|fd} + U_{h|fdm} + U_{r|fdmh} \\ &= U^f(X_f) + U^d(X_{fd}) + U^m(X_{fdm}) + U^h(X_{fdmh}) + U^r(X_{fdmhr}) \end{aligned} \tag{25}$$

and

$$\begin{aligned} P(f) &= F^f[X_f, \forall f \in F] \\ P(d|f) &= F^d[X_{fd}, \forall d \in D_f] \\ P(m|f,d) &= F^m[X_{fdm}, \forall m \in M_{fd}] \\ P(h|f,d,m) &= F^h[X_{fdmh}, \forall h \in H_{fdm}] \\ P(r|f,d,m,h) &= F^r[X_{fdmhr}, \forall r \in R_{fdmh}] \end{aligned} \tag{26}$$

where each variable is defined as follows:

$$\begin{aligned} X_{fdmh} &= [X_{fdmhr}, \forall r \in R_{fdmh}] \\ X_{fdm} &= [X_{fdmh}, \forall h \in H_{fdm}] \\ X_{fd} &= [X_{fdm}, \forall m \in M_{fd}] \\ X_f &= [X_{fd}, \forall d \in D_f] \end{aligned} \tag{27}$$

If we keep the variables in their original form, then the model for P(f) will include all the explanatory variables $[X_{fdmhr}, \forall fdmhr \in FDMHR]$. The definition of composite variables allows the treatment of X_{fdmh}, X_{fdm}, X_{fd}, and X_f as single variables. In other words, these variables are expressed as a specific function of their elements. For example, we express

$$X_{fdmh} = g[X_{fdmhr}, \forall r \in R_{fdmh}] \tag{28}$$

where g is the composition function. The functional form of the composition rule requires further assumptions.

There are a variety of possible composition schemes. One such scheme that was derived from an assumption of additive utility function (3) is as follows:

$$X_{fdmh} = \sum_{r \in R_{fdmh}} X_{fdmhr} \cdot P(r|f,d,m,h) \tag{29}$$

This composition scheme is essentially a computation of the expected value of the original variable. Another way to observe this is to rewrite Eq. 29 and use the definition of conditional probability as follows:

$$X_{fdmh} \cdot P(f,d,m,h) = \sum_{r \in R_{fdmh}} X_{fdmh} \cdot P(f,d,m,h,r) \tag{30}$$

Thus, the composite variable as defined by Eq. 29 is in accordance with a consistency requirement that the expected value of a variable is maintained. If X is a price variable, then Eq. 30 says that the expected expenditure is consistent in the different stages of a recursive model.

Clearly, there are many other schemes of creating the composite variables, among them a simple sum,

$$X_{fdmh} = \sum_{r \in R_{fdmh}} X_{fdmhr} \tag{31}$$

or the value for the "best" route (10),

$$X_{fdmh} = X_{fdmhb} \tag{32}$$

where r = b is the best route according to some criteria.

Often, several price variables are combined to form a generalized price. Then, the composite variable is a composition of the generalized price instead of each variable separately (3, 8).

Constructing a composite variable from several explanatory variables together amounts to maintaining equal marginal rates of substitution among those variables in the different probabilities of a recursive structure.

Thus, given a separability assumption, a specific sequence assumption, and an assumption on the mathematical form of the composite variables, the overall travel demand model can be formulated as a recursive structure.

A simultaneous structure requires the estimation of an equation that includes a large number of explanatory variables. On the other hand, each equation in a recursive structure includes only a subset of the explanatory variables that are included in a simultaneous model. In addition, the number of variables is reduced by the construction of composite variables. Therefore, a recursive model can be easier to implement, computationally and analytically, than a simultaneous model.

The separability and the sequence assumptions required by a recursive travel demand model are equivalent to an assumption of a conditional decision structure. The choice of a particular fdmhr combination is made from a relatively large set of alternatives. It makes sense to partition the set of all alternatives into collections of nonoverlapping subsets. Consider, for example, 2 choices: destination and mode. The set of all alternative combinations of d and m, DM, is large. We can partition DM into the subsets M_1, M_2, ..., M_d, ..., M_D, where each subset includes all the alternative modes to a specific destination. The assumption is that the traveler is, first, choosing among these subsets or choosing a destination and, second, choosing within the chosen subset or choosing a mode. The choice of mode is now a function of only the characteristics of available modes to a given destination. The choice of destination depends on some measure of the expected attributes of all modes to a given destination. The utility function of a dm combination is assumed to consist of 2 parts: one for each choice. The choice of destination is based on the utility of the destination, which is also dependent on the expected attributes from the modes available to this destination.

However, we can also partition the set DM according to modes as follows: D_1, D_2, ..., D_m, ..., D_M. When we apply choice models to this or the previous sequence we do not expect the predictions to be the same. The problem is, therefore, to know when the consumer decomposes his or her decision into stages and what partitions are used.

If we modeled the choice of an fmdhr combination as a deterministic optimization problem, it would not be important what partitions were used. The reason that we expect different partitions to give different results is due to the probabilistic choice mechanism and the computation of expected attributes from lower stages.

The problem with travel decisions is that we cannot find a unique natural sequence of partitions that will be generally applicable. Therefore, a simultaneous structure is superior to a recursive structure. In general, the simultaneous structure of a travel demand model consists of the following conditional probabilities:

$$
\begin{gathered}
P(f \mid d, m, h, r) \\
P(d \mid f, m, h, r) \\
P(m \mid f, d, h, r) \\
P(h \mid f, d, m, r) \\
P(r \mid f, d, m, h)
\end{gathered}
\tag{33}
$$

Under particular behavioral assumptions we can place restrictions on this general structure and obtain alternative simultaneous structural forms. Consider the following simultaneous structure:

$$
\begin{gathered}
P(f \mid d, m, h, r) \\
P(d \mid f, m, h) \\
P(m \mid f, d, h) \\
P(h \mid f, d, m, r) \\
P(r \mid f, d, m, h)
\end{gathered}
\tag{34}
$$

The conditional probabilities of mode choice and destination choice are not conditional on the chosen route because we cannot generally identify alternative modes or destinations for a given route.

The choices that are conditional on f in either a simultaneous or a recursive structure are defined only for $f > 0$ because it does not make sense to define alternative trips when no trip is taken. It may be argued that for some trip purposes the choice of trip frequency is based on some measure of expected accessibility and is not dependent on the actual values of d, m, h, and r. Therefore, it is natural to partition according to f and, for each f, have all possible combinations of mdhr.

If for some trip purpose the choice of time of day is constrained or limited to alternative times for which the traveler can be assumed to be indifferent, then it is possible to partition according to f and, for each f, have all possible combinations of m and d. Then, partitioning according to dm combinations creates the sets of alternative routes for a given trip. This decomposition implies the following structural probabilities:

$$
\begin{gathered}
P(f) \\
P(d \mid f, m) \\
P(m \mid f, d) \\
P(r \mid f, d, m)
\end{gathered}
\tag{35}
$$

The choices of mode and destination are simultaneous, but recursive with respect to f. The choice of route is recursive with respect to f, d, and m. This is essentially the structure that is assumed in the empirical study reported elsewhere (1). Time of day was excluded because the sample included only off-peak shopping trips.

It should be clear that in simultaneous and recursive structures we can derive any conditional or marginal probabilities. (However, only the structural probabilities are causal.) Therefore, for forecasting, it is possible to use the joint probability directly or any combination of marginal and conditional probabilities provided that their product is equal to the joint probability. For example,

$$\begin{aligned} P(f, d, m, h, r) &= P(f) \cdot (Pd \mid f) \cdot P(m \mid f, d) \cdot P(h \mid f, d, m) \cdot P(r \mid f, d, m, h) \\ &= P(f) \cdot P(h \mid f) \cdot P(m \mid f, h) \cdot P(d \mid f, h, m) \cdot P(r \mid f, h, m, d) \qquad (36) \\ &= P(f) \cdot P(h, m, d \mid f) \cdot P(r \mid f, h, m, d) \end{aligned}$$

DIRECT AND INDIRECT TRAVEL DEMAND MODELS

A distinction was made between simultaneous, recursive, and independent travel demand models. It was based on the behavioral assumptions of the model. Another distinction that is often made is between direct and indirect travel demand models (8). This distinction, however, is based on the way that the travel demand model is used for forecasting.

A direct demand model predicts directly the joint probability $P_t(f, d, m, h, r)$, or the volume V_{idmhr}, as a function of all the explanatory variables. In an indirect travel demand model the joint probability, or the volume, is predicted with several intermediate steps. Each step corresponds to a single choice or to a single subscript of the volume. For example, one equation can predict the number of trips taken by the household, another equation will distribute trips among the various destinations, and so forth. Hence, in a direct model a forecast is made with a single equation, while in an indirect model a forecast is made by a multiequation model.

There are a variety of possible indirect models in which an intermediate step may predict directly more than one choice. For example, one equation can predict the number of trips taken by the household to a certain destination, another equation will split these trips among the various modes of travel, and so forth.

From the forecasting point of view it makes no difference whether we use a model as direct or as indirect. The way a model is used for forecasting should be determined only on the basis of computational efficiency considerations.

The sequence used for forecasting does not necessarily have a behavioral interpretation. Even a recursive model could in principle be used for forecasting in an indirect fashion that does not correspond to the structural sequence.

In this paper we are concerned with the behavioral structure of travel demand models. However, we can express any given model in many different ways. Therefore, an obvious question to ask is, How can the behavioral structure of a given model be recognized?

In general, the answer to this question is that the behavioral structure cannot be determined unless the model is written in its structural form. This answer could be explained by the analogy of a structure of simultaneous equations. Given a reduced form, which is used for forecasting, it is impossible to determine the original structure. (A reduced form of a system of simultaneous equations is the solution of endogenous variables in terms of the exogenous ones.) However, in travel demand models that were structured with composite variables, the structure may be discerned. It is possible to recognize the sequence through the order of composition (e.g., order of summation) that is maintained in a composite variable no matter how the model is expressed.

EMPIRICAL PROBLEM

As mentioned earlier, the complexity of the overall travel demand function stems primarily from the large number of alternatives and attributes that call for a large number of variables. To appreciate the dimensions of the overall travel demand function, consider the following example of travel choices.

Suppose that for a certain trip purpose a person has the following options: 2 daily trip frequencies (1 trip or no trip), 4 destinations, 2 modes of travel, and 2 times of day (peak or off-peak). The total number of alternatives facing the decision-maker is 17 (16 one-trip alternatives and 1 no-trip alternative). Suppose that for each 1-trip alternative there are only 2 price variables, travel time and travel cost. (The price of a no trip is 0.) The total number of price variables is 32. If we increment each choice by 1 additional option, we have 91 alternatives and 180 price variables.

It appears that the joint probability may be too complex and the number of variables too large to be condensed into a single relation. The most important question is whether we can calibrate a choice model with such large numbers of alternatives and variables. Using a recursive structure, we will have to calibrate 4 choice models but with the number of alternatives in each model equal to the number of options for the corresponding choice. The data requirements are identical for both structures unless further assumptions are made.

It is not clear whether it is less expensive to calibrate 4 models each with a small number of alternatives rather than 1 model with many alternatives (assuming, of course, that estimation of a joint probability is feasible).

Under the presumption that the implementation of a recursive model is easier and less expensive, is the additional expense to implement a simultaneous model justified? The answer is unclear. Costs can be compared only together with the benefits. Therefore, we need to know how the simplifying assumptions of a recursive model affect the results of the prediction process.

These are critical issues that can only be addressed by an empirical study. The evidence from the calibration of alternative structures in another study (1) indicates that (a) it is feasible to calibrate the simultaneous model and (b) the calibration results are highly sensitive to the assumed structure. This empirical evidence is not absolutely conclusive, however, because it is based on a small sample and only on a subset of the travel choices for a single trip purpose. Future research is needed to extend the empirical evidence to different data sets, larger samples, and a complete set of travel choices for all trip purpose categories.

SUMMARY AND CONCLUSION

A multidimensional choice situation can be represented by a simultaneous or recursive model structure. The paper described assumptions of each structure and argued that, in the absence of restrictive assumptions about behavior, travel decisions are more realistically represented by a simultaneous model structure. It is simple to estimate a recursive structure, for each choice model contains fewer alternatives and variables. The primary issues in the selection of a strategy for calibration are (a) whether calibrating the simultaneous model is feasible and (b) what effect the use of a recursive rather than a simultaneous model structure has on the estimated parameters.

In particular, the calibration strategy is independent of the method of prediction to be used. That is, both the simultaneous and recursive models can be used as direct prediction models based on the joint probabilities or as indirect prediction models by deriving any desired set of marginal and conditional probabilities.

Empirical evidence for a 2-dimensional choice situation indicates that calibration of the simultaneous choice model is feasible and equally important and that calibration as a recursive structure leads to different parameter estimates, which are very sensitive to the order of decision-making assumed. Additional research is required to verify these results and to extend them to more complex choice situations.

REFERENCES

1. Ben-Akiva, M. E. Structure of Passenger Travel Demand Models. M.I.T., PhD thesis, 1973.
2. Bock, R. D., and Jones, L. V. The Measurement and Prediction of Judgment and Choice. Holden-Day, San Francisco, 1968.

3. A Disaggregate Behavioral Model of Urban Travel Demand. Charles River Associates, Inc., 1972.
4. Leontief, W. Introduction to a Theory of the Internal Structure of Functional Relationships. Econometrica, Vol. 15, No. 4, Oct. 1947.
5. Luce, R. D. Individual Choice Behavior. Wiley, New York, 1959.
6. Luce, R. D., and Suppes, P. Preference, Utility and Subjective Probability. In Handbook of Mathematical Psychology (Luce, R. D., Bush, R. R., and Galanter, E. eds.), Vol. 3, Wiley, New York, 1965.
7. Malinvaud, E. Statistical Methods of Econometrics. Rand McNally, Chicago, 1966.
8. Manheim, M. L. Practical Implications of Some Fundamental Properties of Travel Demand Models. Highway Research Record 422, 1973, pp. 21-38.
9. Muth, R. F. Household Production and Consumer Demand Functions. Econometrica, Vol. 34, July 1966.
10. Quandt, R. E., and Baumol, W. J. Abstract Mode Model: Theory and Measurement. Journal of Regional Science, Vol. 6, No. 2, 1966.
11. Strotz, R. H. The Empirical Implications of a Utility Tree. Econometrica, Vol. 25, No. 2, April 1957.
12. Strotz, R. H. The Utility Tree—A Correction and Further Appraisal. Econometrica, Vol. 27, No. 3, July 1959.

Structure of Disaggregate Behavioral Choice Models

Stein Hansen, Møre Og Romsdal Distriktshøgskole,
Molde, Norway

This paper reviews the foundations of some of the choice models most frequently used in transportation planning and outlines the strengths and weaknesses of these approaches in the analysis of travel behavior. The first part deals with algebraic utility theory. The foundations of the textbook approach are briefly reviewed and an evaluation is made of the characteristics and economics of time allocation models. The different algebraic utility structures implied by the algebraic demand models most frequently found in practice are discussed. The second part of the paper attempts to link economic utility theory to that approach developed in mathematical psychology, and the distinction is made between fixed and random preference models. The practical models in this field are derived from a probabilistic choice approach, and the development of the well-known logit formula is briefly outlined. Certain similarities to the separability properties discussed in the first part of the paper are indicated. The paper closes with suggestions of the direction of further development of simultaneous models or new theoretical support for particular choice sequences or both.

Modern analyses of travel behavior have primarily been concerned with choice rather than demand as a point of departure. However, travel demand is frequently used to label travel choice models. As a consequence, the relation—or lack of such—among utility, choice, and demand should be understood by analysts who determine what traveler preferences are and evaluate transportation policy and investment schemes.

Two analytical approaches are available for the description of individual choice behavior: algebraic and probabilistic.

Although probabilistic elements play an important role in any transportation planning model, a distinction is made in this paper based on the underlying behavior assumptions as expressed in the consistency axioms of choices. Thus, econometric models based on traditional microeconomics and extensions thereof are considered algebraic, whereas choice models based on thresholds in choice, random utility indicators, and "almost optimizing behavior" are considered probabilistic.

ALGEBRAIC THEORIES OF CONSUMER CHOICE

Foundations

The microeconomic theory of choice deals with a decision rule by which consumer purchases are made under given market conditions. It links desires and action and provides the means for transforming utility restrictions into demand properties. Since demands are observable but utility is not, any check on theory requires translating assumptions on the latter into properties of the former. Then if individual demands do not have these properties, the theory does not give an adequate explanation of individual behavior.

The decision unit in traditional microeconomic theory acts in a pure exchange economy with n commodities. The unit is described by his consumption set $X = (X_1, \ldots, X_n)$, which is a closed, convex, and bounded subset of commodity space S; his preferences U, which is a complete, continuous, twice differentiable, and strictly convex preordering of X; and his initial endowments $\overline{X} = (\overline{X}_1, \ldots, \overline{X}_n)$, which is a vector in S.

The behavior of the decision unit is derived from these assumed characteristics: He regards all commodity prices, $p = (p_1, \ldots, p_n)$, fixed regardless of his own actions, and he chooses the greatest element for U in his budget set, $X \epsilon S | p \cdot X = p \cdot \overline{X}$. Consequently, the indifference map of choices in this model is compatible with the conclusion that unique and continuous demands exist and express the equilibrium point for the consumer in the sense that maximum utility is attained (15, 19, 23).

As a consequence of the various constraints just introduced, the demand functions must satisfy the following properties:

1. Reallocations of the budget due to income and price changes respectively must continue to exhaust total income (the adding-up property);
2. Multiplying all prices and income with the same factor should leave demands unaltered (the homogeneity property);
3. Demand for a specific commodity cannot increase as its price increases and all other prices remain unchanged, and income changes (raises) just enough to compensate for the price increase (the negativity property); and
4. The compensated cross-demand effects are symmetric,

$$\delta X_i / P_{j_{U=\overline{U}}} = \delta X_j / P_{i_{U=\overline{U}}}, \text{ for all } i \neq j \tag{1}$$

This ensures integrability or choice consistency and rules out the possibility that demand functions (or choice functions) are such that a sequence of price and income changes will lead the consumer through a series of positions, each of which is preferred to the previous one, but which in the end lead back to the starting point (the symmetry property).

The pure microeconomic choice theory presented here is not sufficient to specify an operational model. More specific behavioral assumptions are needed for that purpose. Before an assessment is made of the demand models in applied consumer choice economies, a couple of other recent approaches to the deterministic microeconomic analyses of consumer choice are reviewed.

Characteristics and Consumer Demand Theory

It has been argued that the pure microeconomic theory of choice does not offer a satisfactory account of why some goods are consumed more than others or why some goods are not purchased at all. A further difficulty arises with the introduction of new goods. This creates particular difficulties in constructing cost of living index numbers and in accepting further consumption of outdated commodities by a group of homogeneous individuals.

Lancaster (21) suggested that these difficulties can be lessened by regarding the elements of the set of alternatives by which the consumer orders his preferences U as bundles of characteristics c associated with goods X rather than as bundles of goods—consequently, U(c). Thus, for example, the various means of travel from a given home base to a given work base constitute a closely related group of goods because they, and they alone, supply the characteristics with respect to arrival time at work and commuting comfort.

Formally, let g be a fixed number representing the total number of characteristics attainable from all goods in the economy. Let c_j represent the objectively measurable quantity of the j th characteristic and $c = (c_1, \ldots, c_g)$. With each commodity bundle X is associated a specific vector of characteristics such that

$$c = h(X) \tag{2}$$

The consumer decides on purchases by maximizing U(c) subject to Eq. 2 and the usual budget constraint $p \cdot X = R$. Defining

$$U(X) = U[h(X)] \tag{3}$$

and assuming the existence of the basic utility model properties, we can derive demand functions having properties similar to those discussed above. Certain problems may arise, however.

A unique bundle of characteristics does not necessarily imply a unique bundle of goods. No problems arise so long as the number of distinct goods does not exceed the number of characteristics, but modern complex economies are probably characterized more by goods than by characteristics, and this is the world we set out to model. In this case, the quantity of none of the goods would be uniquely determined. One consequence of the goods-characteristics model is then that the goods-demand curves may be perfectly elastic at a given price. The commodity demands would then be demand correspondences, which in terms of the theory of the previous section would follow from a relaxation of the strictly convex assumption to one of weakly convex indifference curves in commodity space.

Little is known at present of the practical importance of the Lancaster approach. But it surely has some interesting theoretical properties that make it possible to illuminate economic problems that are insoluble by traditional means.

Microeconomic Theories of the Allocation of Income and Time

Some recent developments in microeconomic theories of consumer choice have focused on the time allocation problem and have recognized that leisure covers time used for consumption, commuting, and sleeping, which are necessary activities in order to perform further work (2, 8, 11, 12, 16). The increasing interest in this field is probably due to the idea that in wealthy countries people behave as if time is a scarce resource.

In attempting to construct a "general theory of the economics of time allocation," Bruzelius (8) proposes to integrate the traditional consumer choice theory, discussed in the previous section, with a similarly pure theory for time allocation. This is motivated from the shortcomings of both theories. The pure theory of time allocation rests on a utility function defined for time activities only. The quantities are measured in time units. Utility is maximized subject to a time resource constraint only.

In general, the utility generating activities are connected with both time and goods; i.e., the consumer will usually not indulge in something that is a pure good or a pure time activity. A general theory should require that the consumer allocation problem be described in terms of the 2 dimensions, the simpler extreme problems being special cases.

The "general model" suggested by Bruzelius (8, pp. 9-15) is as follows: The utility function

$$U(X_1, \ldots, X_n, T_1, \ldots, T_n) \tag{4}$$

where

X_i = quantity of good i and
T_i = time used along with the use of X_i,

is maximized subject to the following constraints:

$$\sum_{i=1}^{n} P_i X_i - r_w T_w - V \leq 0 \tag{5}$$

where

P_i = price of good i,
r_w = wage rate,
T_w = work time, and
V = exogenous income.

Equation 5 expresses the economic budget constraint

$$\sum_{i=1}^{n} T_i + T_w - \overline{T} \leq 0 \tag{6}$$

where $\overline{T}$ = total time. Equation 6 expresses the time resource constraint. In case of an inequality, the constraint is closed by a slack variable T_{n+1}.

$$g_i(X_i,\ T_i) \leq 0,\ \text{for } i = 1,\ \ldots,\ n \tag{7}$$

Equation 7 expresses physical relations between the time and the good variables that enter into the activity-producing process.

$$X_i \geq 0,\ T_i \geq 0,\ T_w \geq 0 \tag{8}$$

Equation 8 expresses the nonnegativity constraints on the endogenous variables in the model.

To compare this model with the traditional consumer demand theory, we consider the first order conditions for maximum utility (8, p. 13). The interpretation of these conditions can be carried out in a variety of ways depending on the explicit character of the physical relation (Eq. 7). The following explicit version of Eq. 7 is chosen for illustration:

$$g_i = a_i X_i - T_i \leq 0 \tag{9}$$

where it is assumed that $X_i = 0 \Leftrightarrow T_i = 0$. This can be interpreted to say that to each amount of the good X_i there is a minimum of time that must be allocated to it, but this minimum may be exceeded. Or, to look at it the other way, associated with each level of T_i there is a maximum amount of X_i, but the consumer may choose a lower level. According to this model,

1. The marginal utility of X_i should equal the marginal utility of monetary outlays plus the marginal utility of saving time in producing the particular activity multiplied by the number of units of time a_i required as a minimum per unit of X_i; and
2. The marginal utility of time in activity i should equal the marginal utility of time as a resource plus the marginal utility from saving time in commodity i multiplied by 1 (because of the choice of Eq. 9).

This approach has additional features that should be appreciated in applied economics. If the utility function (Eq. 4) is written in terms of the utility generating activities Z_1, $\ldots$, Z_n,

$$U = U(Z_1,\ \ldots,\ Z_n) \tag{10}$$

then Eq. 7 may be viewed as a household production function. Although the X_i and T_i have been treated as scalars above, X_i actually is a set of market goods, X_{i1}, X_{i2}, $\ldots$, X_{in}, used in producing Z_i, and similarly for T_i. This theoretical approach yields not only information on which market goods are close substitutes and which are not [in a way similar to that described by Lancaster (21)] but also justification for the use of weakly separable utility functions. This property of the model implies that the marginal rate of substitution between any 2 factors (markets goods and time) producing Z_i

is independent of the quantity of any good not used in this particular process or, equivalently, the ratio of the marginal utilities of the 2 factors depends only on the factors used in that particular production process (27). Consequently, this approach gives theoretical justification for reducing the number of cross effects to be quantified in a planning context.

Price of Time

The concept of the price of time has initiated a lot of research by people involved in transportation planning. In accepting the modeling techniques reviewed here, one must make a clear distinction between the price of time as a resource and the value or price of saving time.

The first of these stems from the fact that the consumer may regard time as a scarce resource (e.g., the constraint in Eq. 6) and expresses the willingness to pay to have an additional unit of time were this possible.

The value of time saving concerns the willingness of the consumer to pay to have time reduced in one activity in order to allocate it to some other activity. In principle there is no reason why this price should not vary from activity to activity or from consumer to consumer and be either higher or lower than the price of time as a resource.

Utility and Demand in Deterministic Models

We can now assess the fruitfulness of the algebraic modeling approach. Starting from the demand functions described earlier, we conclude that there are n income responses and n^2 price responses that are of immediate interest to the analyst. That is, data for estimation purposes must be sufficient to yield $n(n + 1)$ pieces of information if the demand equations are to be estimated without further a priori information. The properties of these demand functions come in handy in this context because the data needs are considerably reduced as a consequence of the a priori restrictions imposed by these properties.

The homogeneity property gives n restrictions, the adding-up property gives $n + 1$ restrictions, the symmetry property gives $\frac{1}{2}n(n - 1)$ restrictions, and the negativity property gives n inequalities. If we ignore the inequalities, the unrestricted $n(n + 1)$ responses are thus reduced to $(n - 1) \cdot (\frac{1}{2}n + 1)$, and that obviously is a considerable improvement with respect to basic data needs. Still, however, there are likely to be too many simply because n is usually large and data are seldom plentiful.

As a consequence, our discussion of some explicit demand functions will be related both to the consistency aspect and to the question of practical application. I intend not to provide a complete list of demand models applied in transport economics but to compare basic differences in the behavioral structure of a few frequently used models in comparative statistics. By far the simplest demand function to be used is

$$X_i = b_i(R/P_i), \text{ for } i = 1, \ldots, n \tag{11}$$

where R = income or total expenditure, and X_i and P_i have been defined already. Obviously, the coefficient $b_i \geq 0$ and $\sum_{i=1}^{n} b_i = 1$. This set of functions implies a utility function of the form

$$U = \prod_{i=1}^{n} X_i^{\beta_i} \tag{12}$$

where β_i = structural coefficient. This model implies the following demand properties:

1. All budget elasticities of demand are unity implying straight Engel curves through the origin (Engel curves express demand solely as a function of the consumer's income);
2. Expenditure on each commodity is a constant, and when R is given all the own-price-elasticities are equal to -1;
3. It follows from the specification (Eq. 11) that all cross elasticities are 0; and
4. The Slutzky equations

$$\frac{\partial X_i}{\partial P_j} = \left[\frac{\partial X_i}{\partial P_j}\right] U = \text{constant} - X_j \cdot \frac{\partial X_i}{\partial R} \tag{13}$$

make it clear that because of properties 1 and 3

$$\left[\frac{\partial X_i}{\partial P_j}\right] U = \text{constant} > 0$$

which means that all pairs of commodities are net substitutes.

The model (Eq. 11) is clearly inconsistent with the empirically well-established Engel's law, which states that the proportions of the budget devoted to certain groups of commodities vary considerably as the budget changes (7, p. 1173). This is a strong argument against the application of the model.

Another simple (from the econometric point of view) class of demand functions are those that are linear in $P_1, \ldots, P_n$, R (or can be transformed into a linear form). The most obvious is

$$X_i = \sum_{j=1}^{n} \frac{P_j}{P_i} a_{ij} + b_i \frac{R}{P_i} \tag{14}$$

where a_{ij} = structural coefficients, for i, j = 1, ..., n. The theory of consumer demand developed in the above implies that there exist numbers $s_1, \ldots, s_n$ such that Eq. 14 can be written as

$$X_i = s_i + \frac{b_i\left[R - \sum_{j=1}^{n} P_j \cdot s_j\right]}{P_i} \tag{15}$$

This model, developed by Stone, is known as the linear expenditure system, and has been one of the most important in empirical demand studies (15, pp. 315-318).

Equation 15 says that expenditure on commodity i can be divided into 2 parts: the purchase of a fixed quantity s_i(survival minimum) and a constant fraction b_i of what is left after all the bare survival quantities of all commodities have been bought. The demand functions imply a utility function of the form

$$U = \prod_{i=1}^{n} (X_i - s_i)^{b_i} \tag{16}$$

This model implies that, if $R > \sum_{i=1}^{n} P_i s_i$, then all commodities are normal (positive income elasticities), all pairs of commodities are net substitutes (see definition below Eq. 13), and the demand for each commodity is inelastic with respect to its own price (15, pp. 315-318).

The model is capable of behaving more in accordance with Engel's law than the simple model (Eq. 11). Although the Engel curves still are straight lines, they do not pass through the origin but rather through the point $s_1, \ldots, s_n$. Thus, it is perfectly possible for the budget share for food, for example, to decrease as the budget increases.

Another demand model often seen in applied transport economics is the log-linear.

$$\log X_i = \log C_i + \sum_{j=1}^{n} a_{ij} P_j + b_i \log R \tag{17}$$

where C_i = constant, for $i, j = 1, \ldots, n$. This is a constant elasticity model where the homogeneity restriction requires $\sum_{i=1}^{n} a_{ij} = -b_i$. The difficulty with Eq. 17 and several other applied demand models is that it is either extremely difficult or impossible to find a traditional static algebraic utility model from which the complete set of demand functions chosen can be derived. [Several papers contain an exercise in deriving explicit demand functions from utility functions (4, 9).]

Only the trivial case where $b_i = -a_{ii}$ and $a_{ij} = 0$ for $i \neq j$, which turns Eq. 17 into Eq. 11, is capable of making this derivation easily come through. Equation 17 can, however, almost be derived from an indirect additivity type of utility model (7, p. 1204).

Given the direct utility function in terms of X_i and the logically derivable demand functions $X_i(R, P_1, \ldots, P_n)$, an indirect utility function

$$U = U[X(R, P)] \tag{18}$$

is implied that relates the maximum utility attainable to the exogenously determined level of prices and income. Since any such function can be interpreted as the dual of the direct utility function, minimizing it subject to given P and R will lead to the demand equations.

Only in a special case will directly and indirectly additive utilities occur in the same model. Assuming additive indirect utilities

$$U = \sum_{i=1}^{n} U_i \left(\frac{P_i}{R}\right) \tag{19}$$

implies strong behavioral constraints. Brown and Deaton (7, p. 1201) showed that for all indirectly additive models the uncompensated cross-price elasticities are identical for all goods affected and depend only on the good whose price has changed:

$$(\partial X_i/\partial P_j)\,(P_j/X_i) = (\partial X_k/\partial P_j)\,(P_j/X_k), \text{ for all } i, k \neq j \tag{20}$$

It is, however, worth noting that Brown and Deaton (7, p. 1203) conclude that in all relevant respects the linear expenditure system, which implies linear demands, is superior to the indirect additive utility model.

The last travel demand model to be commented on is closely related to a well-known variant of the gravity formula, which can be derived from entropy maximization (30).

$$X_{ik} = A_i B_k e^{-C_{ik}/\beta_0} \tag{21}$$

where

X_{ik} = total travel (for all households) from i to k,
A_i = number of households at i,
B_k = structural coefficient, and
C_{ik} = cost of a round trip from i to k.

Assuming an integrated logarithm utility model,

$$U = U_0 + \sum_k [(\beta_k + \beta_0) X_k - \beta_0 X_k \log X_k] \tag{22}$$

where

U_0 = constant,
$\beta_0, \ldots, \beta_k$ = structural coefficients, and
X_k = number of household trips to k.

Beckmann and Golob (4) have shown that Eq. 22 leads to

$$X_k = e^{\beta_k/\beta_0 - C_{ik}/\beta_0} = \beta_k \cdot e^{C_{ik}/\beta_0} \tag{23}$$

If all households at i have identical utility functions, the aggregate gravity formula (Eq. 21) follows. This particular model does, however, violate the nonsaturation axiom since the marginal utilities $\partial U/\partial X_k$ approach $-\infty$ for large values of X_k.

Equation 22 is an additive utility model that leads to very simple demand functions (Eq. 23). No cross effects are assumed to exist; consequently, the model is incapable of dealing with some of the most urgent policy problems in transportation planning today.

Our review of algebraic demand models has indicated that either practical models are directly based on the theory or they are designed so that one or more of the theoretical properties can be subjected to empirical testing. Despite the common basis in algebraic utility theory, the models in use may appear surprisingly dissimilar and reflect quite different assumptions regarding the reactions of the decision unit to price and income changes resulting from policy decisions.

As a consequence, one should be somewhat careful when postulating econometric travel demand models. More efficient models may result once the aim of the study is clearly defined and the behavioral assumptions on which the explicit model is to be based have been chosen. The first question the analyst will face in choosing his set of assumptions is, Will the choice of assumptions influence the major conclusions to be drawn from the analysis? Only a couple of such problems frequently faced by travel demand analysts are discussed here. Should a theory of travel choice behavior be mode specific or mode abstract? Are separability assumptions acceptable? Are sequential choice assumptions acceptable?

The first question has been discussed in previous works (3, 6, 9, 26, 28). A mode-specific model treats each travel mode as a specific commodity with its own demand schedule. This is principally in line with the traditional theory of consumer choice. A mode-abstract model, on the other hand, regards travel by different modes between 2 points in space as distinct observations appearing in the same econometric equation. This modeling approach is philosophically in line with Lancaster's characteristics approach (21).

Assuming that the same independent variables are all relevant and the only relevant variables in both models, we can construct a mode-abstract model to be a special case of a mode-specific model including several modes, provided the regression coefficients of each explanatory variable can be assumed to be mode independent. This hypothesis can be tested by means of Chow's equality test (10), which can be applied to the mode-specific model.

The assumption of separability is essential when the travel market is analyzed alone or when travel and housing are treated as one commodity subgroup to be distinguishable as a group of commodities and services. We have earlier indicated that acceptance of the household production functions in utility models justifies the use of weakly separable utility functions in demand studies. If we can also assume that the household production functions are homogenous to the first degree, the number of parameters of the family of demand functions for the market goods is drastically reduced, and simpler and more manageable demand (choice) models become available (27).

Whether to simplify further by introducing even stronger separability assumptions is a question of the trade-off between realism and computational ease, although shortage of data may force further simplification. One should, however, always ask what consequences further separability assumptions will have on analytical conclusions. The following types of separability are frequently found in the literature (15).

1. Pearce separability implies that the marginal rate of substitution (MRS) between any 2 goods within a given group (travel and housing or perhaps only travel) is independent of the quantity of any good but those 2.
2. Homogenous separability (want independence) implies homothetic indifference surfaces for a given group with respect to origin. In other words, the demand elasticities of each good within the group with respect to expenditure on the particular group (travel) is unity. This particular type of separability requires that one must never group luxuries, near luxuries, and necessities.
3. Strong separability implies that the MRS between any 2 goods in any distinct groups (travel and food) is independent of any good in any third group (clothing).
4. Additive separability implies the existence of continuous functions $v_1, \ldots, v_n$ such that, for all feasible X, $U(X) = \sum_{i=1}^{n} v_i(X_i)$.

It is frequently assumed that "what consumers in fact do is to set aside or commit sums of money for broad general purposes, and decide at the appropriate time on the detailed disposition of these sums" (15, p. 153).

Separability assumptions give a further possible justification for such a budgeting procedure in which the decision to commit a sum of money to a particular purpose is taken, not on the basis of detailed knowledge or prediction of the prices of individual goods on which it is to be spent, but rather on a notion of the general level of those prices.

Green (15, pp. 154-156) shows that only homogenous separability will meet the requirement that a 2-stage budgeting procedure of the "within-group type" be consistent in the sense that it leads to the same optimal vector of quantities as if one had found directly the quantities by means of the general 1-stage budgeting procedure in traditional choice analyses.

From the outline earlier in this paper, the reader may be bothered by one of the implications of homogenous separability—that of unity demand elasticities with respect to group budgets. However, the budget constraints may be adjusted so that a linear expenditure model appears. As indicated earlier, this model implies demand elasticities with respect to expenditure that may perfectly well be consistent with Engel's law.

Having chosen among the various degrees of separability to justify simpler models, a traffic analyst may be faced with the next question, Are the behavioral theories reviewed compatible with a specific order in which the various travel choices follow each other?

Although to introduce separability assumptions on theoretical grounds seems worthwhile, the question of sequential assumptions is hardly compatible with the static models reviewed above. One may perhaps argue that the sequence chosen in most urban transportation planning models is a consequence of the time horizon relevant to each choice. That is, choice of home residence is a long-run decision to the household, whereas choice of route to travel along is a short-run decision. Consequently, different sets of variables should explain these choices, and treating them separately may be both practical and theoretically justifiable. However, the question of which choice is made first does not seem to be compatible with the static algebraic choice models above.

Even though static theory seems to be incompatible with particular travel choice sequences, a sequential estimating procedure may be strongly recommended if it can be shown that the parameter values to be estimated will not be influenced by the choice of choice sequence. Such independence is perhaps present when the decision-maker is facing very simple decisions, and perhaps homogenous separability can be assumed. In such a case, the practical model can be significantly simplified, and research to clarify the role of the particular sequence chosen ought to be given high priority before decisions are made with regard to further model developments.

If parameter estimates can be shown to be sensitive to the choice of sequence in traffic models, this should lead planners to seriously reconsider the use of present urban transportation models in selecting transportation policies and perhaps to concentrate on developing dynamic utility maximizing models based on a utility tree approach.

PROBABILISTIC ANALYSES OF CHOICE

Foundations

Efforts to test the validity of algebraic choice theory have not provided it with an overwhelming amount of support. One possible explanation is that observable conclusions of the theory have not been correctly interpreted in light of the data base used in testing. The consumer may certainly misjudge his actual preferences or permit them to be altered by random shocks. By recognizing such possibilities, analysts may give new implications of utility maximization to provide more appropriate foundations for empirical tests.

The assumption should be that consumer behavior has a probabilistic consistency and not a deterministic consistency. Several recent authors have approached the analyses of choice behavior by describing it as a probabilistic rather than a deterministic phenomenon. Two basically different theories may form the basis for a probabilistic choice theory.

One deals with a consumer whose preferences obviously exist and can be assumed to be fixed, but he himself is not completely aware of what they are. Nevertheless he must still make decisions even when facing such uncertainty. On such occasions the consumer cannot always be expected to pick the utility maximizing bundle from his budget set. The consumer makes errors in determining his optimal commodity bundle. The probabilistic models developed on this basis are referred to as fixed preference models.

Alternatively, suppose that the consumer's preferences themselves are subject to random shocks. Thus, a sudden traffic accident may increase his desire relative to other commodities for better safety devices, or a sudden inconvenient delay may change his commuting pattern. Randomness is present, but for a different reason than in the fixed preference models, and models based on these premises are referred to as random preference models. Katzner (19, pp. 161-167) has briefly formalized the distinction between these 2 basic approaches.

In the fixed preference models, each choice does not necessarily represent a utility maximizing point in commodity space. Consequently, the functions relating the chosen commodity bundles to prices, income and the random term that shows deviations from optimum choices, cannot always be interpreted as demand functions. A fixed preference model may be required to yield as a result of repetitive choices an "average" commodity bundle compatible with the utility maximizing bundle. Observing only one choice in commodity space that violates basic demand properties consequently does not suffice to refute demand theory.

Assuming a random preference model implies random demands since each choice is such that maximum utility is attained. Empirically, even such a model may lead to the perhaps incorrect rejection of demand theory.

Using data for a limited time period may yield irrationality as a conclusion, although the reason for the observed changes in behavior is due to the random elements influencing the consumer's preferences. In reality, each choice comes from a different utility maximizing relation.

To model this assumed optimizing behavior in practice is an extremely difficult task, and practical choice models have therefore chosen a much simpler point of departure. Rational behavior within the framework of a pure theoretical random preference model may contradict the basic axioms in the more pragmatic probabilistic choice models to be presented in the next section. Hildenbrand (18, pp. 414-420) has, for example, shown that rational behavior on the average within a rather general pure theoretical random preference model may be inconsistent with the basic choice axiom of Luce to be discussed later. Stochastic transitivity, according to Marschak's meaning (27, p. 318), is another assumption violated by the rational individual in Hildenbrand's theory.

Probabilistic Choice Models in Practice

In the application of demand or choice theory to practical problems, the usual procedure is to define a limited time period of analyses for which cross-sectional choice data are collected from a random sample of individuals. The preferences of the individuals in this population can be described partly in nonrandom terms that reflect representative tastes and partly in random terms that reflect individual idiosyncracies in taste, whatever the reasons for these are.

One fairly general model of this kind has been presented by McFadden (25, pp. 9-11). An individual in the population faces J alternatives, each described by a vector of attributes X_j. The individual has a utility function that can be written in the form

$$U = V(X) + E \tag{24}$$

where V is nonrandom reflecting representative population tastes and E is random reflecting the individual idiosyncracies in tastes for each attribute vector X. The probability that an individual drawn at random from the population will choose alternative i among the J alternatives, then, equals

$$\begin{aligned} P_i &= P_r\,[V(X_i) + E_i \geq V(X_j) + E_j, \text{ for all } j \neq i] \\ &= P_r\,[E_j - E_i < V(X_i) - V(X_j), \text{ for all } j \neq i] \end{aligned} \tag{25}$$

Charles River Associates (9) showed that explicit models based on the assumption that each individual maximizes his utility and further based on Eq. 25 are derivable from a probabilistic choice theory first developed by Luce (22) and Marschak (24).

The basic starting point in this theory of individual choice behavior is a choice axiom (25, p. 7). The most important implication of this choice axiom is the independence-of-irrelevant-alternatives condition. Originally developed by Arrow (1) in an algebraic context, this condition is that a comparison of 2 alternatives according to some algebraic criterion like preference should be unaffected by the addition of new alternatives or the subtraction of old ones (recall the various separability definitions given earlier).

The probabilistic version of this axiom should require that the ratio of the probability of choosing one alternative to that of choosing the other not depend on the total set of alternatives available, and this is exactly what is implied by Luce's choice axiom. Only the ratio of the 2 probabilities and not the probabilities themselves is invariant to changes of the irrelevant alternatives (note the similarity to the concepts of separability discussed above).

Another property of Luce's choice model regards transitivity. The choice axiom is a probabilistic version of the transitivity axiom in deterministic choice theory. The Luce model can also be shown to imply the existence of a ratio scale (22, p. 23) that is unique except for its unit and independent of any assumptions about the structure of the set of alternatives. Let T be a finite set such that, for every $S \subset T$, P_s is defined. Let the elements in T be the numbers 1, 2, ..., i, j, ..., J. Then,

$$P_s(i) = \frac{U(i)}{\sum_{jES} U(j)} \tag{26}$$

Our interest is now concentrated on the explicit probability function for the random variables E_i and E_j and the random variable $E = E_i - E_j$.

Assuming that $V(X_i)$ and $V(X_j)$ are linear in their unknown parameters, we can show that a wide variety of functional forms for the probability function are consistent with random utility theories of binary individual choice. The set includes the frequently used logit, probit, and truncated linear models. The logit model results if (a) $E = E_i - E_j$ has the logistic cumulative distribution and (b) E_i and E_j are statistically independent of the identical reciprocal exponential distribution, which is a distribution frequently used in the study of extreme values (20, pp. 332 and 344),

$$P_r(E_i \leq E^*) = e^{-e^{-E^*}} \tag{27}$$

The logit in the binary case is defined as

$$\log \frac{P_{ij}(i)}{1 - P_{ij}(i)} \tag{28}$$

and the following probability function is derived:

$$P_{ij}(i) = \frac{1}{1 + e^{-E}} \tag{29}$$

where $P_{ij}(i)$ means the probability of choosing i from a set $\{i, j\} \subset T$. Substituting from Eq. 25, we can write

$$P_{ij}(i) = \frac{1}{1 + e^{-[V(X_j) - V(X_i)]}} = \frac{1}{1 + \frac{e^{V(X_i)}}{e^{V(X_j)}}} = \frac{e^{V(X_j)}}{e^{V(X_j)} + e^{V(X_i)}} \tag{30}$$

Choosing e^V as the explicit form for the positive valued function U in Eq. 26 reveals that the logit model is consistent with Luce's ratio scale, which Marschak's has called the strict-utility function (24, p. 322).

Before evaluating this particular choice model, let us examine a more general approach, multiple choices. Assuming $V(X_j)$ and $V(X_i)$ are linear in their unknown parameters α and assuming the distribution properties of the random terms E_i are the same as in the binary case result in the multinominal logit formula (9, pp. 5.15-5.28):

$$P_J(i) = \frac{e^{\alpha' X_i}}{\sum_{j=1}^{J} e^{\alpha' X_j}} \tag{31}$$

This model may be called an explicit form of the strict-utility function in the multiple choice sense (24, p. 324).

It has been established (9, p. 5.19) that the assumption that the random utility function has a reciprocal exponential distribution is equivalent to the independence-of-irrelevant-alternatives axiom. This means that the odds $P_J(i)/P_J(k)$ of choosing alternative i over alternative k are independent of the presence or absence of third alternatives. This is easily seen if we look at the model in the following way:

$$\frac{P_J(i)}{P_J(k)} = \frac{\dfrac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}}}{\dfrac{e^{V_k}}{\sum_{j=1}^{J} e^{V_j}}} = e^{V_i - V_k} \tag{32}$$

from which the multinominal logit follows:

$$\log \frac{P_J(i)}{P_J(k)} = V_i - V_k = \alpha'(X_i - X_k) \tag{33}$$

The probabilistic choice model (Eqs. 24 and 25) can also be derived from a different set of assumptions regarding individual choice behavior. Point of departure is the economics-of-time model in the first part of the paper. To use this model in analyzing aspects of travel choice, let X_1 be the number of visits to a particular spot, X_2 the number of car trips, and X_3 the number of transit trips. Consequently, $X_1 = X_2 + X_3$. Individuals are assumed to maximize utility and will always choose the mode with which the largest Lagrangian value (derived from first order condition for maximum utility) is associated.

Introducing a set of rather strict separability assumptions can show that the individual chooses the alternative with the lower generalized cost. If individuals are drawn at random from a population, a random element should be added to the generalized cost formulas. By assuming the same statistical properties as for the strict utility choice model, Bruzelius has shown that the same explicit econometric choice models are derived (logit, probit, and so on).

The extensive analyses by Charles River Associates referred to above reject the multiple-choice generalizations of random utility models, where other probability distributions of the random utility elements are assumed, as analytically intractable or otherwise impossible to work with. (Charles Lave, University of California, Irvine, has in private communication expressed the same ranking based on computational efficiency.) For this reason, the multinominal extensions of the frequently used probit model and the truncated linear model are not discussed in this paper. An extensive discussion of these models is given in another report (9).

The conclusion to be drawn, before further discussions of the strengths and weaknesses of the logit model, is that the binary logit model is the only binary probability model for which the multinominal extension is practical at present.

The reliance on the choice axiom, which makes the model rest on the independence-of-irrelevant alternatives condition, is the principal strength as well as the principal weakness of the logit model. A similar conclusion follows from a critical examination of the separable time-allocation model developed by Bruzelius.

There is nothing in the separability property implied by Luce's axiom above that limits the discussion to subsets regarding only the various aspect of travel choice. The independence property holds for any subset, and the analogy to separability in deterministic utility models should be noted. The weakness of relying on this independence assumption in the logit model is not necessarily worse than relying on a similar separability assumption in algebraic choice models.

Luce evaluates his choice axiom in concluding his analyses of individual choice behavior (25, pp. 131-134). It could well happen that the basic choice axiom will hold when a situation is analyzed one way but not when it is viewed another way. The problem in practice is to know when a subject decomposes a decision into 2 or more stages; this is again the problem of knowing how a subject conceives the alternatives. The validity of this probabilistic choice theory seems to depend on the definition of alternatives, and alternatives should be defined in such a way that a subdivision of the decision into

2 or more stages is of no importance with respect to the final result. The only purpose of such a staging procedure should be to simplify the practical work with the model. These comments are very similar to those found in the section on the separability properties of deterministic choice models. That independence may be an implausible, strong assumption is excellently illustrated in the Charles River Associates report (9, pp. 5.25-5.26):

> Suppose an individual faces the alternatives of one auto mode and one bus mode, and chooses the auto mode with probability 2/3. Now suppose a second bus mode is introduced which follows a different route, but has essentially the same attributes as the first bus mode. Intuitively, the individual will still choose the auto mode with probability 2/3, and will choose either of the bus modes with one-half the probability 1/3 of choosing some bus mode, or 1/6. However, the independence of irrelevant alternatives condition requires that the relative odds of choosing the auto mode over either of the bus modes be 2 to 1, implying the probability of choosing the auto mode drops to 1/2 and the probability of choosing each bus mode is 1/4. The reason this result is counter-intuitive is that we expect the individual to lump the two bus modes together, not treat them as "independent" alternatives.

This example suggests that application of the strict-utility model should be limited to multiple-choice situations where the alternatives can plausibly be assumed by the decision-maker to be distinct and independent. Care must then be taken in specifying the available alternatives and decision-making structure when this multiple-choice model is used.

A simplifying consequence of the strict-utility model is that new modes, routes, or destinations may be introduced without recalibration of the model once the parameters have been estimated. The new choice aspects are introduced simply by the addition of new terms to the denominator of the particular strict-utility function in question.

The consequence of the choice axiom is that the odds with which the previous alternatives are selected are independent of the introduction of new alternatives. The probabilities of choosing the previous alternatives will, of course, decrease when new alternatives appear, but the old odds remain unchanged as a consequence of the independence of irrelevant alternatives (9, pp. 5.20-5.23).

This model property is a valuable simplifying aspect provided the problem on which the model is applied is considered simple enough to be modeled by means of this probabilistic choice approach.

The Charles River Associates model, referred to above, uses the independence property in a way that leads to an indirect travel demand model. This means that the logit model is applied to each choice, and a particular choice sequence is implied. Tests of parameter sensibility to alternative choice of sequences are not plentiful, and the procedure is difficult to evaluate against a simultaneous approach where the logit model is applied to the joint probability of the various travel aspects. However, Ben-Akiva (5) certainly confirms the suspicion that parameter estimates seem to be sensible to choice of sequence. It seems natural, therefore, to approach the sequencing problem from a decision-tree point of departure and, thus, have the preferred sequence as a result of utility maximization. This would, in principle, do away with the purely technical problems of different sequences leading to different parameter estimates.

The final point to make in this evaluation is perhaps rather academic but nonetheless of interest to those working with the econometrics of travel-choice analyses. Two different theoretical developments have been shown to yield the same econometric choice model. Unless the behavioral assumptions are explicitly stated from the very start, the logit model will be underidentified in the sense that further a priori information is needed to tell what we are really "explaining" by means of the econometric model.

CONCLUSION

Algebraic theories have been a basic point of departure in formulating choice and demand models. The discussions regarding stochastic or absolute consistency in choosing have to some extent been confused by too little precision in formulating probabilistic models. Recent works (14, 18, 19, 25) have clarified these aspects of choice analyses, and the present state of the art indicates that only probabilistic models are worthwhile in practice. As long as such models are developed from a rather traditional micro-economic platform, there is not so much theoretical evidence in favor of the Luce-Marschak approach as one may think by studying the present travel choice literature. The importance of the Luce-Marschak models has primarily been to challenge economists to take another look at the world, and as a consequence the theoretical basis of probabilistic choice models now in use has been clarified with respect to strengths and weaknesses and certain desirable simplifications have been theoretically justified. This regards first of all certain weak assumptions of choice independence or separability. Variables should be carefully defined so that the separability properties necessary for model operation do not violate the realism of the model. The sequences chosen in present travel demand and choice models do not seem well founded in theory, and it is expected that this field will be looked into more closely in the future. The outcome of this work may be a sounder theoretical basis as justification for particular sequences or a switch to simultaneous models.

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REFERENCES

1. Arrow, K. J. Social Choice and Individual Values. Wiley, New York, 1951.
2. Becker, G. A Theory of the Allocation of Time. Economic Journal, 1965.
3. Beckmann, M., and Golob, T. A. A Utility Model for Travel Forecasting. Transportation Science, 1971.
4. Beckmann, M., and Golob, T. A. On the Metaphysical Foundations of Traffic Theory: Entropy Revisited. Paper presented to the 5th International Symposium on Theory of Traffic Flow and Transportation, Berkeley, Calif., 1971.
5. Ben-Akiva, M. E. Structure of Passenger Travel Demand Models. M.I.T., PhD thesis, 1973.
6. Brand, D. Travel Demand Forecasting: Some Foundations and a Review. HRB Spec. Rept. 143, 1973, pp. 239-281.
7. Brown, A., and Deaton, A. Surveys in Applied Economics: Models of Consumer Behaviour. Economic Journal, 1972.
8. Bruzelius, N. Economic Theories of the Allocation of Time: A Survey. University of Birmingham, M. Soc. Sci. dissertation, 1972.
9. A Disaggregated Behavioral Model of Urban Travel Demand. Charles River Associates, Inc., Cambridge, Mass., Rept. 156-2, 1972.
10. Chow, G. C. Tests of Equality Between Sets of Coefficients in Two Linear Regressions. Econometrica, 1960.
11. de Donnea, F. X. The Determinants of Transport Mode Choice in Dutch Cities. Rotterdam Univ. Press, 1971.
12. DeSerpa, A. C. A Theory of the Economics of Time. Economic Journal, 1971.

13. Georgescu Roegen, N. The Pure Theory of Consumer Behaviour. Quarterly Journal of Economics, 1936.
14. Georgescu Roegen, N. Threshold in Choices and the Theory of Demand. Econometrica, 1958.
15. Green, H. A. J. Consumer Theory. Penguin Modern Economics, 1971.
16. Gronau, R. The Value of Time in Passenger Transportation: The Demand for Air Travel. NBER, New York, Occasional Paper 109, 1970.
17. Hensher, D. Review of Studies Leading to Existing Values of Travel Time. Commonwealth Bureau of Roads, Australia, 1973.
18. Hildenbrand, W. Random Preferences and Equilibrium Analyses. Journal of Economic Theory, 1971.
19. Katzner, D. W. Static Demand Theory. Macmillan Series in Economics, London, 1970.
20. Kendall, M. G., and Stuart, A. The Advanced Theory of Statistics. C. Griffin and Co., London, Vol. 1, 1969.
21. Lancaster, K. Consumer Demand: A New Approach. Columbia University Press, New York and London, 1971.
22. Luce, D. Individual Choice Behavior. Wiley, New York, 1959.
23. Malinvaud, E. Lectures in Microeconomic Theory. North Holland Publ. Co., Amsterdam and London, 1972.
24. Marschak, J. Binary Choice Constraints and Random Utility Indicators. In Mathematical Methods in the Social Sciences (Arrow, K. J., Karlin, S., and Suppes, P., eds.), Stanford University Press, 1959.
25. McFadden, D. The Theory and Measurement of Qualitative Consumer Behavior: The Case of Urban Travel Demand. University of California, Berkeley, Working Paper 1, Sept. 1972.
26. McGillivray, R. G. Demand and Choice Models in Modal Split. Journal of Transport Economics and Policy, 1970.
27. Muth, R. Household Production and Consumer Demand Functions. Econometrica, Vol. 34, No. 3., 1966.
28. Ruijgrok, C. J. Unpublished note. Netherlands Institute of Transport, Rijswijk, Feb. 1973.
29. Uzawa, H. Preference and Rational Choice in the Theory of Consumption. In Mathematical Methods in the Social Sciences (Arrow, K. J., Karlin, S., and Suppes, P., eds.), Stanford University Press, 1960.
30. Wilson, A. G. Entropy in Urban and Regional Modelling. Pion Ltd., London, 1970.

Conference Papers
on
Traders
Versus Nontraders

Conditions for Successful Measurement in Time Valuation Studies

M. E. Beesley, London Graduate School of Business Studies

This paper arose out of the feeling that in the last few years progress in getting usable values of time has not matched progress in theoretical understanding. Time values are most useful, one supposes, in project evaluation. For this, estimates of the opportunity cost of time—its value to the consumer in alternative activities—and estimates of the values of specific disutilities associated with the activity of traveling are both useful. It seems perfectly legitimate now to distinguish the "valuation of time in general" and its "valuation in a particular use," to quote Evans (1). For example, until 1969, in British and European work at least, there seemed a growing and useful consensus from empirical studies that one could value the opportunity cost of leisure time at about 25 percent of the relevant wages and salary and that transport time elements such as walking and waiting could be assigned twice these values. More recent British work has seemed to upset this growing consensus.

I shall argue in effect that better theoretical insight has coincided with less attention to the conditions predisposing to successful measurement; the quality of data and the experimental situations have been relatively neglected. In any case, it is certain that better estimates will require a good deal of attention to the selection or creation of study opportunities, and I wish to explore the conditions here. The points are developed first with regard to binary choice situations for convenience in exposition and because most studies have taken this form.

In transport sector evaluation we are obliged to adopt an account of the value of time in general—the rate at which it is substituted at the margin of transport and nontransport activities. We can also hope to go further: to specify the value (or cost) of within-mode travel. But the latter may not always be possible. If so, we can fall back on the generalized opportunity cost measure. The assertion that, for evaluation purposes, this would be better than omission would be hard to prove, but it is intuitively appealing. The focus here will be on evaluation of investments. As we shall see, the requirements of evaluation on the one hand and prediction of modal choice on the other may conflict; what is efficient procedure for one may not be so for the other. Also, in what follows, I concentrate on nonworking time as the most debatable of items in evaluation.

My argument is that there has, in varying degrees, been insufficient attention to the following elements necessary for a satisfactory outcome of a binary choice study:

1. The separate populations for which values of time are fitted should be homogeneous;
2. The choices observed should refer to a situation in which the demand for travel approaches zero;
3. There should be no ambiguity in the measured (cash) outlays;

4. The more "traders" (i.e., those sacrificing time for cash, or vice versa) the better; and
5. The trader should be well distributed with respect to revealed minima, and maxima, observations.

The paper shows why these points are important and presents other statistical requirements that have been noted elsewhere for good studies (2). Harrison and Quarmby (2) summarize these as follows: Each variable that may be important in an explanatory equation should exhibit sufficient variance in the data; and variables expressing time and cost should not be collinear. In terms of binary choice, as we shall see, this requirement appears in a particular guise. Also, they remark, "The analysis technique must show a sufficiently high level of explanation of behaviour"—i.e., be subjected, if possible, to formal tests of significance. And they added, "The sample analysed must show non-trivial proportions making different choices"—which again has a particular significance for binary choice.

Most binary choice studies have been of different modes. A subtheme of the present paper is that to be efficient in predicting modal choice is not necessarily to be efficient in deriving values of time. I also consider the bearing of the argument on alternatives to binary choice studies. Having established the importance, in principle, of observing the conditions for a "good" study opportunity, the paper then considers how far recent British studies have fulfilled these conditions. Because they appear to have considerable shortcomings, I draw the conclusion that there are as yet insufficient grounds to reject earlier notions about values of time.

EXPERIMENTAL CONDITIONS

My starting point is that of a study consisting of binary choices by consumers. I assume that the best evidence derives from observations of actual choices. I ground this on the assertion, not to be further considered, that evidence of what consumers do, or have done, as part of their experience is better than what they might do or seem to do in hypothetical conditions set up by the observer (laboratory tests). Also I assert that, as a matter of practice, consumers can give far better evidence when choice is confined to 2 options than when choice is multiple; i.e., consumers tend to think in terms of, and more accurately report, single alternatives. Having said this, one immediately encounters the difficulty that a special weight is then thrown on the assumptions about, and evidence for, the homogeneity of the classes of people to whom the measurements are held to apply.

One needs to classify consumers first because one has to identify, operationally and as economically as possible, who is to be affected by an investment or policy change and second because one hopes thereby to ease the problem of estimating within acceptable error limits. Thus, one also chooses to group consumers together to obviate or lower the cost of explanation. One may be more or less successful in bringing these requirements together. For example, if we can regard consumers within defined income brackets as homogeneous, it is a great computational convenience. But this may, on the one hand, not serve to illumine behavior and, on the other, not distinguish among policy options in a useful way (e.g., if choice of policy does not involve greatly varying mixes of income groups). The test of a successful system of categorization is thus not only its robustness in maintaining explanatory power but also its relevance to decisions.

In the case of binary choice, particular emphasis is laid on selection of population classes because any definite outcome depends on a grouping of individual observations. The information from a single observation is at best one minimum or one maximum estimate; to fix specific values of time, one must observe examples of each and assume them to be drawn from the "same" population.

Our first requirement of a good study opportunity is therefore a clear justification of homogeneity assumptions and their relevance, when selected, to decisions. There must be good a priori reasons for supposing the samples to contain "like" people.

There is a good case for using experiments not directly involving prices—for example, administered in laboratory conditions—to test whether the conventional definitions of traveling (for example, into income classes) do distinguish sets of people having like values of time. One example would be to apply nonmetrical scaling devices to samples of people confronted with hypothetical choices among several modes, such as conventional bus, taxi, dial-a-bus, and jitney, for their journey to work. The interest in this would be to see whether those who were revealed as regarding alternatives as close substitutes conform to conventional classifications of consumers, or whether they must be recognized differently. Once satisfactory classifications are established in this way, one can proceed more confidently to the observed, real-world choices involving trade-offs between cash and time.

The second requirement concerns demand for travel. One can distinguish several levels at which binary observations may be attempted. Basically one regards transport activities as inputs to commodities or services that must be consumed at specific locations. One could observe choices between commodities or services at the top level of the hierarchy; choices among places at which these commodities are consumed at the second level; (conventional) mode choices to each given place at the third level; and choices of routes within a mode at the fourth level. In transport, those below the first level have been attempted; they represent respectively distributional, modal, and route choice studies. Clearly it is possible to envisage successful observations at any level. Recent theoretical insights have taught us also to look at these levels in another way: as bundles of attributes to be thought of as attaching to alternative commodities, alternative places of consumption, and the like. At any level above the lowest choices, features of a lower level will combine. (Thus a mode choice necessarily involves a route and a particular selection from a set of attributes.) As the level rises so, one would expect, would the complications—the complexity and number of attributes. Other things being equal, one expects a simpler, more manageable exercise in the lower the level observed. But the opportunities to make such observations, or to save their cost, may not occur in the same way. Decreasing complexity may have to be bought at the price of fewer relevant observations.

Clearly also, the binary choice observation does not permit a direct link with conventional estimates of demand for services or commodities. A given observation can be defined either as an acceptance or a rejection of one of a pair of alternatives. Estimation of demand requires distinguishing between acceptance and rejection to get a quality-price relation, whether that price be reckoned in cash, as is usual, or in time, as is occasionally encountered in demand studies. To put the matter another way: In estimating from binary choice one always assumes the rejected alternative to be one that would have been selected had the first not been available. This is plausible, for example, in considering the journey to work, where one can assume, for the relevant range of observations, that the elasticity of demand for getting to work at all is near zero. For other situations of (derived) demand for travel, this is not so plausible; thus, the selection of the binary choice approach implies that the underlying demand conditions are favorable. Estimating demand, on the other hand, essentially involves testing for rejection of the goods or service.

With binary choice, the connection with conventional demand estimates, if it is to be achieved, must be done by combining populations with different measured values of similar attributes to yield a total volume-price relation measured in terms of time or cash. Standardization of attributes across the combined sets is also required to be recognizable as normally labeled commodities or service in a given market. Where one chooses to declare a relevant market (in terms of the above discussion, at the commodity or place or modal level) depends on the purpose or policy in hand. A fully articulated connection between binary choice and market observations is thus likely to be difficult. But because a connection with normal demand estimates is often desirable both for policy formation involving actions by operators in real markets and for cross-checking, the choice of opportunities to make measurements to value time should be influenced by the existence of conventional demand measurements or their potential derivation from independent data. If, then, a study of valuation can be clearly linked with conventional demand estimates, so much the better.

The third requirement for a good study opportunity concerns measuring the costs involved. Unless it can eliminate the differences plausibly, a successful study must distinguish at least 2 components of time and should choose situations in which ambiguity in the cost variable is minimized. Where cash outlays are clearly related to sacrifices of income, no problem arises. Difficulties will arise where costs themselves may represent opportunity costs or advantages not necessarily reflected in cash outlays. Then it becomes a matter of judgment whether to make time or cost the variable to be explained. This problem is at its most acute where choice involves car costs. The conventions usually adopted in studies that involve car costs are clearly extremely unsatisfactory. Normally, studies involving car costs have sought to impute a reasonable account of outlays on car trips—the resource costs involved, e.g., gasoline and parking.

Occasionally, when reported car costs are observed to vary by users, an attempt is made to use perceived car costs. These are essentially the costs that, from trial runs with alternative possible imputed costs, appear to give best fits in models of modal split that include time and cost elements. The resultant costs may diverge from resource costs and hence give rise to a series of problems about the appropriate valuations to take in cost-benefit studies. But, in fact, the relevant concept is the opportunity cost of the car, and that may vary widely according to factors such as whether its use on a trip deprives anyone else of use or whether it is to be used for further trips during the day. There is no a priori reason to suppose that an imputed average cost per mile is representative of the total true opportunity cost or, indeed, that car users' opportunity costs are distributed in any particular way with regard to alternative imputed average costs. The fact that respondents, when asked to define their car costs in terms of cash outlays, vary in their responses enormously may be due as much to genuine variance in opportunity costs as to a failure to perceive costs correctly. Moreover, there is an obvious difficulty for respondents to translate their experiences into what may seem rather irrelevant terms, namely, cash. Thus, choices involving cars must be expected, other things being equal, to yield rather unfavorable potential measurement conditions unless consistently large specific cash outlays are involved (e.g., high parking fees or tolls). Again, this depends on the level at which choice is to be observed. For example, a study at the route level of speed and cost trade-offs in which drivers are observed to choose to travel faster or slower may (if one can believe that differences are substantial enough to be perceived) escape the criticism. Studies of commuters not facing high parking charges will not, because there the ambiguities about car costs are at their most acute.

The fourth requirement concerns traders. This is a question of the factors that influence the number of effective observations among a data set. We may proceed from a simple example. Essentially, the explanation of the value of time spent traveling is derived from what I have called traders, i.e., those respondents showing a choice of the following type:

$$\begin{array}{l}\text{50 minutes}\\ \$0.75\end{array}\left\{\begin{array}{l}\text{is preferred to}\\ \text{is not preferred to}\end{array}\right\}\begin{array}{l}\text{30 minutes}\\ \$1.25\end{array}$$

The value of time should be understood as the amount that compensates the person in question for his or her sacrifice of time. It is not the price that a person has to pay in a given situation to save time; that would be, and often is, less than the amount that he or she would be prepared to pay. The traders are important because they can be used to demonstrate the limiting values attached to time, i.e., what is or is not sufficient cash compensation for gains or losses in time.

In an earlier article (3), I made the rather heroic assumption of indifference to walk-wait and specific public transport proportions in choices. So it is clear, contrary to the implications of some critics since, that I was attacking the problem of what one would now call the opportunity cost of time and recognized the problem of what one would now call the "intramodal" utility. These traders represented 27.5 percent of all responses, whereas apparently illogical choices, e.g., those that preferred 50 minutes and $1.25 to 30 minutes and $0.75 (or up to 50 minutes or $1.25 in the latter option), accounted for 6.3 percent. Dominant choices, i.e., where both time and cost were inferior and rejected, accounted for the remaining 66 percent.

With a simple choice situation, i.e., no ambiguity about cost or time, clearly the more traders the better. The greater then is the possibility of stratifying the data successfully to test issues such as variance with income. That is, one can concentrate on the issue, which is crucial to using such choices, whether the sets used really are homogeneous, and, if not, in what respects are they not, so that separate estimates can be made. Notice, however, that statistical success also requires a reasonable balance between what are called above minimum and maximum observations from traders. In fact, as shown by the diagram in my article (3), my data were relatively short on maximum observations. Had one attempted more than a simple explanation (as reported there, others were contemplated but rejected because the data were not sufficiently good, I thought, to stand up to such sophistication), this might well have appeared as a formal difficulty with error terms. (The maxima and minima observations were weighted for their frequency in my estimates, again contrary to the assumption of at least one critic since!)

The general conditions for observing traders were probably rather favorable in the case of my study. London is possibly one of the richest of all cities in alternative transport routes and modes. Yet only just more than a fourth of the observations appeared as traders. Since I also started from quite a large sample overall (1,109), it is natural to inquire what is involved in attempting to split the simple observations into components. Clearly, sample size requirements may rise drastically if inferences have to be confined to traders. But do they?

In what follows, I assume there are really at least 2 components in the observed time, say, opportunity cost and comfort. Our example of a trader becomes $50x + 50y + \$0.75 - 30x + 30y + \$1.25$, where x = opportunity cost and y = comfort. This adds little to our information. We need something further to distinguish proportions of comfort on each alternative. Suppose we observe 30 minutes of walking on the first, and 20 minutes on the other. (This is relatively easily observed: The consumer can report it, and it is a category we all intuitively think is so distinct from other parts of the journey as to require labeling only. Such an instinct may be correct for walking, but for other dimensions of comfort, such as crowding, one has to rely on actual observations to distinguish the choices. This raises, quite substantially, the research cost.) Now we can say the observation is $50x + 30w + 20z + \$0.75 - 30x + 10w + 20z + \$1.25$, where w = walking and z = other modal time. To use this information, we have a choice of procedures. We can combine traders in such a way as to match similarities (for example 20z on each side above) and isolate values. This again puts up the sample size requirements. However, we can see whether we can add to the traders observations by bringing in the other categories, dominants or illogicals.

Consider a dominant, e.g., $30x + \$0.75$ is preferred to $50x + \$1.25$. If, with further evidence, this can be converted into a trader, e.g., $30w + 20x + \$0.75$ is preferred to $50w + 10x + 40y + \$1.25$, where the notation is as before, this becomes an observation from which information can be extracted. A necessary condition is that a sacrifice on the noncash side is revealed since the cash gain remains unchanged. Not all dominants will show this on disaggregation. And the nature of the value thus revealed is always a maximum because cash is preferred to time. Unless, therefore, observations can be found with cash sacrifices also, these extra observations will have limited value for estimation purposes.

So, to get a balance, can one bring in (apparent) illogicals? Clearly, yes; there are possible sets of revealed weights that will transform them into either dominants or traders, of which the traders are useful for estimating purposes. Hence, the illogicals and the dominants could yield a possible set of ratios of values for the disaggregated items that, given that the observed set of people are really rational, enable some test values to be accepted. Depending on whether the people concerned sacrifice costs or not, these will be minima or maxima. Thus, information can be increased from these sources. But disaggregation will not always reveal traders, and revealed traders must be balanced between maxima and minima. On the other hand, if original traders are subjected to disaggregation, they always provide information, for there is no selection of possible values for the constituents that will change them into illogicals or dominants. (Of course, the values to be fitted to them may not coincide with the corresponding values for the rest of the disaggregated observations; i.e., adding all observations may not increase explanatory power. But that merely would throw doubt on the homogeneity of the sample population.)

So, in the consideration of the relatively small numbers of illogicals—or potential maxima—seemingly typically observed and the potential for disaggregating traders, an important indication for the success of studies seems to emerge: The more traders the better still seems to be a useful rule of thumb, meaning those in which a simple time and cost trade-off is observed. An important corollary seems to follow from these arguments about what can be observed in binary choice situations. Whatever the sophistication of the statistical estimation technique used, the underlying limitations—that information must be capable of transformation into the trader form—apply and so do the requirements of a good potential distribution of traders between maximum and minimum values.

Much of the recent work has formulated the problem in terms of statistical methods designed to contrast the characteristics of 2 populations, e.g., by discriminant analysis. Often this has also taken the form of discriminating modal choice, e.g., between public transport and cars. The technique is more powerful than the graphical approach in my earlier article (3). But whether an observation happens to be a choice in favor of bus or rail is irrelevant. Which way a choice goes in terms of modes depends on the objective opportunities open to the population. So to formulate the problem instead as one of modal choice, where the modes are recognizable everyday modes, is to constrain the estimation unnecessarily. The right choice of attributes is all that is required. So all attempts to improve on the (supposed?) simplicity of the trade-off approach involving reformulation as a modal-choice problem have involved some loss in explanatory power from the point of view of estimating values of time.

That is, of course, one aspect of the fact that what is efficient procedure for time valuation may not be so for modal-split prediction. Each has different objectives. The conditions for success in observations for modal-split problems may well be considerably different. For example, for many modal-split purposes a high incidence of dominant choices is not necessarily limiting. If modes are clearly identified as superior or inferior for most of the sample population, so much the better; one can, and should, dispense with complicated explanations.

But what of alternatives to binary choice observations? Many of the points made above about homogeneity, costs, and statistical requirements apply to these also. The distinguishing characteristic is the use of more aggregate data; and they often involve, explicitly or implicitly, choice among ends to which travel time and cost are devoted. The principal source of data is urban transportation studies. One can, for example, seek to explain the modal choice between zones in terms of the time and cost characteristics of the modes. If one standardizes to trip purpose (eliminating irrelevant activities) and if one standardizes to trip length (eliminating the possibility of rejection of this purpose), one might observe the changing proportions of people by mode from a given zone to others. This then becomes formally equivalent to a binary choice problem. Thus, if we observe that between zone a and zones b and c respectively the modal characteristics are

Zone	Mode 1		Mode 2	
Movement	Time	Cost	Time	Cost
a to b	50	30	30	50
a to c	30	20	20	10

and 50 percent take mode 1 in the first and 80 percent in the second, one has information that can be redrawn; for example, 5 trading such that 50t and 30c is preferred to 30t and 50c and 5 vice versa. One can describe the second as having 8 dominants and 2 illogicals. Supposing, then, indifference between the a-b and a-c options as objectives for travel, one can estimate over the combined set. It does not matter, of course, how many people there are in the zones; the information essentially comes from the different modal time-cost proportions and the distribution over traders and the rest. Apart from difficulties of defining homogeneous sets, one supposes the potential useful observations to be quite limited. A recent application of this approach is commented on later.

A second approach takes one activity, say, work, and compares the relation between the distribution of interzonal trips and the time-cost characteristics of one or more modes constituting paths between zones. This necessarily introduces the notion of acceptance and rejection of attributes of the activity, for a willingness to make given zone-to-zone movement depends not only on the characteristics of the zone population and cost of time of the paths but also on the trade-off with utilities in the activity, which itself must be equally attractive apart from travel costs. Again, the data requirement rises.

An opportunity to standardize the activity arises where, for example, an important leisure-time target can be distinguished. An example by Mansfield (4) is the Lake District. If one assumes that, in respect to the Lake District's attributes, all populations are similarly distributed (they regard it for example as offering pleasures in equal measure), one can then seek to explain a differing incidence of trips made to it among populations according to the latter's differential expenditure of time and cost to reach it. Clearly, it helps if modes can be standardized across populations at the same time. (Mansfield necessarily considered car journeys only.) In terms of the levels of observations referred to earlier, one selects a given location for an activity and the same mode, but different routes.

If there are then differing proportions of times and costs in the trips made, one can infer time values from the relation between these and the propensity among the population to make trips. Reduced to its simplest form, the following gives the percentage of those making a trip from the zone to the objective, the time and cost, and the differences from each to the next nearest:

Zone	Percentage	Time	Cost	Differences		
				Percentage	Time	Cost
e	1	50	30	-50	+10	+ 5
d	2	40	25	-60	+ 5	- 5
c	5	35	30	-50	+15	+10
b	10	20	20	-16	+10	+ 5
a	12	10	15			
Avg				176	+40	+15

It is hypothesized that the average percentage difference, 176/4, is explained by the average time difference, 40/4, and the average cost difference, 15/4. Thus, the ratios of time and cost differences—here 40 and 15—are weighted by their contribution to the differences in trip-making to give an estimate of time value. This approach has the merit of providing potentially an estimate both of time values and of demand. It is close, indeed, to the Clawson method of estimating demand of a leisure activity (5). Given the value of time, it becomes possible to relate increasing use with decreasing total cost. From the point of view of time values, however, there are obvious difficulties. Opportunities for observation depend heavily on car journeys, with attendant cost difficulties. The number of observations, dependent on zones, are typically few. On the other hand, large zonal populations perhaps are more persuasive in terms of homogeneity. But the leisure objective must be conspicuous and plausibly unique. This limits observations useful for decomposing to find time values.

In summary, alternatives to direct observations of consumer choices pose very similar problems to those found with the traditional binary choice models. And they seem to encounter quite severe limitations of observations from the point of view of time valuation. Viewing the field, one cannot help regretting that authors have not sought to build more on work of their predecessors. Product differentiation seems to have been a main objective: Each new study seeks to innovate either in technique or observations. Trying to replicate results with new data and to improve methods of estimation is thoroughly helpful, of course. What is not helpful emerges when one attempts to set up criteria for likely success. For example, if the division among traders, dominants, and illogicals is as important as the earlier arguments suggest, it would have been most useful to have known, in each study, their incidence and characteristics. If, through attention to the underlying limitations of inference from data, it were possible to improve comparability among studies, then it might become possible to recognize more clearly, by juxtaposition of studies, what value of time in the sense of opportunity cost is. This should be a common characteristic, and some tendency to approximate to a common value over all studies should emerge.

SOME RECENT VALUATIONS

Although we expect to find generally better or worse conditions for discovering time values, we must conclude that adopting any one partial approach involves trade-offs between requirements. Let us now review the findings of recent studies in the light of the discussion. An excellent start is given by Harrison and Quarmby (2). Further, there are the papers and proceedings of a 1970 value of time conference (6).

Let us first consider an alternative to binary choice models. Blackburn (6), in a nonlinear model of the demand for travel, developed a model to account for decisions to travel and choose mode in 20 California city-pair markets. There were 4 modes—air, car, bus, and rail—and 2 principal attributes of modes, time and cost, were estimated. A most sophisticated estimation procedure and heroic assumptions (e.g., about car costs) produced an estimated standard error of estimate of approximately the same size as the average and twice that of the median, estimated, values of time.

The disparity between average and median values is explained by Blackburn as due to the fact that the means (from $4.55 per hour for $2,000 income per capita, 1960 dollars, to $5.55 for $3,500) reflect the population as a whole, not merely those who travel. As he says, "Those individuals who would pay $20 to avoid an hour in transit do not travel." The implication is, of course, that attributes should be extended to include disutilities in travel: What was measured was not the "pure opportunity cost of time."

It is likely that this kind of study will always encounter great data difficulties. Quandt (6), in discussing the development of such models, says, "The most important improvement needed in data would be the creation of a reliable and highly disaggregated data base, preferably with information on a household level." If these were available, of course, other approaches become more feasible too. For urban areas, de Donnea (6, p. 176) fixes the difficulty with models proposing to use, for example, aggregate city-zone data when he remarks, "The most fundamental weakness of aggregate models is that only rough and average measures of transport system characteristics in each city zone can be included among the explicatory variables." Within-zone variance may easily swamp useful between-zone variations.

The objective of binary choice studies has been not necessarily to derive time values but often to predict more efficiently modal split, particularly between cars and public transport. As indicated earlier this can conflict. One wishes to distinguish values for components of time and not necessarily to constrain one's explanations to modes that are themselves unspecified aggregates of attributes. One essential problem with car-public transport choice is the overwhelming general superiority of the car. For many practical purposes, one probably would get useful and simple predictions of modal split by using time measures alone. Improvement in prediction in urban areas is probably as much a matter of securing more detailed measures of actual point-to-point times as complicating the explanations of reported alternatives by respondents. This is particularly true in planning entirely new modes, e.g., "travellators" to assist pedestrians. There, one needs only a simple behavioral notion—that people save time—but also a great deal of attention to the opportunities to save it. Cost and other variables are secondary.

However, as we saw earlier, there are great difficulties with using car data in any case because of defining costs. Recent work has indeed stressed the great variation of time value results that are possible with different accounts of car costs (6, p. 204). No one has yet succeeded in stratifying for conditions to recognize varying opportunity costs; that respondents themselves vary greatly in car cost assessments is confirmed (7, 8). Because of car cost difficulties and the basic need to sample for situations in which traders can be found and balance between maxima and minima can be achieved, it is natural to look to urban studies depending chiefly on public transport alternatives or walking choices.

In such studies (2), a distinction emerges between values of time (meaning, though the authors' intentions are not always explicit, an opportunity cost of time) in studies of public transport and those of car-public transport choices. My own study and those of the Institute d'Amenagement d'Urbanisme de la Région Pariesienne (LAURP) and of Lee and Dalvi report estimates varying from 30 to 43 percent of the income of travelers. Studies by Quarmby and Stopher that report bus-car or public transport-car choices estimate a value of 20 to 25 percent. Studies that average overall modes by Local Government Operations Research Unit (LGORU) and by Barnett and Salman estimate a value of 20 to 25 percent for in-vehicle time and 14 to 33 percent varying with income respectively.

Since each of the studies involving cars chose an average car cost rather arbitrarily (best fit tests between different imputed values fail to discriminate cost very sharply, unsurprisingly), one might be inclined to opt for the higher values as more representative of opportunity cost of time because they avoided the difficulties.

But the studies obviously did not succeed in eliminating other mode-related utilities entirely. How serious is this? The LAURP study specifically measured for walking and waiting, finding that these factors had twice the effect on choice as did in-vehicle time. This effect has been confirmed elsewhere by Quarmby and by the LGORU studies. But the mere presence of walking and waiting in the public transport choice studies would not be sufficient to invalidate the estimates; there would have to be significantly measurable differences in proportions as between choices. And present work suggests this important element might well be waiting, not walking. Thus Veal's preliminary study (9) of leisure journeys (to libraries) involving, among other things, bus-walk choices indicates little difference between walking and in-vehicle values of time; on the other hand, it showed the familiar doubling of values of waiting. Waiting itself is, of course, normally a much smaller part of total commuter travel than walking and probably would not show up strongly. Veal's results (between 20 and 30 cents an hour, but the sample likely contains many low-income users of libraries) also seem to indicate a lower value of (in-vehicle) time than earlier public transport studies. So we are left, still, in doubt. But there is, a priori, reason to suppose that studies involving car choices cloud rather than clarify the issue.

A similar comment may be made in respect to another main issue: whether and to what extent "pure" values rise with income. We would expect some absolute rise, and perhaps the most plausible expectation is a value more than proportional to income (corrected for factors such as household dependents) of the respondent. Again there is a tendency for the answer to become less clear if car choices are involved, though public transport choice studies are certainly not unequivocal, and Quarmby's public transport-car study reported proportionality. Recent work by LGORU, refining earlier commuter studies (10), makes a very pertinent comment here, however. After arguing in general to confine valuations to what we call traders, the authors found that, when so confined, comparatively few observations in higher income groups remain: "In this situation, it would perhaps be surprising if any strong relationship (of values with income) were found" (10, p. 6). Since traders are necessary, we argue, to any successful estimation, judgment must again be suspended until more appropriate data are found and worked on.

A recent study, started in 1969 and still proceeding, has dealt with multiple mode choices facing travelers crossing the Solent (between Hampshire and the Isle of Wight in England); the choices are ferry, hovercraft, and hydrofoil, with or without cars. Data on alternative journeys were secured from a large sample of 3,342 passengers. From our earlier arguments, one can set up the circumstances in which one would expect reliable estimates of values of time. These would include a large incidence of regular users (so relying on those in a position to form realistic views of alternatives); responses such that passengers would not reject an alternative if faced in fact with the nonavailability of the preferred alternatives; respondents not involved in a car option; a large incidence of trading among alternatives; and among the latter a balance of acceptance and rejection of time savings. Unfortunately, the interim report so far available does not allow one to construct these numbers (11). But we learn from the report that only between 5 and 11 percent of respondents travel once a week or more, that between 2 and 7 percent of the total reporting alternatives are commuting, and that another 1 to 3 percent travel for education. Well over half the sample uses the modes once a year or less frequently. In these circumstances, it is perhaps not surprising that time values (calculated from models set up to explain modal choice) indicate "a range of between 15 and 858 p an hour." The authors remark, "Discriminate analysis should refine these values considerably." One may confidently predict that unless the underlying data turn out to be favorable in the sense we have described it will do nothing of the sort!

Perhaps the most significant recent study, from the point of view of promising to upset received ideas of the value of time, has been that by the Transport and Road Research Laboratory on choices made by motorists in Italy (12). This report states, "Only limited data were collected on income, but the indications are that in non-working time the overall average value of time per head is slightly above the average family income and that in working hours it is over double the average income." The relation between values in work and out of it is not unexpected, but the nonworking value of time derived from journey-to-work choices and other (leisure time) journeys, at double instead of 25 percent of wages or salaries, is no doubt a challenge to the accepted official practice and the more serious because it emanates from an official source. On inspection, however, it aptly illustrates many of the points we have made.

The study concerns autostrada and alternative route choices on trips to Rome and Milan. The number of answered questionnaires was high—more than 5,000. The study, though concerned with cars, was not confined to them; and the difficulties of car costs were avoided at least in part by the presence of an important cash outlay on the autostrada alternative—the toll. A sophisticated statistical approach to route choice (logit analysis) was run alongside a simpler approach derived from my own study. Let us appraise the study in the light of our implied "checklist" for studies.

First, homogeneity of the population for whom estimates were made was ensured chiefly by confining observation to Italian cars, carefully keeping controls on sampling proportions of interviewed to total traffic, and avoiding main holiday periods. These, combined with the closely paralleled choices (autostrada and ordinary roads often run close together), arguably provided the best yet reported means of deriving generalizations for populations.

Second, the choice of level of observation fulfilled the binary condition of plausibility in eliminating or controlling for demand elasticity much more for journeys to work than for others, which could range significantly up to journeys of 2 hours or more on which differences between alternatives could rise above 1 hour in time.

Third, cost problems were not entirely avoided. Costs were assumed only to vary between the toll on the autostrada and the free road. We are not given an estimate of total car costs with which to compare this; but these in any case would be highly suspect. Opportunity cost is more likely to be a problem in commuter studies. Gasoline and other outlays, insofar as they were wrongly omitted (and this is probably a very small blemish), would probably be higher on free roads and more certainly where these were urban. If included, they would tend to lower measured values, for time differences were unaffected.

Fourth, whether there were sufficient traders and whether they were distributed well between minima and maxima is difficult to tell because the study did not address these problems directly. One real difficulty is that it was assumed implicitly that there was no need to study possibly different attributes among the choices. This omission is conspicuous for the autostrada choices, which internal evidence confirms. Thus, for example, there were apparent illogicals. More important perhaps, a sample of motorists were asked their reasons for choosing between the alternatives.

The most important difference with respect to the autostrada and the ordinary road seemed to be that the former was "more comfortable." Surprisingly large numbers claimed the ordinary road to be quicker than the autostrada. This perhaps throws some doubt on the identification of route choices and also indicates that an unknown, and perhaps large, item accounting for the high time values is the lessened disutility of travel by autostrada. It would, presumably, have been possible to test the hypothesis that values of time were lower by autostrada than by ordinary roads. However, even ignoring the question of the value of autostrada comfort, there is some evidence in the study of difficulty with the numbers of effective trader observations and their distribution between minima and maxima.

This study cannot, therefore, be said to conform to the requirements for a successful time valuation study. The last study to be noted here throws some light on the issue of the difference made to results by using simple or more sophisticated methods. This study (13) brought together data from several commuting studies and, among other things, compared in some detail the differences made to values of time estimates by using on the same data a discriminant or "limiting time value" approach. The latter is essentially the procedure in my earlier paper. It turns out that limiting the data set to traders makes a considerable difference to results and that, as one might expect from the points made earlier, formulating the problem as a choice between modes or estimating time values directly (via limiting time values or LTV) also shows great differences. Thus, according to the report (13, p. 15), "The inclusion or exclusion of non-trade-off individuals can have a considerable effect on the time values obtained from discriminant analysis and that by following the correct procedure of formulating a hypothesis about time values and examining the consistency of observed data with the hypothesis, not only is the best value of time less than that obtained by discriminant analysis, but also, perhaps surprisingly, the explanation of observed mode choice is improved."

For the authors "time value" means what was called earlier "opportunity cost of time." Values of time were very much higher for the discriminant form. This result, and that of improved mode-choice prediction, is derived from a model in which it is hypothesized that value of time is the same for all individuals; the model selects the value of time that best explains modal choice. One should perhaps not take the "better modal prediction" result too seriously, both because the difference in performance is very small and because it may in any case have been due to the particular form of LTV criterion to get the best values. (The criterion was the proportion of persons misclassified. This weights everyone equally: There is no a priori reason not to pay some attention to the degree to which persons are misclassified.) On the time value issue, however, there is little doubt of the difference. The authors summarize their evidence as showing that the best estimate of the value of total commuting time (from the LTV technique) is 0.63 an hour; they found little to support or refute the hypothesis that income is systematically related to time values. It is worth noting that the 0.63 is much closer to former ideas of values than was the TRRL study (12) emphasized above. [The authors also ran models of modal split from which the coefficients of walking and waiting compared with in-vehicle time were about 2:1, much as expected (13, p. 37).]

However, one cannot deny that the LGORU study still exhibits some of the typical difficulties we noted earlier. Thus, there are strong grounds for rejecting the notion that a very wide value of time is consistent with the reported results (13, Figs. 1, 2, and 3, p. 38). There was a marked imbalance in maxima and minima in the most used commuter data (13, Tables 9 and 11). Most of the estimates were performed on choices involving a car; doubtless car cost (not discussed) imported much noise. It is perhaps significant that the results that most clearly show considerable evidence of a limited range of time values are those for a subsample of 96 traders in London whose reported choice was bus-tube. Earlier arguments would strongly point to this choice being the best to observe in London because difficulties stemming from car costs are absent; the modes reported are the most widely used alternatives for commuting; and even modal differences, when considered in terms of total door-to-door journeys, might well be least for that pair of modes. [Six choices were reported: (a) bus-tube, (b) bus-rail,

(c) bus-car, (d) tube-rail, (e) tube-car, and (f) rail-car. No determinate value of time is discernible in b through f in the sense that, within the range of time values considered from 0.5 to 1.0, no one value gave fewest misclassifications (13, Table 7, p. 22). Those familiar with London will know that the most likely pair to eliminate relative disutility, tube-rail, is unfortunately not so widespread as bus-tube, and the sample, drawn at random, duly turned up with only half as many observations.]

CONCLUSIONS

A review of recent British studies on the value of time indicates that the established figures should not be abandoned without much more attention to the circumstances of the observations on which the studies were based. The apparent increase in variance of measured values has coincided with a shift toward much less favorable conditions for making useful observations and estimates. One cannot finally arbitrate the issue of whether to rely on the higher or the lower of the measured values now available until, among other things, the detailed incidence of actual and potential traders and their distribution between maxima and minima, any bias imported by car costs, and the implications of disaggregation of time savings or losses in binary choice have been investigated. There is a need to reduce the studies in common terms. Issues of estimation of values of time should be separated from those of modal choice. The authors of the LGORU study also stress the importance of using traders to estimate values of time. They point to 4 areas in which their use could now be directed: to measure values of component times, to develop measures of sensitivity, to apply the technique to existing data sets, and to observe individuals who make 2 choices involving respectively gains and losses of money against time (13, p. 16). These are indeed worthwhile pointers; but the argument of this paper is that the greatest payoff will be in intensive sampling where measurement conditions and opportunities are most favorable, and it is to the determination of these that we should devote our ingenuity.

REFERENCES

1. Evans, A. W. On the Theory of the Valuation and Allocation of Time. Scottish Journal of Political Economy, Feb. 1972.
2. Harrison, A. J., and Quarmby, D. A. The Value of Time in Transport Planning: A Review. Sixth Round Table, Economic Research Centre of the European Conference of Ministers of Transport, Paris, Oct. 1969.
3. Beesley, M. E. The Value of Time Spent Travelling: Some New Evidence. Economica, Vol. 32, May 1965; reprinted in Urban Transport: Studies in Economic Policy, Butterworth, London, 1973.
4. Mansfield, N. W. Recreational Trip Generation. Journal of Transport Economics and Policy, Vol. 3, No. 2, May 1969, pp. 152-164.
5. Clawson, J. M., and Knetsch, J. L. The Economics of Outdoor Recreation. 1966.
6. Time Research. Gt. Brit. Department of the Environment, Note 16, May 1970.
7. Lee, N., and Dalvi, Q. Variations in the Value of Travel Time: Further Analysis. Manchester Schools, pp. 192-193.
8. Planning the Journey to Work. Local Government Operations Research Unit, No. 73, Aug. 1970.
9. Veal, A. J. The Value of Time on Short Urban Leisure Trips: A Pilot Survey. Time Research, Gt. Brit. Department of the Environment, Note 27, April 1971.
10. Interim Report on Research Study on Value of Time. Gt. Brit. Department of the Environment, Oct. 1971.
11. Interim Report on Solent Travel Study. Time Research, Gt. Brit. Department of the Environment, Note 26, Sept. 1971.
12. Dawson, R. F. F., and Everall, P. E. The Value of Motorists Time: A Study in Italy. Gt. Brit. Transport and Road Research Laboratory, Rept. LR 420, 1972.
13. Modal Choice and the Value of Time. Local Government Operational Research Unit, March 1973.

Alternative Behavioral Approaches to Value-of-Time Models With Implications for Nontraders

Shalom Reichman, Department of Geography,
Hebrew University, Jerusalem

In the choice mechanism leading to the decision to travel, several categories of nontraders of time-cost attributes can be identified and probably make up most of the traveling population. Alternative conceptual approaches to the choice mechanism are reviewed, and their relative merits are discussed in terms of their implications for nontraders. Utility theory, the prevalent approach, is based on the premise that the value of time is a significant choice variable in the trading behavior of the trip-maker. For this, 3 behavioral assumptions are required: utilities can be added so as to obtain generalized costs, attributes can be compared between alternative modes, and alternatives can be clearly separated rather than lumped together. The theory of decision-making, and particularly the modified lexicographic approach or elimination-by-aspects model, possibly provides simpler and more realistic sets of behavioral assumptions: the grouping of attributes by the degree of their being shared by alternatives and the search mechanism that considers first vital and subsequently compensatory attributes. Absolute levels of costs and times can be considered as vital attributes, and costs or time savings as compensatory attributes. Also, following the logic of the elimination-by-aspects model, the present policy of developing additional transit modes is more likely to hurt existing transit modes than to decrease the level of car-owner, nontrader traffic.

The decision to travel includes, in theory, a component of choice, if only in terms of the costs and time attributes of the various transportation modes. In practice, a large number of trips are decided without specific consideration of these system characteristics or attributes. Nontraders are usually identified as travelers whose revealed preferences do not include a trade-off between travel time and travel cost. Three main categories of nontraders may be defined on the basis of the role of time and cost attributes in the trip-making decision.

1. Nontraders who do not face real choices between costs and time. These are usually referred to as travelers facing a predominant choice (1). In such a situation, the probability of choosing mode k over mode 1, when both time and costs characteristics are in favor of mode k, is 1.0, and that of choosing mode 1 is 0. In many of these deterministic choice situations travelers are also characterized as belonging to mode-captive choice decisions.
2. Travelers who face a predominant situation similar to that indicated above but who, instead of choosing mode k, select the inferior mode 1. In this case we have to assume that, irrespective of time and costs, other attributes are more important. For the sake of simplicity, these could be labeled comfort-oriented travelers.
3. Nontraders whose choice situations are confined no longer to mode characteristics but more generally to all other components of travel demand or to individual preferences. One example is a situation where generalized costs of the trip for both mode k and mode 1, though unequal, exceed a certain threshold, so that no trip is generated in the first place. In the case of such latent travelers, no trade is being observed between the various system characteristics.

Evidence from existing mode-choice and value-of-time surveys reveals that choice situations in which the travelers could be classified as nontraders according to the definitions of categories 1 and 2 probably constitute the majority of choice situations facing travelers, especially in urban areas.

To begin with, in many suburban areas with poor transit services, travelers are virtually car-captive since cars are the dominant alternative. Another example may be drawn from travel mode studies in Israel (2), where it was found that heads of households with private cars in the large cities use their cars for 95 percent of their trips. It is suggested that a significant proportion of these trips are made by the inferior mode inasmuch as alternative transit services with reasonable levels of service are available.

Finally, the detailed travel mode studies that resulted in the derivation of travel time values were performed on relatively restricted and selective samples. These samples range from 4,100 usable responses in a 9-state survey in the United States (3) to about 200 "pure" binary choices in Skokie, a U.S. suburb (4). Typically, a recent study in the Netherlands indicated that, out of 2,616 work trips in Rotterdam, only in 482 trips did travelers face a real-world choice and could, therefore, be included in the travel time evaluation model. In the reduced subsample of people facing a real choice, 75 percent used the private car (5). It appears that the number of events, or trips, where mode choice is deterministic by far exceeds that with time-cost trade-offs.

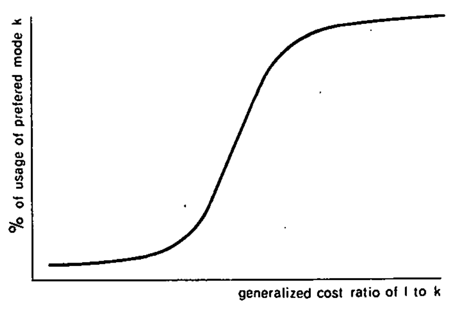
UTILITY THEORY, VALUE OF TIME, AND NONTRADERS

A number of recent studies have focused on the relation between utility theory, or consumer behavior theory, and the trading behavior of individuals to derive travel time values (6, 7). The most detailed review of the theoretical approach is presented in the Charles River study (7) and need not be repeated here. However, it is appropriate to raise the question to what extent are the theoretical constructs applicable to the behavior of nontraders. In particular, the problem arises as to whether values of travel time derived from choice situations can be used to predict changes in the traveling behavior of nontraders.

To simplify the discussion, let us suppose to begin with that only categories 1 and 2 are being investigated so that all observed events may indeed be combined in a single distribution based only on time and cost combinations (Fig. 1). Three important behavioral assumptions are required to project values of travel time derived from pure choice situations to cover the entire range of the distribution of mode usage: the additivity of the utility function, the evaluation of generic attributes rather than mode-specific attributes, and the separability between alternatives.

The additivity of utilities is an issue common to most economic studies based on consumer behavior. What is assumed is that the utility or disutility of a given attribute can be added to those of other attributes. In fact, the concepts of generalized costs or inclusive price found in the mode-choice literature are explicitly derived on the basis of the additivity of attribute utilities, especially costs and times. The validity of this assumption can be said to have been tested in the careful analyses of small samples of travelers. The analyses indicated that trade-offs between attributes apparently account for the revealed preference of one mode or route over the other. However, for mode-captive travelers in a dominant choice situation, the assumption of additivity cannot be tested in detail.

Figure 1. Hypothetical distribution of mode usage by system characteristics.



The assumption of the existence of generic rather than mode-specific attributes is equally essential for the derivation of values of travel time. What it assumes, in effect, is that attributes such as time and costs can be compared between modes rather than within a given mode. It can be argued that there exist choice situations, such as a route-choice situation, where values of travel time can be determined within a given mode. Furthermore, since there are no substantial differences between the values derived from route choice and those derived from mode choice, it may be reasonable to infer that generic rather than mode-specific attributes are indeed being evaluated by the traveler.

In the case of this assumption, a legitimate query may be raised as to its applicability to nontraders. We already know that nontraders usually belong to categories of travelers who face extreme choices or even do not have real-world alternatives. Can it be assumed that, even for those mode-captive travelers, the evaluation of system characteristics is based mainly on generic attributes? An argument can be put forward, for example, that the tendency to treat costs and times as generic attributes may be income dependent. Stated alternatively, at very low and possibly at high incomes, attributes might tend to be rather mode specific. A logical conclusion would, therefore, be that time-cost comparisons between modes in the case of nontraders are conceptually similar to those made with respect to abstract new modes for which empirical evidence of mode-specific effects is lacking.

Closely related to this issue is the third assumption that is inherent in the consumer behavior approach and is based on stochastic utility maximization, namely, separability between alternatives. In the context of value of travel time, this assumption implies that effective choice alternatives can be identified as being separate or independent, provided that they have attributes different from those of any existing alternative. However, in a binary-choice situation a problem arises when another alternative is added that has similar attributes to either one of the previous alternatives. Should the new alternative be regarded as a separate alternative and, consequently, reduce the probability of choosing any of the former, or should it instead be "lumped" together with the existing alternative that has similar attributes? In the latter case, which is contrary to the separability assumption, the probability of choosing each of the 2 lumped alternatives will be reduced, while that of using the alternative with dissimilar attributes will remain virtually unchanged.

When the assumption is applied to nontraders, who presumably have relative choice odds of 1 or 0, the question arises, Of what should a new alternative consist so that it might affect this probability? The problem can be reformulated in a different way: If a train is added as an alternative to a car and a bus, then whenever the bus and train have similar time and cost attributes they should be lumped together as a single alternative. In the case of nontraders such a procedure might intuitively be the real-world procedure, though it violates the conditions of the separability assumption.

So far we have discussed some problems related to the extension of assumptions of consumer behavior theory to cover the extreme cases of mode usage, that is to say nontraders, whenever choices are presumed to be made on the basis of measurable system characteristics, such as by category 1. These assumptions are no more helpful, and indeed less so, when we consider categories 2 and 3. It is assumed a priori that factors other than ratios of measurable system characteristics affect mode choices of both comfort-oriented and latent travelers, and consequently the use of value-of-time models to predict their behavior is irrelevant.

For categories 2 and 3, it is not possible to simply add a random (or error) component to the quantifiable relations. Categories of nontraders have been explicitly made on the presumption that in 2 categories the nonquantifiable elements, either in the identification of system characteristics or in the evaluation process, form separate and indeed major components of the revealed behavior.

In summary, consumer behavior theory and its component of value of travel time are based on a set of assumptions that are less tenable when applied to nontraders than to traders. In view of the fact that most travelers are probably nontraders, alternative methods should be sought to predict the behavior of nontraders, preferably in the area of decision-making theory. Some new developments in this field, which are relevant to our argument, will be briefly discussed below.

THEORY OF DECISION-MAKING AND ITS RELEVANCE TO NONTRADERS

Decision-making theory focuses on the process by which a course of action is chosen, irrespective of the context of such an action. Transportation choice clearly represents such a process and is characterized by the need to identify and evaluate multiple attributes. There are numerous procedures for selecting alternatives with multiple attributes. MacCrimmon (8) reviewed 10 different approaches to the selection of multiple-attribute alternatives and then suggested that a combination of procedures is probably more reasonable than selecting merely one specific procedure. In our case, the question naturally arises, Which additional decision-making procedure should be modeled to predict the deterministic choice of nontraders, which results in the selection of a unique mode?

As suggested by the discussion in the preceding section, simple choice mechansims appear to provide reasonable accounts of the decision-making process of certain categories of nontraders, perhaps even better than the existing consumer behavior.

The notions of dominance or satisficing, for instance, may explain the behavior of nontraders as a special case of utility maximization. Dominance can be suggested as the main mechanism whenever mode k is better than mode l in all compared attributes, or system characteristics. Instead of reducing the dimension of the choice situation, as is the case of adding utilities, one should retain its full dimension, compare attributes separately, and reject the alternative that has no attribute better but at least one worse than the other alternative.

Satisficing, on the other hand, appears to be the appropriate choice mechanism when the weights of the attributes may be difficult to determine. Here a tolerable level of each attribute is assumed to be present in the decision-maker's mind, and after an attribute-by-attribute comparison of the alternatives, the alternative that has an attribute below the accepted level is rejected. Again there is no need to assume additivity of utilities.

On the basis of this argument, the behavior of mode-captive travelers, whose alternatives are virtually nonexistent, can be explained by a dominance or satisficing decision-making procedure that requires no information on value of time.

Many nontraders, though, face alternatives that are not disjoint in the sense that the various transportation modes share several attributes, nor are they dominated so that other decision-making procedures would have to be used, depending on the nature of the alternatives. Here we might distinguish between car owners and noncar owners as 2 fundamentally different decision-making situations. Alternative modes, namely, trains or buses, for noncar owners are characterized by similar attributes that probably have similar ranges of scales. Also, the use of each mode may complement rather than be independent of the other. In view of these characteristics, additive utility, or else trade-offs, may indeed represent choice procedures of noncar owners.

Our main interest, however, lies in the decision-making procedure of car owners, particularly in the binary choice of car or transit modes or, more specifically, in the trinary choice of car, train, or bus. Here we can identify 2 transit modes that are similar, and one mode that is partly disjoint. In these situations, the decision-making procedure or rule might take the form of the modified lexicographic approach recently developed in the elimination-by-aspects (EBA) model (9).

According to the lexicographic approach (similar to the method of finding a word in the dictionary), attributes are assumed to be ranked on the basis of their (unknown) importance, and a search procedure is initiated to find out whether each alternative possesses the required attribute. This is repeated by a decreasing order of importance of attributes until any alternative without all required attributes is rejected.

The EBA model goes beyond the lexicographic approach in several major ways. No fixed prior ordering of attributes is assumed, and the similarity of alternatives can be ranked on the basis of the grouping of shared attributes. Furthermore, with the addition of a probabilistic choice process, these properties of the EBA theory provide a major departure from the principle of independence of irrelevant alternatives. Instead, a more general choice theory is presented that is based on the property of multiplicative inequality, whereby the probability of choosing 1 alternative x from a set of 3 alternatives x, y, and z is at least as large as the probability of choosing x from a binary choice of x, y and x, z in 2 independent choices.

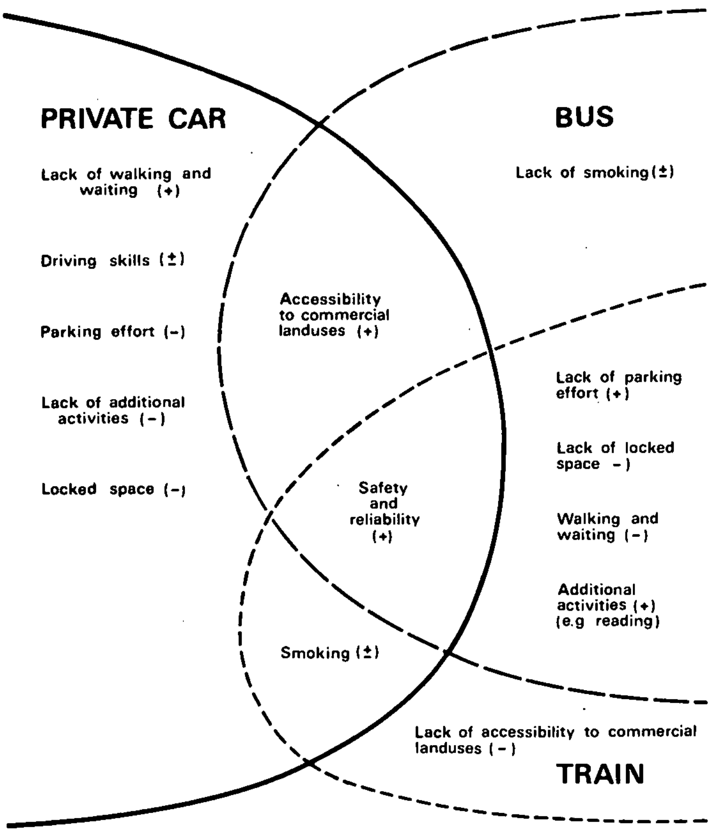
The intent here is not to elaborate on the various mathematical properties of the EBA model. Instead, concepts of EBA will be used primarily to indicate an alternative procedure to the modal choice procedure of car owners; the alternative procedure might complement the existing trade-off approach implied by value-of-time studies. More particularly, the behavior of nontraders will be examined on the basis of the shared and nonshared attributes of private car owners.

Let us assume that trip times and trip costs of transportation modes can be readily measured and scaled (10) and that there are other attributes that are difficult to measure. Some of these attributes are desirable (+), others are undesirable (-), and certain ones are desirable or undesirable (±), depending on the preferences of the traveler.

Figure 2 shows some arbitrary and discrete attributes of the 3 modes. Three groupings emerge: (a) attributes shared by all modes, (b) attributes shared by pairs of modes, and (c) attributes not shared by any other alternative.

The hypothesis to be investigated in this choice situation is that the more unshared attributes an alternative has, the more likely it is to be uniquely accepted or rejected, depending on the desirability of the attributes and on the preferences of the decision-maker. For car owners, whose alternatives have the largest amount of unshared attributes, the decision rule might include several steps: the elimination of alternatives on the basis of a few aspects, which are so important that their presence or absence is

Figure 2. Representation of attribute groupings for 3 transportation modes.



sufficient to eliminate an alternative, and subsequently the compensation between measurable aspects (time and costs) or between these and the nonmeasurable aspects.

DISCUSSION OF APPROACHES

The relative merits of the 2 behavioral approaches presented in the preceding sections may be compared with respect to the mode-choice situation in general, the specific weight of time and cost savings in mode choice, and the policy implications for reducing the population of nontraders.

The differences between the utility and lexicographic (or EBA) approaches in a mode-choice situation lie in at least 2 main areas.

1. Reduction of the complexity of multiattribute choice situations. It is a well-observed phenomenon that individuals tend to simplify the complexity of problems (11). In the case of a mode-choice problem, the decision rule according to EBA procedures is likely to be simpler than that of utility maximization. The first approach includes only unshared or partly shared attributes, and in the latter approach no reduction in the number of considered attributes is specified.
2. Rationality of the decision rule. For dominating choices, there should be no significant difference between the 2 behavioral approaches. On the other hand, when unshared discrete attributes are compared, different decision criteria can be envisaged, depending on the behavioral approach that is assumed to be operating. If an alternative is rejected because it does not possess a desirable attribute or else possesses an undesirable aspect, then according to the strict rationality of the utility approach it follows that the weight of this attribute is necessarily more important than the sum of all other attributes that were not yet considered in the decision procedure. The modified-lexicographic approach does not require such a strict interpretation of rationality, so that people may indeed make "wrong" decisions by giving to a certain attribute more weight than they would in other circumstances.

The second problem area where significant differences between the 2 approaches might occur relates more specifically to the way times and costs are considered in the choice situation. Here the lexicographic approach is clearly more tractable in reflecting real-world decision-making. To begin with, it allows a distinction to be made between "vital" attributes, which are so important that each may in fact eliminate an alternative, and "compensatory" attributes, each of which can be traded off for other compensatory attributes. For instance, absolute values of travel time and money may belong, in theory, to the group of vital attributes, while time and cost savings may belong to the group of compensatory attributes. This classification might be useful, to begin with, in distinguishing between urban and interurban trips. Interurban trips are characterized both by the considerable money and time outlays and by the wide variations in these attributes between modes. Hence, absolute costs and times on interurban trips can be viewed as unshared or unacceptable attributes between modes.

In most urban areas, on the other hand, it can be argued that absolute levels of cost and time outlays for an average trip do not exceed a satisficing or acceptable threshold for all modes. Consequently, according to the lexicographic approach, these attributes may be considered as shared attributes and, therefore, should not play a determining part in the decision procedure of mode choice. Time and cost savings, however, are presumably important compensatory attributes in urban trips. What probably occurs in the case of urban mode-choice situations is that time and cost savings are considered with other unshared or partly shared discrete attributes, such as those given in Table 1. If any of these other unshared attributes happen to belong to the group of vital attributes, then time or cost savings may not play any role in the decision procedure since alternatives could be eliminated a priori on the basis of the presence or absence of vital attributes.

Two important policy implications might evolve from the above discussion. First, value-of-time studies have limited relevance not only for nontraders facing dominant

Table 1. Discrete attributes shared and unshared by 3 transportation modes.

Type	Shared by All Modes	Shared by Pairs of Modes	Not Shared by Other Modes
Desirable	Safety and reliability	Lack of parking effort, accessibility to land uses, additional activities (e.g., reading)	Locked space
Undesirable		Walking and waiting, lack of locked space	Parking effort
Mixed		Smoking	Driving skills

choice situations but also for a wider population of travelers, particularly those who are mode captive. If indeed decision-making procedures are performed on the basis of EBA concepts, mode-captive travelers will likely eliminate alternative modes on the basis of vital attributes rather than compensatory aspects.

Second, the present policy of developing additional transit modes appears to run contrary to the logic of the lexicographic approach. The more similar 2 alternatives are, vis-à-vis a third one that has fewer shared attributes, the more likely that they will hurt each other more than affect the dissimilar alternative. Consequently, improved transit modes are not likely to succeed in significantly decreasing the level of car-owner, nontrader traffic. On the other hand, transportation modes that share more attributes with private cars, such as personal rapid transit and car rentals, are more likely to reduce the number of nontrading car users. Alternatively, a policy of suppressing some of the existing unshared attributes of private cars, such as lack of walking and waiting, might achieve similar results in enhancing the attractiveness of transit modes.

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REFERENCES

1. Beesley, M. E. The Value of Time Spent in Travelling: Some New Evidence. Economica, Vol. 32, May 1965, pp. 174-185.
2. Reichman, S., Eliash, A., and Barashi, D. Travel Behaviour in Israel. Israel Institute of Transportation Planning and Research, Tel-Aviv, 1974.
3. Thomas, T. C., and Thompson, G. T. Value of Time Saved by Trip Purpose. Highway Research Record 369, 1971, pp. 104-117.
4. Lisco, T. E. The Value of Commuters' Travel Time: A Study in Urban Transportation. Univ. of Chicago, PhD thesis, 1967, p. 40.
5. de Donnea, F. X. The Determinants of Transport Mode Choice in Dutch Cities. Rotterdam Univ. Press, 1971, pp. 49-53.
6. Watson, P. L. The Value of Time and Behavioural Models of Modal Choice. Univ. of Edinburgh, PhD thesis, 1971.
7. A Disaggregated Behavioral Model of Urban Travel Demand. Charles River Associates, Inc., Final rept., March 1972.
8. MacCrimmon, K. R. Decision-Making Among Multiple-Attribute Alternatives: A Survey and Consolidated Approach. Rand Corp., Memorandum RM-4823-ARPA, Dec. 1968.
9. Tversky, A. Elimination by Aspects: A Theory of Choice. Psychological Review, Vol. 79, 1972, pp. 281-299.
10. Reichman, S. Conceptual Problems of Travel Time Evaluation. Highway Research Record 446, 1973, pp. 21-27.
11. Slovic, P. From Shakespeare to Simon: Speculations—and Some Evidence—About Man's Ability to Process Information. Oregon Research Institute, 1972.

Price and Value of Time

Reuben Gronau, Hebrew University, Jerusalem

Early studies of the value of time seemed to use the terms "value of time" and "price of time" interchangeably to define the value or the shadow price people place on their time. It has been pointed out recently that it may be worthwhile to distinguish between these 2 terms, reserving the term "price" for the amount of money people have to forgo to save 1 unit of time and the term "value" for the amount of money people are willing to pay to save 1 unit of time (2). It has also been alleged that some of the studies claiming to have estimated the value of time have in effect estimated the price of time and that the conventional methods of analysis of binary choice (e.g., discriminant analysis, probit, logit) may be appropriate for the analysis of modal split but are completely inadequate for the estimation of the value of time.

These issues are examined here, and a new method is suggested for the estimation of the value of time. I have not yet applied this method in practice, so I can claim not that it is a better empirical tool but only that it is more comprehensible to someone who has the estimation of the value of time in mind.

The usual way of estimating the value of time in a situation of binary choice is based on the equation (I have intentionally omitted the constant term b_0 from this formulation)

$$X_i = b_1(P_2 - P_1) + b_2(T_2 - T_1) + e \qquad (1)$$

where X_i is a dummy variable denoting whether the traveler used mode 1 ($X_i = 1$) or mode 2 ($X_i = 0$); P_i is the money cost involved; T_i is the elapsed time; and e is the residual in the regression equation. The coefficients b_1 and b_2, obtained by using probit, logit, or discriminant analysis, measure the effect of price and time differentials on the modal choice. The ratio of the coefficients, b_2/b_1, is interpreted as the value of time.

This method has recently come under fire on 2 counts: (a) a statistical one—though b_1 and b_2 may be highly significant (i.e., their random error is relatively small), their ratio may be subject to a large variability; and (b) a conceptual one—the ratio b_2/b_1 is not an estimate of the value but rather the price of time (2). The first of these reservations is an empirical one and calls for new methods of estimation that will reduce the random error of the value of time estimate and increase its reliability. The second is more substantial and calls for a reexamination of the theoretical basis underlying Eq. 1.

Conventional analysis confines the decision of modal choice to 2 measurable characteristics: the money cost of traveling by a given mode P and the opportunity costs of time V(T), where T denotes traveling time. Adhering to this simple model, I ignore for the time being other characteristics of the mode that may affect the traveler's choice (factors conveniently lumped together as comfort and convenience). If we assume for simplicity that there exist only 2 alternative modes of travel, the traveler's decision criterion is assumed to depend on the generalized cost function Π.

$$\Pi = P + V(T) \tag{2}$$

A traveler prefers mode 1 to mode 2 if the generalized cost function of 1 is less than that of 2,

$$\Pi_1 < \Pi_2 \tag{3}$$

If we assumed that the value a person places on each unit of his time K is the same and independent of the length of his trip

$$V(T) = KT \tag{4}$$

we can rewrite the generalized cost function

$$\Pi = P + KT \tag{5}$$

Mode 1 is preferred if

$$\Pi_2 - \Pi_1 = (P_2 - P_1) + K(T_2 - T_1) > 0 \tag{6}$$

Alternatively, the traveler's decision criteria can be reformulated in terms of the value of time K. A person prefers the faster mode 1 if

$$K > (P_1 - P_2)/(T_2 - T_1) = K^* \tag{7}$$

K^* is the additional amount of money the traveler has to forgo in order to save 1 unit of time, i.e., the price of time. Thus, travelers with a value of time that exceeds the price of time will choose the faster mode, and those with a value of time that is smaller than the price of time prefer the slower one. [If the average value of time varies with T, we could not formulate the decision criterion in these terms. If $V(T_i) = K_i T_i$, a person prefers mode 1 if $P_1 + K_1T_1 < P_2 + K_2T_2$; i.e., if $K_1 > (P_1 - P_2)/(kT_2 - T_1)$, where $k = K_2/K_1$.] For example, if the air fare is \$24 and the train fare is \$12 from New York to Boston and the traveling time is 2 and 4 hours respectively, then everyone with a value of time exceeding \$6 per hour prefers the plane and those with a value of time short of \$6/hour prefer the train, \$6/hour being the price of time.

It is clear from the last example that one needs no data on modal split to compute a price of time. A reliable travel agent providing the data on fares and traveling time by the various modes should suffice. It may be argued that the traveler's conceptions of the price differential and the time savings differ from those of the travel agent, but even then, one does not need information on modal choice to estimate the "perceived" price of time but better data on the person's perceptions about traveling time and costs.

Data on modal choice become important when one tries to estimate the value of time. Observing the modal split of a group of travelers facing the same modal choice who seem to be homogeneous in terms of the value and (perceived) price of time, one would expect the whole group to make the same choice. The observation that different members of the group make different choices indicates that it was apparently wrong to assume that all members are homogeneous with respect to their values or price of time or both. (Another explanation, which I have ruled out, is that there are more than 2 factors affecting the modal-choice decision.)

Let us first assume that there is no error of measurement of the price of time (i.e., there is no error in the estimates of the price differential and the time differential). Intragroup differences in choice, therefore, originate from intragroup differences in the value of time. Let the group's mean value of time be μ; then

$$K = \mu + \epsilon \tag{8}$$

where ϵ is a stochastic term varying from person to person. By Eq. 6 a person prefers the faster mode if

$$(P_2 - P_1) + \mu(T_2 - T_1) > (T_1 - T_2)\epsilon = u \tag{9}$$

The specific assumptions about the distribution of u determine the statistical method used to estimate Eq. 1. If the assumptions hold, then a comparison of Eqs. 1 and 9 indicates that the ratio b_2/b_1 serves as an estimator of the mean value of time μ.

For example, let it be assumed that u has a normal distribution with standard deviation of σ_u.

$$u \sim N(0, \sigma_u) \tag{10}$$

The probability that the traveler uses the faster mode is

$$\begin{aligned} \text{Prob}\,[X_t = 1] &= \text{prob}\,\{(u/\sigma_u) < [(P_2 - P_1) + \mu(T_2 - T_1)]/\sigma_u = Z\} \\ &= (2\Pi)^{-\frac{1}{2}} \int_{-\infty}^{Z} \exp(-y^2/2)\,dy \end{aligned} \tag{11}$$

Estimating Eq. 1 by the probit method yields the coefficients of Z; i.e., b_1 is an estimate of $(1/\sigma_u)$, b_2 is an estimate of (μ/σ_u), and the ratio b_2/b_1 is an estimate of μ. There is, however, no way of isolating the other parameters of K, e.g., the standard deviation σ_ϵ. The variability of the stochastic variable u reflects both the variability of K and the variability of the time differential $(T_2 - T_1)$. Thus, the conventional method yields a point estimate of the mean but no additional information of the distribution of the value of time.

There is, however, an alternative method of estimating the value of time based on Eq. 7. Confronted by a price of time of K^*, the person chooses the faster mode if $K > K^*$; i.e., if

$$\mu - K^* > -\epsilon \tag{12}$$

Thus, one should estimate

$$X_t = a_o + a_1 K^* + e \tag{13}$$

where the estimation method depends on the assumed properties of ϵ. If, for example, it is assumed that the intragroup distribution of the value of time is normal

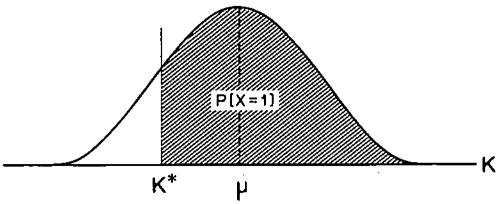
$$\epsilon \sim N(0, \sigma_\epsilon) \tag{14}$$

the probability of choosing the faster mode is (Fig. 1)

$$\begin{aligned} \text{Prob}\,[X_t = 1] &= \text{prob}\,[-\epsilon/\sigma < (\mu - K^*)/\sigma_\epsilon = Z^*] \\ &= (2\Pi)^{-\frac{1}{2}} \int_{-\infty}^{Z^*} \exp(-y^2/2)\,dy \end{aligned} \tag{15}$$

The coefficients of Z^* can be obtained by estimating Eq. 13 within each socioeconomic group by the use of the probit method where a_o = est (μ/σ_ϵ) and a_1 = est $(1/\sigma_\epsilon)$. Hence, a_o/a_1 should yield an estimate of the mean value of time μ, and $(1/a_1)$ should yield an estimate of the dispersion of the distribution. Furthermore, if it is assumed that the mean value of time varies systematically with the socioeconomic characteristics of the

Figure 1.



group (say, income, education, age, sex, family composition, purpose of trip) but σ_ϵ is constant, one can introduce this relation directly into Eq. 13. Let $\mu = \alpha Y$, where Y is a vector of characteristics, and α of coefficients, then one can estimate

$$X_t = aY + a_1 K^* + e \tag{16}$$

where a_1 = est $(1/\sigma_\epsilon)$ and a = est (α/σ_ϵ), to obtain estimates of the determinants of the value of time. [An application of this method for the estimation of the value of time of housewives is given in another report (1).]

It seems to me that, if the major purpose of the study is the estimation of the value of time and if intragroup difference in modal choice can be attributed exclusively to differences in the value of time, the new method (Eqs. 13 and 16) provides a more natural framework for the analysis. This conclusion is not much affected if one opts for the alternative explanation, i.e., that the value of time is the same for all the members of the group ($K = \mu$, $\sigma_\epsilon = 0$), but there exist errors in the measurement of the price and time differentials. In this case u and ϵ depend on the errors of measurement and not on the random component of the value of time. If it is assumed that the errors have a normal distribution, u has a normal distribution and one should use Eq. 1 for the estimation of the value of time $K = \mu$. On the other hand, if it is assumed that the error in the measurement of the price of time K^* has a normal distribution, Eq. 13 is preferred. Finally, if one allows for both error in measurement and a random component in K, one cannot separate in the estimate of the standard deviation of the stochastic term obtained through Eqs. 1 and 13 the part that is due to the variability of the value of time and the part that originated from the error of measurement. In the last case one has to be consoled with the estimate of the mean value of time, but one cannot obtain any additional information of the shape of the distribution.

In conclusion, it seems that from a theoretical and methodological point of view the new method has a slight edge over the conventional one. However, the question of which is better cannot be settled on theoretical grounds but depends largely on the empirical evidence. One method may serve as a better prediction of modal split, in the sense that it provides a better fit, but may be an inferior method for the estimation of μ because of the large variability of the ratio of the relevant coefficients. The variability of the price of time as well as the variability and multicollinearity between the price and time differentials should affect the final outcome. At this stage we have to reserve our final judgment until the empirical results are in.

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REFERENCES

1. Gronau, R. The Effect of Children on the Housewife's Value of Time. Journal of Political Economy, Vol. 81, No. 2, Pt. 2, March-April 1973, pp. S168-S199.
2. Hensher, D. A. Valuation of Travel Time: An Alternative Procedure. Third Conference of Economists, Economic Society of Australia and New Zealand, Adelaide, Australia, May 1973.

Conference Papers on Extension of Present Methodology

Separable Versus Simultaneous Travel-Choice Behavior

Daniel Brand, Department of City and Regional Planning,
Harvard University

After an initial discussion of the implications for travel modeling of alternative travel-choice behavior assumptions, 2 of these assumptions are discussed and analyzed in detail. The assumptions are separable and sequential travel choice versus simultaneous travel choice. Subsumed within this separable-simultaneous dichotomy are long-run activity location decisions and short-run travel decisions. Alternative methods of applying travel models based on the various assumptions are presented, and their strong and weak points are discussed.

The objectives of this paper are

1. To bring together and discuss the rationale for various strands of previous work in assuming separable-sequential and simultaneous travel-choice behavior in travel demand modeling and
2. To provide a common point of departure for discussion of extensions of present methods of modeling travel-choice behavior.

MODELING TRAVEL-CHOICE BEHAVIOR

Existing travel demand models are classified as short-run or long-run demand models according to whether short-run travel decisions (choices) are assumed to be made separately from long-run activity location decisions. The additional classification of direct and indirect demand models is used to describe whether the short-run travel decision is assumed to be one simultaneous "joint" choice or a series of separate choices (e.g., mode, destination, frequency). In this section, certain travel modeling implications of these behavioral assumptions are discussed.

Modeling Short-Run Travel Behavior

Travel-choice behavior modeled in direct demand models assumes that all attributes of an entire trip are known and considered simultaneously by the traveler. As shown in Figure 1, this behavior can be described as involving the simultaneous consideration of all the attributes normally associated with each of the 5 conventional descriptors of travel: frequency, time of day, destination, mode, and path. If each path through the travel decision tree is considered an alternative travel choice whose attributes are considered simultaneously "in competition" with the attributes of all the other travel choices, the models can become very complex. The number of choice combinations to be considered and modeled simultaneously is the product of the number of alternatives within each of the travel choices. For example, a simultaneous model of travel that considers 3 modes, 2 times of day, 20 destinations, and 1 path requires the modeling of ($3 \times 2 \times 20 \times 1$) or 120 travel choices for each origin. [This number may be reduced by eliminating zero-probability choices in calibrating models that satisfy the independence axiom (see next section).] The number of explanatory variables and the allowable interactions among variables that may be assumed to explain (model) simultaneous travel behavior can multiply very rapidly for realistic travel-choice situations in urban areas.

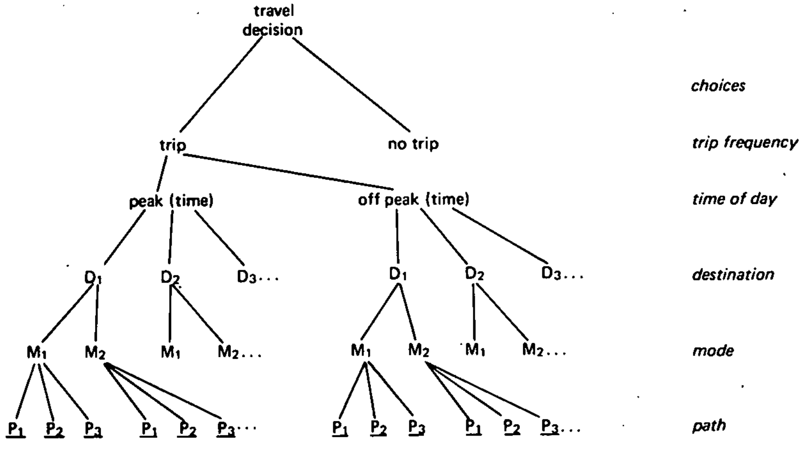
The need for "simple robust models" has been well articulated (2). Calibrating models for large numbers of alternatives (choices) with very low probabilities of choice is difficult in the extreme. Attributing properly the separate effects of large numbers of (possibly highly correlated) attributes describing complex choice environments (where calibration techniques often require certain assumptions, e.g., normality or homoscedasticity) boggles the mind. (One may speculate that the "number of variables required to predict probability of choice is finite and rapidly approaches the limit of human discrimination.") For these reasons, travel demand models must be reduced in complexity in some plausible way.

Restricting the choices available restricts the products or attributes the traveler is assumed to evaluate in making his travel decision. Restricting the choices that are presumed available to the traveler appears to be the way in which choice-specific travel demand models can be reduced in complexity. However, this involves making some important assumptions on the separability and the sequence of travel choices.

The assumption that travelers behave as though they sequentially consider (travel) choice-specific attributes (Fig. 1) means that there is a hierarchy of travel decisions in which certain travel decisions are made independently (separately) of others. In turn, other travel choices (e.g., higher level choices like destination, Fig. 1) are made given that lower level choices (e.g., mode) are predetermined.

There are 2 ways to model such sequential travel behavior. The first assumes that the relative valuation of choice attributes is constant throughout the set of travel choices. This requires that models of the independently made lower level travel decisions be calibrated based only on a subset of attributes describing those choices. The estimated (and preserved) utilities from the lower level choices are then added to a set of attributes on the basis of which the higher level choices are made. The traveler, it is assumed, makes some sequence of choices, and the earlier choices are based on independent and separate evaluations of personal utility (separate) from the "later" conditional or "constrained" choices. For example, the time of day (shopping purpose) choice was modeled (10) on the assumption that "there is a utility associated with the trip itself which is additive to the utility or disutility associated with the choice of time

Figure 1. Presumed hierarchy of travel choices.



of day, which is additive with the utility associated with the place to which the trip is made. . . ."

Thus, the choice of mode is modeled separately and prior to the destination choice and is assumed to be independent of the overall number of trips between the origin and destination. Similarly, the choice of time of day is assumed to be made independently of the choice of destination.

The attributes that are assumed additive must map on the (sequential) choices. Otherwise, a choice-abstract model results. [Choice-abstract models assume that the attributes of travel choices are considered or perceived by the traveler independently of the objects or facilities that carry or support or propel the traveler (7).] If difficulty is encountered, either the travel choices can be redefined or the supply-side description of choices (e.g., mode) can be abandoned and sequential choice-abstract models can be developed (7, p. 246).

The assumption of sequential travel choices, given that travelers perceive their choices as described by attributes inseparable from choices, is a difficult assumption to make. Yet it is an attractive strategy for reducing the complexity of travel demand models because it greatly reduces the number of interaction terms in the model. The other strategy is to reduce the number of independent variables that are assumed to influence travel behavior. That is, reduce the number of attributes the traveler is assumed to evaluate in his travel decision-making process without excluding interaction. Because the attributes that the traveler evaluates are identified with particular travel choices, this second strategy for reducing model complexity is more appropriate to choice-abstract models than to choice-specific travel demand models. [Choice-specific models assume that the attributes of travel choice are considered or perceived by the traveler together with the objects or facilities that carry or support or propel the traveler (7).]

A second way to model sequential travel behavior requires the still stronger (more difficult) assumption that some travel choices are made completely independently of other travel choices and that the relative valuation of choice attributes common to 2 or more travel choices is not necessarily the same in successive travel choices. This represents a third-level assumption regarding the consideration and valuation of the attributes (i.e., the relative marginal utilities) of the choice situation confronting the traveler. These 3 levels of assumptions are summarized in order from the weakest to the strongest (or most heroic) assumption.

1. All the attributes of the choice situation confronting the traveler are considered simultaneously. The complete trip is one decision. The relative valuation of the attributes is constant in any travel choice in the hierarchy shown in Figure 1.
2. There is a hierarchy of travel decisions in which certain travel decisions are made independently of other decisions. However, the relative valuation of choice attributes is constant in any complete travel decision (i.e., any single path through the travel decision tree shown in Fig. 1).
3. As in assumption 2, there is a hierarchy of travel decisions in which certain travel decisions are made independently of other decisions. However, the relative valuation of choice attributes common to 2 or more travel choices is not necessarily the same in successive travel choices.

The first assumption is the easiest to make. It requires the concomitant assumption of constant relative valuation of attributes in component travel choices of a complete travel decision.

The second (strict utility) assumption is made for ease of estimation (reducing the number of variables in the models to be estimated relative to the first and third assumptions). It requires some sequence of travel choices to be assumed for purposes of estimation as discussed above. Inclusive prices must be used to preserve the previously estimated utilities in strict utility models. The separately calibrated models using inclusive prices may be combined and applied simultaneously, or sequentially in any order.

The third assumption is the present assumption of UTP models that completely and independently estimate the different travel choices with different valuations of the independent variables in each model. The traveler, nevertheless, must face the same values of the independent variables in more than one component travel choice. For example, "the costs of the various modes influence not only the choice of mode but also the selection of destination and the determination of whether the trip should be made at all" (10). The most damaging indictment of the third assumption is that the sequence of application of the models determines the results. That is, no unique equilibrium can be reached with these models so long as flow and congestion conditions and the resulting travel costs change in any way from those used to calibrate the models. That is, even if the conventional series of models (including trip generation) were system sensitive, the sequence of their application determines the network equilibrium reached after more than one iteration. In addition, of course, the third assumption poses the problem of what appropriate value to place on user benefits (e.g., time savings) in evaluation of transportation system alternatives when different valuations of the independent variables are assumed in each component travel choice.

From the above discussion, the conclusion may be drawn that the assumption is easier to make that travel choices are separable than that travel choices are made in some sequence. This assumption implies only that the marginal rates of substitution (trade-offs) among attribute variables that govern one travel choice do not vary among travel choices. Stated another way, this means that the trade-offs or ratio of "weighted" attributes that explain one travel choice are independent of the other choices.

It is with the last statement that 2 important results from separate disciplines can be joined. In mathematical psychology, this is a statement of separability property of the independence-of-irrelevance-alternatives axiom (21, 22). In economics (utility theory), at the conditions assumed at equilibrium (see Appendix), the ratio of the marginal utilities of 2 choices is equal to the ratio of their "weighted" attributes (i.e., their revealed "prices"). The relative marginal utilities of the attributes of a choice situation can be solved for (inferred from) observed data on the choices made (31).

Thus, the assumption of separable travel choices potentially allows complex travel choices to be broken down into simple travel choices whose relative marginal utilities can be inferred from observed data. However, a sequence assumption is necessary to determine which (separable) travel choice will be "simply" modeled, the inferred relative marginal utilities from which will be preserved in the remaining travel choices. Before the possible plausibility of any sequence and separability assumptions is discussed, the important properties and implications for travel demand modeling of the independence axiom will be described.

Independence-of-Irrelevant-Alternatives Axiom

The independence-of-irrelevant-alternatives condition (21) implies that, for any 2 alternatives i and j having a positive (nonzero) selection probability, the relative odds of choosing j over i in a set containing only the 2 alternatives are equal to the ratio of their probabilities of being selected from any larger set of alternatives containing both i and j. This can be expressed as (26)

$$\frac{P_{ji}}{P_{ij}} = \frac{P(j:A_1)}{P(i:A_1)} \qquad (1)$$

where

P_{ji} = probability of selecting j in a 2-element set $A_1 = i, j$;
P_{ij} = probability of selecting i in a 2-element set $A_1 = i, j$;
$P(j:A_1)$ = (nonzero) selection probability of choosing j contained in any set A_1; and
$P(i:A_1)$ = (nonzero) selection probability of choosing i contained in any set A_1.

This condition states that the odds that alternative j will be chosen over i in a set containing both are independent of the presence of irrelevant "third" alternatives in A_1.

This is the separability property of the independence-of-irrelevant-alternatives axiom (21, 22).

"Strict utility" is defined by Luce (21) as being the function $h(Z_{ki})$ that satisfies Eq. 1 for the binary case i = 1, 2. That is, the relative odds of choice or share of, say, travel, P_i/P_j, between any 2 alternatives i and j are simply some function of the variables describing the 2-choice alternatives (and no others!).

$$\frac{P_i}{P_j} = \frac{h(Z_{ki})}{h(Z_{kj})} \tag{2}$$

where

P_i = probability of choosing i;
P_j = probability of choosing j;
$h(Z_{ki})$ = strict utility of i; and
Z_{ki} = (scale) variables, k, describing i.

The actual odds or probability P_i of choosing alternative i from a larger set of alternatives can vary, of course.

The binary-choice strict-utility model, Eq. 2, generalizes into a multiple-choice model only if the independence axiom holds, that is, only if the probability of a choice from a subset of alternatives is independent of what other choice alternative may also have been available. The resulting multiple-choice strict-utility model is (21)

$$P(i{:}A) = \frac{h\,(Z_{ki})}{\sum_{j\epsilon A} h\,(Z_{kj})} \tag{3}$$

for j = 1, ..., i, j, ..., where

$P(i{:}A)$ = probability of choosing i from a set of alternatives A;
$h(Z_{kj})$ = strict utility of alternative j in the set A, a monotonic function of the scale variables Z_k describing j; and
$j \epsilon A$ = complete set of alternatives between which a choice is made.

An exponential transformation of the strict utilities (and an abandonment of set notation) yields the multinomial logit formula:

$$P_i = \frac{e^{v(z_{ki})}}{\sum_{j=1}^{J} e^{v(z_{kj})}} \tag{4}$$

for j = 1, ..., i, j, ..., J.

Equation 4 says that the probability that a traveler will choose alternative i out of a set of J alternatives is directly proportional to its strict utility $V(Z_{ki})$ (a monotonic function of attributes k of the alternative i) and that the probabilities of choosing one alternative in the set of available alternatives, each with a nonzero probability of being chosen, must sum to one. ["Perhaps the most general formulation of the independence axiom is the assumption that the alternatives can be scaled so that the choice probability is expressible as a monotone function of the scale variables, k, of the respective alternatives" (35). This assumption is called simple scalability by Krantz (19).]

The function $V(Z_{ki})$ in Eq. 4 can, of course, be interpreted and estimated. In the language of the psychologist, it represents some function of the environment that stimulates a decision (33). In utility terms, it represents some function of the attributes of value to travelers of the alternative travel choices. A correct model specification is needed to capture appropriate effects on behavior of variables (attributes) describing the choice situation. A constant term, θ, in an equation for $V(Z_{ki})$, e.g., $\theta_i \prod_k Z_{ki}^{\alpha_{ki}}$, will include the effects of all attributes not explicitly included in the model.

Separability Property

The independence axiom is a general statement that has consequences that can be tested. For example, it says that, if alternative i is preferred to j in one context (choice situation), it is preferred to j in any context for which both are available. Furthermore, if the odds of choosing i over j are 0.7 in one context, those odds will be preserved in any choice situation. The traveler is assumed to exhibit transitivity in his behavior with respect to his "strict utility" $h(Z_{ki})$ versus $h(Z_{kj})$. That is, he values the attributes, Z_k, of any choice, i, the same (ratio scale) relative to choice j regardless of the context. Thus, the probability that an alternative (choice) will be chosen is exactly proportional to its strict utility (therefore, Eq. 3). And from Eq. 2, the relative odds that an alternative will be chosen from 2 alternatives is constant and a function only of the strict utilities of the 2 alternatives. This allows the introduction of new alternatives in a model application without calibration of the model, provided the previously estimated strict utilities are preserved.

In 1962, the author used the separability property of Eq. 3 to calibrate a share model of (multiple) choice among 4 access mode (walk, park-ride, kiss-ride, and feeder bus to line-haul rapid transit) alternatives being tested in Washington, D.C. The model was calibrated with paired aggregate modal-split data from a number of surveys because of the lack of data describing the relative usage of all 4 feeder modes together. This was allowable because of the "startling" behavior of the model (Eq. 3) that "the relative substitutability of any two sub-modes without the third being available is assumed equal to the relative attractiveness of the two in the presence of the third"(5).

McLynn and Woronka (28) used this property extensively to calibrate their "single pair" market share model developed for the Northeast Corridor project. In their model, automobile was used as the "base mode". When difficulties were encountered with certain nonsensical parameter estimates and the single-pair estimates, all single-pair equations were estimated simultaneously. From Eq. 2, it follows that such simultaneous estimation is irrelevant from the point of view of the behavioral grounding of the model, however much it may be desirable to constrain certain parameter estimates.

The property of "separability" of alternatives is not restricted to alternatives among modes. Alternatives can characterize the entire range of choices of trip frequency, destination, time of day, mode, and path, as already discussed. Thus, separate choice models can be calibrated separately and later combined into a travel demand model. However, behavioral assumptions as to the sequence of travel decisions are required, as already discussed. The separability property of the independence axiom was first explicitly recognized and used to calibrate a travel demand model by Charles River Associates (CRA) (8).

Share models have been used in travel forecasting without recognition of their separability properties for many years. For example, the gravity model of trip distribution (36) is a share model whose standard derivation is simple and general (12).

$$
\left.
\begin{array}{ll}
V_{ij} \sim G_i A_j Z_{ij}^k & G_i = \sum\limits_j V_{ij} = \sum\limits_j C_i G_i A_j Z_{ij}^k \\
V_{ij} = C_i G_i A_j Z_{ij}^k & \\
 & G_i = C_i G_{ij} \sum\limits_j A_j Z_{ij}^k \\
 & C_i = \dfrac{1}{\sum\limits_j A_j Z_{ij}^k}
\end{array}
\right\} \qquad (5)
$$

$$V_{ij} = G_i \frac{A_j Z_{ij}^k}{\sum_j A_j Z_{ij}^k} \tag{6}$$

$$\frac{V_{ij}}{G_i} = \frac{A_j Z_{ij}^k}{\sum_j A_j Z_{ij}^k} \tag{7}$$

Equation 5 states that the volumes between zones i and j are proportional to the previously estimated trips generated, G_i, and attracted, A_j, and to the attributes, k, of travel between i and j. C_i is the constant of proportionality, which is solved for in the remaining equations. The result, Eq. 6, is the usual form of the gravity model, which is equivalent to a share model, Eq. 7, for the split fraction of total trips from a zone i destined to zone j. However, the previously estimated "strict utilities" that (may have) resulted in the estimation of the G_i and A_j are not normally preserved.

In fact, of course, no transportation attributes are normally used in the estimation of the productions, G_i, and the attractions, A_j. Empirical evidence to support the use of strict utilities is the juggling necessary to bring the V_{ij}'s into line with the G_i and A_j in any gravity model application. That is, the results of the separately calibrated trip-generation and -distribution models are not (internally) consistent with each other.

The separability property implies that the conventional gravity model should be calibrated only with subregional structures (partitionings) that define distinctly different destination alternatives with nonzero probabilities of being chosen from a particular origin by a particular traveler (type) for a particular trip purpose. This would considerably simplify calibration but would appear to complicate gravity model application, i.e., predicting trip distribution (see discussion in section on applying forecasting models). An understanding of the separability property may thus lead to substantially more effective gravity models. Empirical research is clearly needed.

The derivation of the gravity model (Eqs. 5, 6, and 7) from a simple proportionality statement can easily be generalized to derive any split fraction (e.g., fraction of total regional trips emanating from an origin zone, or fraction of total interzonal trips on each mode). Each split fraction is in turn dependent on the previously derived trip universe being split. The models can then be "solved," one in terms of the next, in one multiple-choice share model. The result is similar to Manheim's "general share model" (24):

$$V_{klmp} = \alpha\beta_k\gamma_{kl}\delta_{klm}\omega_{klmp} \tag{8}$$

where

V_{klmp} = travel between origin k and destination l by mode m and path p,
α = total (regional) travel,
β_k = split fraction of α from origin k,
γ_{kl} = split fraction of $\alpha\beta_k$ to destination l,
δ_{klm} = split fraction of $\alpha\beta_k\gamma_{kl}$ to mode m, and
ω_{klmp} = split fraction of $\alpha\beta_k\gamma_{kl}\delta_{klm}$ to path p.

Each of the terms on the right side of Eq. 8 is intended to be a function of activity system and transportation system variables in Manheim's model.

In summary, in the calibration of a travel demand model, the separability property of the independence axiom implies that the (marginal) probability distribution of choice of mode can be separately estimated and multiplied by the conditional probability distribution of another travel choice, e.g., P (destination, mode), to give the joint probability distribution of both:

$$P(M,D) = P(M)\,P(D|M) \tag{9}$$

provided the previously estimated strict utilities from the modal-choice model are preserved. This operation requires 2 assumptions: (a) that destination choices are made conditional on mode choices and not the reverse, and (b) that the (dis)utility from the mode choice is additive to the utility from the destination choice. Thus, the mode choice is assumed to be independently made from the destination choice (in this case) but not the reverse. Given the separability and sequence assumptions, the choices can be separately modeled, assuming negligible income effects, and later recombined into one joint probability model by simple multiplication of the separately calibrated probability models, as in Eq. 9. Conversely, the joint distribution, P(M, D) must be estimated directly if the sequence and separability assumptions appear too strong.

Modeling Long-Run Activity (Household) Location Behavior

In travel demand forecasting, activity-location choices are assumed to take place in a much larger market than travel choices. Also, the time periods over which activity-location choices are made is assumed to be much longer. If activities are considered substitutes for each other in one market, this requires long-run demand models where activity locations and intensities are allowed to vary. The recent mixed success in land use modeling (20) testifies to the difficulty of describing the attributes of all the related choices in this larger market (which also includes travel choices). Thus, the present state of the art of travel demand forecasting with a few exceptions allows only amount of travel to vary, i.e., to be the dependent variable. [Some demand models have been formulated and calibrated that forecast (long-run) residential location, car ownership, and modal split in one equation set (1, 16). However, these models do not forecast quantity of travel. Nevertheless, the models provide a direction for further work.]

In modeling travel separately from activity location, the attribute variables describing the choice situation must be limited to those "highly" involved in the decision (i.e., close substitutes and complements). Indeed, a necessary condition for utilities derived from separately modeled travel decisions to be considered additive is that their components must be neither competitive (substitutes) nor complementary (23).

Trip purpose is the first way of describing the restricted set of choices that are said to be available to the traveler as an individual decision-maker. No substitution is assumed among trip purposes because the purpose of the trip corresponds to the activities at the trip destinations. The activities in place are taken as given in the partial equilibrium framework. If activities are taken as substitutes, a long-run demand (land use) model results.

The choice ordering implied by assuming that travel choices are made, conditional on activity locations, is represented in Eq. 10.

$$P(T, A) = P(T \mid A)\, P(A) \tag{10}$$

where

$P(T, A)$ = joint probability distribution of travel and activity location;
$P(T \mid A)$ = conditional probability distribution of travel, given activity location; and
$P(A)$ = marginal probability distribution of activity location.

Equation 10 implies the sequence assumption that activity-location choices are made first and precede travel choices. The sequence requires that the strict utilities inferred from activity-location behavior be used in the calibration of the travel demand model. This is, of course, not the way travel models are currently calibrated.

It is, of course, possible to assume that travel and activity location are independent. That is,

$$P(T \mid A) = P(T) \tag{11}$$

This is exactly the assumption that is made when one assumes that there is a sequence of travel-choice decisions in which mode and route choice precede destination choice. That is, these choices are assumed to be made solely on the basis of the (dis)utility of the trip itself. Making this particular assumption of travel-choice ordering (discussed in the next section) is at least consistent with Eq. 11.

In summary, although the logical conclusion of the theory of travel as a derived demand is to allow both short- and long-run travel activity to vary as complements in a general equilibrium framework (7), the assumption is made that we can eliminate the imposing structure this would require and model travel choices separately as an activity with a set of complements (activities) in place and fixed.

The resulting set of attributes needed to describe the choice environment for input to a travel-choice model is correspondingly (greatly) reduced. Further, the choice ordering implied by this assumption is that travel choices are adjusted much more quickly to a change in travel conditions than in residence and work-place location. Modeling the latter requires a dynamic model where changes are measured over relatively long periods. Thus, if a static travel model is assumed, the effects of changes in travel conditions on travel can be modeled (inferred), it is assumed, separately from their effects on activity location. This assumption and its implications are worthy of considerable research.

Aggregate Versus Disaggregate Models

The issue of aggregate versus disaggregate "probability" models permeates most current discussions in travel demand forecasting. The often-used term "disaggregate behavioral" models gives the impression that individual-choice models have a monopoly on incorporating travel behavior. That is clearly unfair, for travel demand models can be derived from behavioral assumptions independently of whether they will use aggregate or disaggregate data.

Choice behavior in disaggregate models must be interpreted as probabalistic. Deterministic choice (i.e., 0, 1 binary) behavior produces uninteresting results when aggregated over all individuals to describe aggregate behavior in a planning application. However, the probability process is assumed to be in static equilibrium and incorporates no time parameter in a behavioral sense; e.g., learning or experience does not change the probabilities (23). Disaggregate travel models should, therefore, be referred to as probabilistic and not stochastic if they are used with cross-sectional data.

The generally strong arguments for using disaggregate models usually include data efficiency arguments. That is, more information on travel-choice situations and behavior is usually available with disaggregate data than with aggregate data. For example, Fleet and Robertson (13) showed that aggregation of trip data to zones reduced the variation in trip-making (trip generation) between observations to only 20 percent of the value at the dwelling unit level. In the process of aggregation, nonlinear relations may also be lost by using averages of explanatory variables. However, disaggregate travel models have not yet demonstrated practical superiority in providing travel information to decision-makers. In fact, we have as yet a way to go in getting models based on individual-choice behavior into the field. [Disaggregate models of some of the conventional UTP steps (i.e., trip generation) will be easy to introduce "in the field" (17).]

However, there is little doubt that the emerging techniques (34) for using travel models based on the behavior of individuals and not the behavior of aggregate numbers of trips will accelerate our understanding of travel-choice behavior. The empirical results of the next few years should greatly improve the travel behavior assumptions discussed in the next section.

Travel Behavior Assumptions

Travel forecasting procedures must have a basis in behavior if planners and decision-makers are to be able to understand and interpret the results of the forecasts. This is true for many reasons. The forecasts that result depend on the behavioral assumptions. Behavioral models are needed for transferability (in space and time) to situations other than those for which the models were calibrated. Behavioral models are needed also for evaluation if the (usual) assumption is to be made that the trade-offs between time and money in a travel-choice situation are valid for user benefit calculations.

Transportation planning concerns itself with making, or contemplating making, changes to or affecting the transportation system. Our interest is in describing the behavior of travelers as they respond to travel choices and the changes in travel choices that confront them. The ability to predict the amount and distribution of travel in any situation is, therefore, only as good as our understanding of the underlying perceptions that travelers have of the choices that confront them.

In travel demand forecasting, therefore, we must confront squarely the validity of our theories that describe relations between people and their locations on the one hand and travel on the other. This involves consideration in particular of how and in what sequence, if any, people view the transportation system that connects or potentially connects their origins and destinations.

Separable Travel Choices

The open question is, What does the traveler perceive in his evaluation of his travel alternatives? Modeling travel directly as a simultaneous decision means including the attributes of every conceivable alternative to a specific choice in any model of that choice. By modeling long-run demand separately from short-run travel, we exclude moving the traveler's residence and work-place location as alternatives to his travel choice. However, such alternative choices remain as traveling to activities at varying locations as an alternative to staying put (destination choice versus no-trip choice); an automobile trip at a different, say, off-peak, time of day as an alternative to a transit trip at the peak hour; and so on.

As noted earlier, the conventional breakdown of individual travel choices is to separately model trip frequency, trip destination, time of day, mode choice, and route choice. Such a breakdown involves a stronger set of assumptions than the assumption of simultaneous travel decisions. The trade-off is generally between a stronger set of assumptions but less complex models and weaker assumptions but more complex and difficult-to-calibrate models. The unanswered questions are, How difficult to calibrate are models that combine travel decisions, and how difficult are they to forecast with?

At least 2 of the conventional travel choices might plausibly and relatively easily be combined, at least for purposes of empirical testing. That is, combining trip frequency and trip destination into 1 set of alternative choices appears theoretically plausible and convenient. Zero-trip frequency is the equivalent of no change in traveler location. Other combinations may also be speculated on. However, some appear more difficult than others, not because of the difficulty in assuming that travel-choice behavior is a simultaneous decision, but because of the separability property of most existing travel models. For example, combining mode and route choice into one decision may be difficult because of the similar characteristics of alternative routes within modes and the overly strong separability property in this situation. [The evidence is that "the addition of an alternative to an offered set 'hurts' alternatives that are similar to the added alternative more than those that are dissimilar" (35).]

Because the basis of calibrating travel demand models using the separability property is to constrain some decisions on the basis of attribute (utility) evaluations made in decisions modeled earlier in the chain, a discussion of travel-choice-separation assumptions cannot proceed far without including consideration of the ordering of the separate choice assumptions.

Choice Ordering

The assumed order of the travel decisions, given a separation, determines which choice situation is used to estimate the initial strict utilities. Empirical testing with alternate orderings and breakdowns can provide some evidence as to "natural" orderings, given the underlying assumption of "conditional" choice behavior. Is there a logical or natural ordering of travel choices? If there is any separation at all, hypotheses can be attempted for specific orderings of the choices. The following hypotheses are some that support the assumption that travel choices are separable and proceed in some sequence or order.

1. Sequential choice ordering based on timing. Traveler decision-making proceeds from the latest to the earliest decisions in time. For example, for a particular trip purpose (choice-of-destination activity), the traveler may be hypothesized to have some notion of the conditions on the available modes and routes when choosing his destination. That is, he has already considered the modes and routes that are available to him. He anticipates and makes choices on routes and modes that may then limit or constrain his available destinations and departure times. (Within a mode, he is apt to have anticipated the conditions on the alternative routes within the mode when he makes his mode choice. This suggests that mode-choice decisions are made after path decisions as opposed to both decisions being made simultaneously.) This implies a logical order of travel-choice decisions running counter to their sequence in time.

The possibility of a logical order of decisions running counter to their sequence in time in the case of travel decisions was discussed already by Beckmann et al. in 1955 (3). This reverse order also gets us around the practical difficulties (probably impossibility) of having to compute supply-sensitive system characteristics (travel attributes) on an area-wide basis for input to (disaggregated!) trip-frequency decisions made at a point (or zone), or for input to a modal-split model that precedes trip distribution. Production functions g(x) for, say, travel times, are well known on a link and route within modal basis (15).

2. Sequential choice ordering based on adjustment time. Models that assume some choice ordering in a sequence could rest their plausibility on the time it takes to adjust behavior to a change in policy. Some decisions (e.g., route choice) can be adjusted more quickly by an individual than others (e.g., an origin change involving a house purchase or a mode change involving a car purchase) because they involve less commitment to their former situation. Thus, sequential choice models that involve adapting to changes in supply considerations can be considered in this sense dynamic or stochastic (4). Conversely, simultaneous-choice assumptions result in models that are in this sense static. Unfortunately, only cross-sectional data exist at present to empirically test most travel demand models.

3. Sequential choice ordering based on experience. Traveler decision-making proceeds from those choices on which there is the most experience to those choices on which there is the least experience. Most, if not all, current travel demand models are based on or can be shown to be equivalent to rational "economic man" assumptions. These yield plausible (if normative) descriptions (models) of travel behavior, but they demand more of man's capabilities than he can generally "deliver." In addition, they assume that the traveler's values, and the choices he confronts, are constant over time. Conversely, there are other descriptions of behavior that assume less (or a bounded set of) knowledge on the part of the individual decision-maker. These provide alternate but as yet largely unexplored bases for modeling travel behavior, and the dynamics of commitment to old and selection of new travel choices as families move spatially and socially over time.

Important theoretical support for separate and sequential choice modeling comes from the theory of decision-making called "satisficing" (25). This theory rejects the notion that there exists a rational economic man who is perfectly knowledgeable and perceptive about all the possible alternatives that confront him and who can compare all possible alternatives with one another to find his optimal choice by manipulating stored criteria describing the alternatives. Satisficing substitutes for this true or complete rationality a hypothesis of bounded rationality. This implies sequential search and limited sets of criteria used for evaluation. That is, in place of simultaneous (or separable and transitive) comparison of all alternatives, alternatives are examined sequentially according to satisficing. And rather than being compared to one another on the basis of a set of (interval scale) operational criteria, the alternatives are compared to a simpler set of minimal criteria until an alternative is found that satisfies the decision-maker. Alternatives are discovered or searched sequentially until a satisfactory alternative is encountered. No attempt is made to exhaust all possible alternatives. Moreover, search for new alternatives will only occur if the traveler perceives a discrepancy between his level of aspiration and his level of reward from the existing behavior.

This "model" in its general formulation can be interpreted as supporting models of sequential travel behavior. Travelers can be considered to evaluate sequentially well-defined travel alternatives in terms of the objects that provide the travel service (modes) and in terms of the benefits from the travel service (destinations). Conversely, the traveler may sequentially apply a limited set of criteria that are used to reject alternatives that do not meet threshold levels of those criteria. (This latter interpretation provides support for choice-abstract sequential models.) In both cases there is support for the hypothesis of choice behavior that involves sequential examination of choices.

We may describe the present trip of a traveler as one path through the tree shown in Figure 1 (assuming he presently makes a trip). If he is dissatisfied with any aspect of his present trip or, if confronted by a new alternative with a promised or expected improved level of service, does he sequentially examine "near" alternatives at only one level of choice? Or does he reconsider many paths involving changes throughout the hierarchy? Or does he simply consider only the new alternative if available and accept it or reject it?

According to the theory of satisficing, there is generally a conservative bias in the system of choice. That is, over time, levels of aspiration tend to adjust to levels of achievement. (It is the difference in the levels that is said to motivate search for new alternatives.) A new alternative may or may not change the traveler's perception of difference between present and possible (future) alternative states if he changes his travel behavior. We clearly need to better understand what those perceptions of difference are, at what level in the hierarchy they occur, in what sequence they occur, and how their relative requirements of adjustment time may operate to eliminate certain choices from the sequence.

The above hypotheses that support sequential travel decision-making are not made as a matter of idle speculation. The current conventional procedure of travel forecasting assumes sequential travel choice and a very particular choice ordering. The choice ordering is allowed to vary only slightly in practice. For example, the place of modal split in the order of trip-choice decisions has been called "the most actively debated issue in modal split" (37). The context of this statement referred to whether modal split should precede or follow trip distribution. The alternatives can be represented by the following 2 model structures (probability statements in this case):

$$P(M, D) = P(D|M)\ P(M) \tag{12}$$

$$P(M, D) = P(M|D)\ P(D) \tag{13}$$

where M = mode, and D = destination. If Eq. 13 were true and Eq. 12 false, destination choice would be independent of the availability of a mode (say, automobile) to reach the destination. This does not seem plausible except possibly in the case of work trips. (In such a case, the car is assumed to be purchased if not available and if necessary for reaching the destination.) In the reverse case (Eq. 12 is true, and Eq. 13 is false), the choice of mode is assumed to be made independently of the choice of destination. For example, the automobile, if available, might be selected for the trip, and the destinations that can be reached by automobile are then considered by the traveler. This appears somewhat plausible (say, for convenience shopping trips), at least more plausible than the reverse sequence. (If this is true, at least for some important trip purposes, it augers badly for transit usage. That is, choice of mode, e.g., transit usage, would be independent of origin-destination transportation system characteristics, including origin-destination pairs in larger cities where transit service may be excellent.)

There is an alternative model structure that poses a way out of the above dilemma if the order of travel behavior is not stable or must be subjected to further empirical testing. Equations 12 and 13 may be rewritten in the following form (11):

$$P(M, D \mid MEX_D) = P(D \mid M)\, P(M \mid MEX_D) \tag{14}$$

$$P(M, D \mid DEX_M) = P(M \mid D)\, P(D \mid DEX_M) \tag{15}$$

where X_D is the set of all decisions made prior to the choice of destination, and $P(M, D \mid MEX_D)$ is, therefore, the conditional probability that M and D will be chosen if mode choice precedes destination choice. Analogous statements apply to Eq. 18. Because MEX_D and DEX_M are mutually exclusive, Eqs. 14 and 15 can be added together to yield

$$P(M, D) = P(D \mid M)\, P(M \mid MEX_D) + P(M \mid D)\, P(D \mid DEX_M) \tag{16}$$

This is an exact expression for P(M, D). Equation 19 is equivalent to Eq. 12 or 13 only if mode choice always precedes destination choice or vice versa. It is also possible to expand Eq. 16 to include all aspects of travel decision-making.

Unfortunately, a solid case cannot be made for many trip-choice sequence assumptions. Our theory is weak, and we must look at whatever empirical evidence is available. Ben-Akiva (4) showed empirically that mode choice, assumed before or after destination choice, or the 2 travel choices modeled jointly all lead to different valuations (relative marginal utilities) of the trip attributes, (e.g., time and money costs of travel). (But this is insufficient evidence to lead to the conclusion that both sequences are wrong or that the separation assumption is incorrect.) His work on estimating the joint probability of mode and destination choice directly is the first demonstration that disaggregate data can be used for simultaneous travel-choice models, though not all travel choices were included. [The first simultaneous choice model using aggregate (zonal) data was by Kraft in 1963. The trip-generation and mode-choice decisions were combined and modeled simultaneously. Again, not all travel choices were included.] By combining choices and modeling them simultaneously, the need for sequence assumptions, but not separability assumptions (except when applying the model directly), is avoided. That is, the separability property of any formula satisfying Eq. 3 (e.g., multinomial logit) allows travel choices to be separated while still preserving the strict utilities. The separability property allows the conditional and marginal probabilities of the travel choices to be computed from the joint probability distribution estimated from the simultaneous model. Thus, for forecasting purposes, models satisfying Eq. 3 may be separated and applied sequentially (indirectly) or combined for application in a direct model (see later discussion of alternative methods).

When travel-choice models are calibrated separately, the alternatives allowed are determined by the conditional probabilities. That is, in Eq. 12, the only alternatives allowed are the destinations that are available or can be reached by mode m. The estimated strict utilities from this set of choices are then assumed to be independent of the choices as soon as the separability property of Eq. 3 is used in travel forecasting (see later discussion of definition of alternative choices).

The hypothesis of simultaneous (i.e., not conditional) travel choices can be easily tested by using standard chi-square tests for differences between marginal and conditional distributions of the same random variable. If there are no differences, the hypothesis of no relation between, say, mode and destination could not be rejected. Because it is relatively easy to show a relation by the chi-square test with large sample sizes, an inability to reject no sequence might be considered evidence that the decisions are being made simultaneously. (However, the power of the test is low.)

Theories of choice that consider different choice-abstract aspects of travel attended to at difference times and in some specific order were discussed earlier. Aspects of travel can overlap with the definitions of travel choices because attributes in the definitions of each are often common to both. Some arguments against transitive value (strict-utility) models can be used in part to advance the case for assuming sequential travel choices and thus advantageous use of the separability property to calibrate demand models.

Similarly, arguments against a logical ordering of travel-choice decisions argue also for strict-utility travel-choice models because such arguments are consistent with assuming a single monotonic function of the scale variables of the alternatives and the single estimation of joint probability distributions of simultaneous travel choices (i.e., "direct" demand models). Therefore, uncertainties as to whether travel choices can be assumed to be separable and occur in some logical order do not point to abandoning strict-utility models. They may point to combining choices and making less use of the separability property in model calibration.

In summary, there may be some clear-cut travel-choice ordering that can be assumed from the standpoint of travel behavior and, thus, lead to the conclusion that probability models for combined choices should be calibrated directly wherever possible. Fewer sequence assumptions can lead to improved use of the separability property for combining separately modeled choices into a demand model. Because the independence axiom excludes, in any event, alternatives with zero probability of being chosen, the data requirements for estimating strict-utility models of combined travel choices can be greatly reduced. Simultaneous (direct) demand models rather than sequential choice models seem indicated from a behavioral point of view, although the discussion cannot be closed in view of the above hypotheses.

COMBINING STRICT-UTILITY SEQUENTIAL TRAVEL-CHOICE MODELS

CRA (8) used the separability property of the independence axiom to calibrate a series of shopping-trip travel models in the following assumed sequence: mode choice, destination choice, time-of-day choice, and trip frequency (including whether to make the trip). Data at the individual traveler level were used. The relative marginal utilities of modal attributes revealed (estimated) in the mode-choice decision were preserved in the next choice modeled, namely, trip destination, by weighting the attributes of travel by mode to each destination by the probability that the mode would be chosen, given the selection of the destination. The weighting and aggregation are done with the estimated parameters from the previous (mode-choice) decision. The previously estimated strict utilities or "inclusive prices" are preserved. A proof is given that this method of combining separately calibrated travel-choice models is consistent with the assumption of additive utilities. There is no summation over the estimated number of trips because the choice of mode is assumed to be independent of the number of trips between an interzonal pair. "Tastes about modes are (assumed) independent of tastes about trip frequency" (8).

The method can be schematically portrayed for the 4 sequential shopping-trip decisions as follows:

$$\left.\begin{aligned} P(\text{mode}) &= f_m(p, s) \\ P(\text{time of day}) &= f_t(\hat{p}, s) \\ P(\text{destination}) &= f_d(\hat{\hat{p}}, s) \\ P(\text{frequency}) &= f_f(\hat{\hat{\hat{p}}}, s) \end{aligned}\right\} \qquad (17)$$

where

p = vector of travel attributes,
$\hat{p}$ = previously estimated strict utility = "inclusive price,"

$\hat{p}, \hat{\hat{p}}$ = inclusive prices previously estimated, and
s = vector of socioeconomic variables.

This is the logical conclusion of the assumption of transitive tastes. (Strict utility suggests that "behavioral time values" have a legitimate place in transportation benefit measurement, assuming transitive tastes!

In summary, the assumption of individuals' evaluating choices such that their probability of choice is expressible as a monotonic function of the choice-specific attributes of all the alternatives (simple scalability or strict utility) has been shown to be the expression of the independence-of-irrelevant-alternatives axiom. This means that the relative probability of choice between 2 alternatives is independent of the attributes of other alternatives in the offered set of alternatives. The transitive nature (strict utility) of the resulting choice behavior results in multinomial, multivariate probability or share models. The separability property of the independence axiom and its resulting multiple-choice share models allow big, complicated travel decisions (e.g., those modeled in direct demand models) to be broken up into smaller, more easily modeled choices. However, these models may be separately calibrated only if separation and sequence assumptions are made. The separately calibrated models can then be linked through their previously estimated parameters into a demand model (i.e., a direct or one stage-pass demand equation). To do so requires use of probabilities (or relative frequencies), not summation of numbers of trips from the prior travel choice in the assumed sequence.

There is, in addition, a set of travel-choice models based on the strong assumption that the choice probabilities are expressible as a function of attributes of subsets of travel choices making up one complete travel decision. This requires the assumption of sequential and completely independent travel choices where the relative valuation of attributes common to 2 or more travel choices, making up one trip decision, is not constant throughout the hierarchy of travel choices (Fig. 1). These models (e.g., the present UTP models) cannot be combined into one direct demand model, but must be applied sequentially in the order in which they have been calibrated, as discussed in the next section.

APPLYING TRAVEL FORECASTING MODELS

Alternative Methods

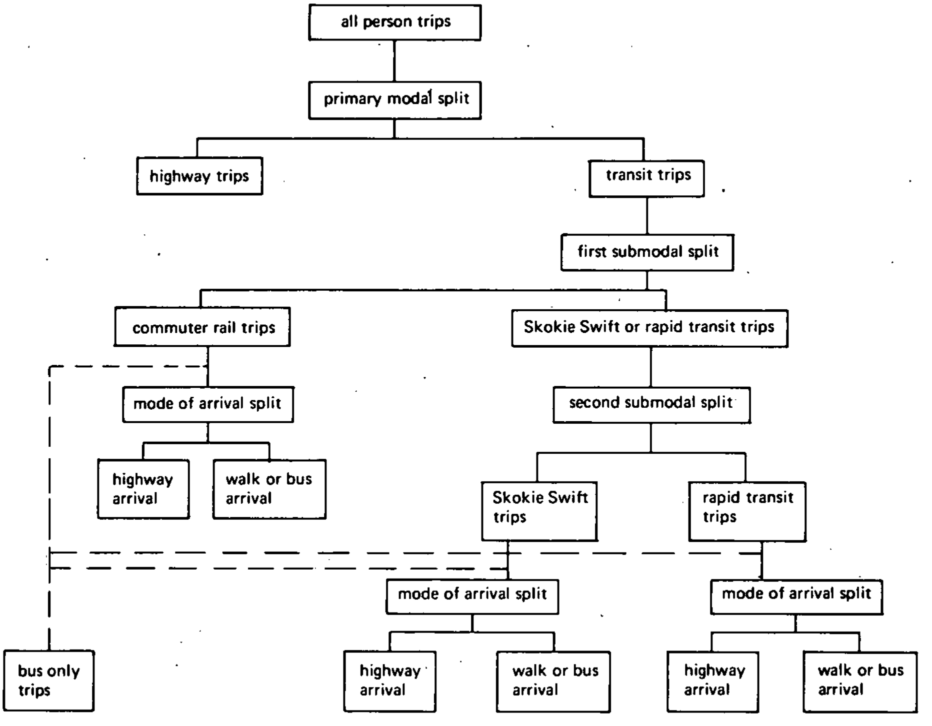
The question remains of how to apply travel forecasting models. Five alternative methods are apparent.

1. Apply the models in chains in their usual UTP order (i.e., trip generation, trip distribution, modal split, traffic assignment);
2. Apply the models in chains as travelers are assumed to order their choices;
3. Link sequentially calibrated travel-choice models parametrically and apply them in one stage (i.e., as a direct demand model);
4. Apply simultaneously calibrated travel models in one stage (i.e., as direct-demand models); or
5. Apply sequentially the conditional and marginal probabilities of separate travel choices derived from the joint probability of a simultaneously calibrated model.

In the first (conventional) strategy of chaining independently calibrated travel-choice models with different relative valuations of independent variables common to 2 or more choices, the sequence of application determines the results. In such cases, the separability property of the independence axiom does not apply among choices. For example, in the application of binary-choice modal-split models in a chain, shown in Figure 2 (32), the results (i.e., splits) calculated higher in the chain are preserved lower in the chain. And in conventional UTP, the trips calculated higher in the chain are normally preserved lower in the chain on any pass through the chain.

The critical problem in method 1 is how to input the system characteristics (attri-

Figure 2. Modal-split chain for commuter travel.



butes) of the choices lower in the chain at points higher in the chain. For example, how in trip generation-trip frequency can the system characteristics for the entire region be aggregated to a single point or zone for input to this first step? The choice attributes can either be summed over (weighted by) trips calculated lower in the chain (e.g., potential functions or gravity-model weighted sums) and brought "up" to be input to higher models in the chain. Or the estimated parameters common to all the ordered-choice models can be used to probabilistically aggregate the choice-specific attributes from the lower level choices. The latter method, as noted before, is the only method consistent with the assumption of additive utilities from sequentially calibrated separable multiple-choice travel models.

If sequential models are derived and calibrated consistently with the (implicit or explicit) behavioral assumptions of preservation of strict utilities in separable multiple-choice models, there is no difference among methods 1, 2, and 3 in the resulting computed network-equilibrium travel patterns. That is, the same separable model may be applied sequentially in a series of separate travel-choice forecasts, or the joint probability distributions of choices may be calculated directly by parametrically combining the separately calibrated choice models as per the independence axiom. However, the sequential application of the models in this case can actually be in any order including methods 1 and 2. The estimated strict utilities are independent of the choices, as per the original behavioral assumption implemented by using the separability property of Eq. 3.

Conversely, from a simultaneously calibrated model satisfying the independence axiom, the conditional and marginal probabilities of travel choice may be derived, and the separate submodels of travel choice may be applied sequentially. Submodels so derived may be applied in any order, including methods 1 and 2. Joint estimation of the choice probabilities eliminates the need for the sequence assumption, but not the separation assumption, for models based on or consistent with the independence axiom.

Models based on or consistent with the independence axiom are separable multiple-choice models. Preference for any method of application is a matter of convenience, control, and purpose of the transportation systems analysis. For example, it is often desirable to be able to compute travel in sequential steps (generation, distribution, and so on) in order to be able to check the intermediate results and exert control over the forecasting process in some way. A direct application of the parametrically combined or simultaneous model may be appropriate if the user is confident of his results and wants to save time and money. If the model has been derived in a fashion consistent with its behavioral assumptions, both methods will produce the desired output for calculating the flow volumes on links in a transportation network. The choice of method should be based on the requirements of different planning environments.

Because the aggregate of trips, not the probabilities, are assigned to a network, a complete run through the sequence will be required to produce the joint probability distributions of travel (including trip-frequency probabilities) needed for aggregating over the total number of individual trip-makers to calculate the aggregate demand. Assignment of trips must also be made to update link and path supply functions for computation of an appropriate network equilibrium. Network equilibration can proceed either through incremental (fractional) loading or by iterating.

Defining Alternative Travel Choices

In the application of separable, multiple, choice-specific travel models (models having the separability property of the independence axiom), great care must be taken in choosing alternatives in order that the separability property not be too strong for the application. The strict utilities in these models are estimated in choice-specific situations even though the separability property of Eq. 3 allows travel choices to be separated for forecasting purposes while still preserving the strict utilities. Truly independent and distinct alternatives as perceived by travelers should be chosen in the application of separable multiple-choice share models. A black bus following the same route as a yellow bus, when chosen as an "independent" alternative, has the effect of reducing the use of automobile (the third choice) in order to preserve the relative odds of choosing automobile over either of the bus alternatives taken singly. This is a misapplication of the separability property because the property would appear to be too strong in this application. In model calibration, the color of the bus does not usually specify or identify a choice, so this seems perfectly clear. The black bus running on a different route from that of the yellow bus between the same origin and destination would have the same effect; and again this effect appears too strong, unless the strict utilities are clearly identified as route (choice) specific. If the yellow bus were now changed to yellow rail transit, and if the multiple choice-specific model were calibrated specifically with rail and bus transit parameters, as well as with automobile parameters, the separability property would appear not to be troublesome. Caution, however, is certainly advised.

Alternative destinations are rarely if ever defined in such a way that choice-specific strict (destination place) utilities are estimated for each destination. That is, the use of socioeconomic variables to describe the (static) trip-end activities amounts to the behavioral assumption of choice-abstract destination-place attributes embedded in an otherwise choice-specific travel demand model. Even more troublesome for the use of separable travel models are the implications of changing the destination alternative set from a small set of alternatives used for model calibration, each having nonzero probabilities of choice, to the usual large number of alternatives, among which trips are forecast in order that a high degree of resolution may be obtained for traffic-assignment purposes. In such cases, forecasting should probably be a 2-step process. That is, forecasts of trips should be made to large aggregations of zones, grouped on the basis that they are distinctly different and real (known) alternative destinations to travelers at the origin. Such grouped destinations might be based on a hierarchy of increasingly regionally oriented work or shopping places for the type of worker or shopper in each zone. Destinations not likely to be known to travelers at each origin would be eliminated from consideration. Forecasts to these zonal aggregations would then be allocated in some way to the small component zones for traffic-assignment purposes (e.g., based on employment share). Another possible way of forecasting is simply to truncate to zero trips to low (calculated) probability destinations, just as low or zero probability destinations were excluded from the data used in model calibration, as per the separability property of the independence axiom.

In summary, in an application of a separable multiple-choice share model (Eq. 3) within a hierarchical level (e.g., mode choice), the implication of the independence axiom is that the introduction of an additional transit alternative (mode or submode other than one for which the choice-specific strict utilities were estimated) will change the probability of choice (modal split) for all the existing modes. The relative share of all the existing modes included up to then in the analysis will be preserved because of the independence axiom. This also means that the cross elasticity of the modal fraction for each old mode with respect to an attribute of the new mode is the same for each of the old modes. For example, the cross elasticity of modal fraction on the old modes with respect to fare on a new transit submode will be equal for all automobile and transit alternatives considered thus far. This precludes a pattern of differential substitutability among modes and, in effect, implies a (mode) choice-abstract model with respect to the modal fraction, but not with respect to aggregate demand, however (8, 28).

A number of specific examples, such as the above black and blue bus versus the yellow and red bus, can be and have been used as criticisms of the overly strong separability properties of the independence axiom in many instances. Much practice will be required in defining alternatives before multiple-choice share models are usable in any but the most straightforward mode-choice situations in which they have thus far been applied with apparent success (e.g., by Rassam, Ellis, and Bennett, 30). One set of arguments in certain situations consists of citing examples where the relative odds of choice in a binary-choice situation are unlikely in fact to be preserved when new choices are offered [i.e., the black and yellow bus argument, or a second Beethoven record added to an original Debussy and Beethoven binary choice (9)]. Luce and Suppes (23) state:

> We cannot expect the choice axiom to hold over all decisions that are divided in some manner into two or more intermediate decisions. It appears that such criticisms, although usually directed towards specific models, are really much more sweeping objections to all our current preference theories. They suggest that we cannot hope to be completely successful in dealing with preferences until we include some mathematical structure over the set of outcomes that, for example, permits us to characterize those outcomes that are simply substitutable for one another, and those that are special cases of others. Such functional and logical relations among the outcomes (alternatives) seem to have a sharp control over the preference probabilities, and they cannot long be ignored.

REFERENCES

1. Aldana, E. Towards Microanalytic Models of Urban Transportation Demand. M.I.T., Cambridge, PhD thesis, 1971.
2. Alonso, W. The Quality of Data and the Choice and Design of Predictive Models. HRB Spec. Rept. 97, 1968, pp. 178-192.
3. Beckmann, M. J., McGuire, C. B., and Winsten, C. B. Studies in the Economics of Transportation. Yale Univ. Press, New Haven, Ch. 2, 1955.
4. Ben-Akiva, M. E. Structure of Travel Demand Models. M.I.T., Cambridge, PhD thesis, 1973.
5. Brand, D. The Derivation and Application of Program Centipede. National Capital Transportation Agency, Washington, D.C., 1962.
6. Brand, D. Travel Demand Forecasting: Some Foundations and a Review. HRB Spec. Rept. 143, 1973, pp. 239-282.
7. Brand, D. Theory and Method in Land Use and Travel Forecasting. Highway Research Record 422, 1973, pp. 10-20.
8. A Disaggregate Behavioral Model of Urban Travel Demand. Charles River Associates, Inc., 1972.

9. Debreu, G. Topological Methods in Cardinal Utility Theory. In Mathematical Methods in the Social Sciences (Arrow, K. J., Karlin, S., and Suppes, P., eds.), Stanford Univ. Press, 1960.
10. Domencich, T. A., Kraft, G., and Valette, J. P. Estimation of Urban Passenger Travel Behavior: An Economic Demand Model. Highway Research Record 238, 1968, pp. 64-78.
11. Ewing, R. Sequential Decision Making and Travel Demand Forecasting. Harvard Univ., Cambridge, Mass., unpublished term paper, 1973.
12. Urban Transportation Planning, General Information and Introduction to System 360. Federal Highway Administration, U.S. Department of Transportation, 1970.
13. Fleet, C. R., and Robertson, S. R. Trip Generation in the Transportation Planning Process. Highway Research Record 240, 1968, pp. 11-31.
14. Hille, S. T., and Martin, T. K. Consumer Preference in Transportation. Highway Research Record 197, 1967, pp. 36-43.
15. Irwin, N. A., Dodd, N., and von Cube, H. G. Capacity Restraint in Assignment Programs. HRB Bull. 297, 1961, pp. 109-127.
16. Kain, J. F. A Contribution to the Urban Transportation Debate: An Econometric Model of Urban Residential and Travel Behavior. Review of Economics and Statistics, Vol. 46, 1964.
17. Kannel, E. J., and Heathington, K. W. The Temporal Stability of Trip Generation Relationships. Highway Research Record 472, 1973, pp. 17-27.
18. Kraft, G. Demand for Intercity Passenger Travel in the Washington-Boston Corridor. U.S. Department of Commerce, 1963, Pt. 5.
19. Krantz, D. H. Conjoint Measurement: The Luce-Tukey Axiomatization and Some Extensions. Journal of Mathematical Psychology, 1964.
20. Lee, D. B. Models and Techniques for Urban Planning. Cornell Aeronautical Laboratory, Inc., Buffalo, 1968.
21. Luce, R. D. Individual Choice Behavior. Wiley, New York, 1959.
22. Luce, R. D., and Raiffa, H. Games and Decisions. Wiley, New York, 1957.
23. Luce, R. D., and Suppes, P. Preference, Utility and Subjective Probability. In Handbook of Mathematical Psychology (Luce, R. D., Bush, R. R., and Galanter, E., eds.), Wiley, New York, 1965.
24. Manheim, M. L. Practical Implications of Some Fundamental Properties of Travel Demand Models. Highway Research Record 422, 1973, pp. 21-38.
25. March, J. G., and Simon, H. A. Organizations. Wiley, New York, 1958.
26. McFadden, D. Revealed Preferences of a Public Bureaucracy. Institute of International Studies, Univ. of California, Berkeley, 1968, Tech. Rept. 17.
27. McLynn, J. M., Goldman, A. J., Meyers, P. R., and Watkins, R. H. Analysis of a Market Split Model. Journal of Research of National Bureau of Standards, Vol. 72B, No. 1, 1968.
28. McLynn, J. M., and Woronka, T. Passenger Demand and Modal Split Models. Northeast Corridor Transportation Project, U.S. Department of Transportation, 1969.
29. Quandt, R. E., and Baumol, W. J. Abstract Mode Model: Theory and Measurement. Journal of Regional Science, Vol. 6, No. 2, 1966.
30. Rassam, P. R., Ellis, R. H., and Bennett, J. C. The n-Dimensional Logit Model: Development and Application. Highway Research Record 369, 1971, pp. 135-147.
31. Samuelson, P. A. Foundations of Economic Analysis. Harvard Univ. Press, Cambridge, Mass., 1947.
32. Schultz, G. W., and Pratt, R. Estimating Multimode Transit Use in a Corridor Analysis. Highway Research Record 369, 1971, pp. 39-46.
33. Stopher, P. R., and Lisco, T. E. Modelling Travel Demand: A Disaggregate Behavioral Approach, Issues and Applications. Transportation Research Forum Proceedings, 1970.
34. Theil, H. Principles of Econometrics. Wiley, New York, 1971.

35. Tversky, A. Elimination by Aspects: A Theory of Choice. Psychological Review, Vol. 79, No. 4, 1972.
36. Voorhees, A. M. A General Theory of Traffic Movement. Institute of Traffic Engineers, Washington, D.C., Spec. Rept., 1955.
37. Weiner, E. Modal Split Revisited. Traffic Quarterly, Jan. 1969.

Disaggregate Behavioral Models of Travel Decisions Other Than Mode Choice: A Review and Contribution to Spatial Choice Theory

Pat Burnett, Department of Geography,
University of Texas at Austin

In recent years, considerable effort has been spent on the disaggregate, behavioral modeling of travel decisions: The rationales of Marble (59), Nystuen (68), and Stopher and Lisco (82, 83, 84) have been used. For obvious practical and policy reasons, much work has centered on intraurban mode-choice decisions and on home-based person trips for work purposes (82). Disaggregation has been accomplished by a focus on the travel behavior of individuals or of subgroups of the urban population; subgroups are defined by either socioeconomic characteristics (29, 49) or class of residential location (for example, city, suburban) or both (70). Preliminary attempts to incorporate more realistic assumptions about human behavior in traditional models (83) have led to probabilistic approaches (82, 87) and to the a priori specification of perceived time, comfort, safety, convenience, and other variables as factors influencing mode choice (11, 84). Attention is now being paid to the measurement of these variables (28, 29, 37, 66, 69, 85). This paper attempts to extend this work by

1. Collating and reviewing literature to assist with the disaggregate, behavioral modeling of intraurban travel decisions other than mode-choice applications in the trip generation, trip distribution, and route assignment phases of current transportation planning;
2. Focusing attention on the importance and salient features of spatial choice models in these contexts, particularly destination choice models for shopping, recreational, and social trips; and
3. Outlining research problems and strategies.

The need for a review paper of this kind is manifest by the variety of unrelated work in several disciplines that bears on travel decisions other than mode choice (the list of references includes journals in behavioral geography, marketing, transportation science, and environmental psychology). There is also a dearth of work on the identification and criticism of common assumptions and methodologies, with the possible exception of very recent and still unpublished papers by Allen and Boyce (2), Brand (13), and Ben-Akiva (9). In addition, the problems discussed below were encountered as the more difficult and important ones in the subject area as the author attempted to develop mathematical behavioral models of destination choice (17, 18, 19).

For the purposes of this paper, it is necessary to assume that travel decisions are "separable" and not "simultaneous." That is, non-mode-choice decisions can be assumed to be made, modeled, and hence discussed separately from mode-choice decisions. Obviously, the separability assumption is a debatable one (9, 15, 57). However, it has not yet been demonstrated to be unrealistic. For example, Ben-Akiva (9) and Liou and Talvitie (57) present conflicting evidence on the timing of different kinds of travel choice. The separability assumption also proved necessary as a simplifying premise for model development in the early disaggregate behavioral work, which is reviewed below. Finally, the assumption is required for pragmatic reasons: It permits a focus of attention on a critique of past work and directions for further research in travel decisions unrelated to mode choice.

SPATIAL CHOICE THEORY AND MODELS OF TRAVEL DECISIONS

Formal Characterization of Destination and Route Choice Models

Decisions are, by definition, choices by individuals, where a choice is a selection from a number of known alternatives (the choice set) and is manifested by an observable action (overt behavior). Obviously, urban travel decisions are a subset of individual choices; the observable action is person trips by time, purpose, origin, and destination. Hence, in urban transportation planning, trip generation models are models of the choice of the timing, purpose, and frequency of trips by individuals in different locations; trip distribution models are models of destination choice; and route assignment models are models of route choice. [Route choice is a decision concerning the path of travel for an activity, such as the journey to work. Destination choice involves the choice of a location at which to conduct a short-duration, recurrent activity (work, shopping, recreation, social visits); it also involves choice of locations to investigate for future long-duration activities, as in search for business, industrial, and residential sites (78).] Now selections of origins, destinations, and routes by individuals at different times and places are locational choices; theories of individual choice behavior within urban spatial structures are therefore particularly relevant for modeling travel.

So far, disaggregate behavioral models of spatial choice broach either the selection of destinations (1, 16, 34, 50, 51, 59, 64, 95) or the selection of routes (73, 79, 93). Formally, models of these decisions deal with the following problem. Given (a) a set of m individuals who are in given locations ($I_1, \ldots, I_i, \ldots, I_n$) and who have identical decision-making processes (often all are utility maximizers) and identical space preference functions (74), and (b) a choice set ($A_1, \ldots, A_j, \ldots, A_n$) of known alternative points or lines for the conduct of a particular activity, a, what is the spatial choice probability, $P_t(A_j/A_1, \ldots, A_j, \ldots, A_n)$, of the m decision-makers choosing alternative A_j for the conduct of the activity a in time period t? (There are very strong homogeneity assumptions in the above. Some of the problems of relaxing them are discussed later.)

The spatial choice probability P_t can be expressed in terms of a conditional spatial choice decision and a trip purpose decision at time t.

$$P_t(A_j/A_1, \ldots, A_j, \ldots, A_n) = P_t(A_j/a\epsilon t) \cdot P(a\epsilon t)$$

This states that the unconditional spatial choice probability of any alternative, A_j, being selected is the product of (a) the conditional probability of A_j being selected, given that activity a is to be conducted in time t, and (b) the probability of choice of activity a in time t. This, of course, follows normal probability laws and also the work of Massy, Montgomery, and Morrison (62).

Spatial choice models, as applied to travel decisions other than mode choice, should thus predict route or destination choices over time as the outcome of 2 processes: the conditional spatial choice process and the activity sequencing process (25). Most work, however, still concentrates on deriving operational, analytical expressions for either one process or the other. Studies of route choice, and models that allocate trips to points or areas within cities, focus on the conditional spatial choice process. Studies of trip linkages over time constitute models of activity sequencing.

For example, the disaggregate, probabilistic, utility or entropy models of Wilson

(98, pp. 65-66) and Beckmann and Golob (8) analyze the decision process of a group in selecting one of a set of destinations in time period t, given that an activity or activity combination is to be undertaken. The authors thus ignore time variations in trips by individuals or groups to an alternative, consequent on trip purpose sequencing and trip purpose changes over time. On the other hand, Markov models of land use linkages during trips, like those of Westlius (94), Sasaki (76), and Horton and Wagner (49), ignore the problem of predicting which of the particular locations of a land use activity will be chosen, given that an activity is selected.

Space-time budget studies (3, 24) attempt to combine the 2 decision processes, but have yet to find a well-articulated conceptual framework or a satisfactory methodology. Pipkin (71), following Nystuen (68), has produced a utility theory model predicting both activity sequencing and spatial choice for an individual on a multipurpose trip from home. However, he takes the trip purpose combination as a datum, so the approach actually generates a sophisticated model of conditional destination choice.

Models of spatial choice for intraurban travel are thus distinguished by their variety and lack of integration. The most important tasks, therefore, appear to be the rigorous testing of the models, the specification of the links between them, and the development of a unified stochastic theory of choice of activity and location over time. Leads in this direction and specific problems to be solved have been given, but not yet followed up, by Garrison and Worrall (31) and Worrall (100).

Importance of Modeling Shopping, Social, and Recreational Trips

Disaggregate, behavioral models of spatial choice are also predominately concerned with shopping, recreational, and social travel. There are seemingly fewer interesting problems in the disaggregate, behavioral modeling of destination choice, route choice, and activity sequencing for the journey to work. Most persons have only 1 workplace and travel directly along the same route to and from home. Moreover, there is a regular, daily sequencing of work activities for the majority of the population.

For other kinds of travel, it is not immediately obvious that activity sequencing and route and destination choice are orderly [though well-known descriptions of order are given by Berry and Pred (10), Hanson (40), Marble and Bowlby (60), Spence (80), and Thorpe and Nader (89)]. The description and prediction of "travel patterns" and the determination of their underlying causal mechanisms are by no means easy, as path-breaking work by Garrison and Worrall (31), Marble (58, 59), and Nystuen (68) showed. In shopping, recreational, and social travel, the number of route and destination alternatives in the individual's choice set fluctuates over time, as he or she starts from different origins or tries out new alternatives. In addition, activity sequencing is irregular and trips may be multipurpose.

From the policy-making point of view, it is obviously a mistake to leave aside the individual's journey to work as an uninteresting spatial choice problem. Moreover, many work-based trips are not simple; they are linked with travel for shopping and other purposes (40, pp. 11-12). Modeling the journey to work as part of an individual's sequence of activities at different locations, therefore, poses questions worth attention and will further the much-needed focusing on both the spatial and temporal structures of trips. However, it seems essential to continue to emphasize shopping, social, and recreational travel. Little work has been done on these kinds of trips (91, pp. 176-177) despite the fact that most person trips in urban areas terminate at commercial land. In addition, although home-based work trips constitute approximately 40 percent of all person trips in metropolitan areas, trips for recreation, shopping, and social purposes also constitute approximately 40 percent of the total. About 15 to 20 percent are for shopping purposes; shopping thus is the most important kind of travel after the journey to work (91, p. 177; 102, p. 33; 103, p. 13). The percentage of trips for nonwork purposes may also be expected to rise as leisure time and incomes increase. There are therefore cogent reasons for continuing to concentrate on shopping, social, and recreational trips in the disaggregate, behavioral modeling of travel decisions other than mode choice (32, pp. 1-3).

PROBLEMS AND STRATEGIES

Three major problems appear to bedevil the development of disaggregate, behavioral models for travel decisions other than mode choice:

1. The aggregation problem;
2. The problem of common choice set definition, that is, the problem of defining for an activity one given set of destinations or routes that are all known by, and therefore constitute relevant alternatives for, every member of a population group; and
3. Problems of including attitudinal and perceptual variables.

The second problem is important because all choice models so far developed, including destination and route choice models, assume that individuals can assign a utility value and thus a preference ordering and choice probability to every alternative in a choice set. Some of the utility values assigned to known alternatives may, of course, be zero (5, 9, 13, 17). However, individuals cannot be held to have formed utilities, even zero utilities, for completely unknown alternatives. It, therefore, does not make sense to develop choice models for individuals who cannot be shown to know and share an identical set of spatial alternatives for a given activity.

The first and third problems are already familiar in disaggregate mode-choice modeling (11, 29, 37, 54, 72, 88). Consequently, a brief evaluation of strategies for their solution in spatial choice studies should assist with some general methodological issues in behavioral transportation research.

The Aggregation Problem

Much of the work on spatial choice carries the main argument for disaggregation to its logical conclusion. Since it is not possible to make inferences about individual or group behavior from observations on a population, methods must be found to isolate the causal decision mechanisms of individuals. Then aggregations can be performed to combine the models for individuals into models for successively larger groups until accurate, controllable population predictions can be made. Models of travel decisions other than mode choice, therefore, initially focus on the behavior of either individuals or small, relatively homogeneous population groups (34, 47, 49, 52, 59, 92).

There is a sporadic but by no means pervasive recognition that problems of ecological fallacy have been replaced by problems of finding ways to add together or combine models for different individuals in different locations at different times. The aggregation problem is particularly acute in Markov models of land use linkages by individuals and groups over time (49, 76). It is also acute in models of group place or space preferences, derived from attitude scaling models of individuals' subjective utility functions (17, 18, 34, 74, 75). In these instances, decision-makers are simply assumed to have identical place utility functions and thus identical destination choice probabilities. Accordingly, a model of travel behavior for a group is assumed to be the same as the model for any individual member of the group. Even if the actual heterogeneity of individuals in terms of place utility functions and spatial choice probabilities is recognized, the consequences of such heterogeneity are not formulated.

Accordingly, a crucial problem for future research is to develop mathematical techniques to enable the prediction of the spatial choices of a heterogeneous group from a model of the individual's decision. Several possibilities may be evaluated here.

A familiar approach, paralleling mode-choice modeling, is to construct separate spatial choice models for population subgroups (one model per group), where each subgroup is demonstrated mathematically to be reasonably homogeneous in terms of socioeconomic characteristics. The mathematical constraint on within-group heterogeneity is supposed to ensure that the group choice model somehow reflects the model for any group member. Aggregating the travel predictions for different subgroups results in better total population predictions. This is the strategy endorsed in modeling spatial choice, for example, by Wilson (98, pp. 31-33, 66), Horton and Wagner (49), Horton and Reynolds (47, 48), and Cole (23). One of the obvious deficiencies of this approach is that it remains just as difficult as in aggregate modeling to claim that the causal mechanisms behind individual travel behavior have been identified: The relations between the model for the group and the model for the individual are usually not spelled out. Further, this approach assumes that socioeconomic variables describing groups will be strongly and causally related to group travel choice behavior. The validity of this assumption has yet to be demonstrated; 10 years of work on analogous brand selection problems in marketing has failed to discover any socioeconomic characteristics that are good explanatory variables of group choice behavior (63). Moreover, even where standard statistical procedures may indicate significant associations between socioeconomic descriptors and travel decisions other than mode choice, the problem of spurious correlation remains. As Huff (50, 51) has argued, any of a large number of social, demographic, and economic variables can reasonably be hypothesized to "cause" travel decisions like destination choice. Moreover, it is likely that these variables are highly intercorrelated. The causal connections between group travel behavior and any subset of variables used to segment a population are therefore still obscure. Accordingly, the relative importance of different socioeconomic characteristics as predictors of spatial choice, and hence as desirable population segmentors, remains unknown.

One consequence is that, although models for population subgroups may fit any number of data sets well, the possibility remains that there will be a poor fit in another case because of changes in the effects of some underlying causal variables not taken into account. A more important consequence is that building separate models for population subgroups will only be a reasonable solution to the aggregation problem if much more attention is paid to the rigorous definition of groups with both homogeneous population characteristics and travel behavior. Newer multidimensional scaling techniques, such as Prefmap and Indscal, are designed to assist with the definition of groups of individuals with similar cognition, evaluation, and preferences for alternatives (77, Vol. 1, pp. 21-47). So far, there has been no experimental exploration of the use of these techniques to assist with defining groups for solution of the aggregation problem in the behavioral modeling of travel decisions other than mode choice (though Dobson and Kehoe give an application to mode choice, 29).

The difficulty remains, of course, that it does not matter whether new or old multivariate techniques show that some socioeconomic variables are associated with route or destination choice, they may still not be the best to use for population segmentation. For example, if a socioeconomic or other variable, which is causally related to a dependent travel choice variable, is unknowingly omitted from a regression equation, the regression coefficients may be very substantially altered, although the explained variation remains high. In sum then, although widely advocated, developing models of spatial choice for mathematically homogeneous population subgroups does not appear to be the best solution to the aggregation problem.

Another, more elegant approach to aggregation is exemplified in the recent work of Beckmann and Golob (8). First, a specific utility equation U is derived. This is an expression for the net benefits of travel by a household at origin i to destination k at time t. It is a function of travel costs, benefits, and number of trips from i to k. Next, the number of trips that will maximize the household's utility is derived, constrained by household income m. Different households at origin i are then assigned different special utility functions U_h and incomes M_h. An expression for the aggregate travel from i to k at time t is finally deduced by linear addition of the expressions for each household that yield the utility-maximizing number of trips. The authors admit that this approach to the aggregation problem in modeling spatial choice is "hardly operational" (8, p. 115). Indeed, as Cullen remarks (24, p. 464): "It is not immediately obvious how one would go about testing the basis of this new utility theory.... The problems of establishing utility ratings on all the individual activities ... performed by an individual would be immense." In addition, there are unresolved questions about trip-to-trip fluctuations and long-run changes in household utility functions. Accordingly, this approach, although theoretically elegant, at the moment appears excessively difficult to apply.

Another method of handling the aggregation problem looks promising for future research. This is the use of standard methods of manipulating probability distributions to enable the prediction of the spatial choice decisions of a heterogeneous group from individual choices. Massy, Montgomery, and Morrison (62) first applied such methods to the problem of predicting the sequence of brand choices of a good by a heterogeneous population group. The same techniques have recently been suggested for travel choices by Koppelman (54) and Aaker and Jones (1). A recent application by Burnett (19), specifically for a simplified destination choice problem, may be used to illustrate the aggregation mechanism, and the kind of model toward which progress can be made.

First, a model is developed for the individual, to predict his or her sequence of choices over time between one class of destination and another for an activity. Specifically, X is defined as a Bernoulli variable whose values represent the outcome of the individual's selections between a destination class 0 and a destination class 1 on each of n successive choices. It is next assumed that the individual has a constant probability p of a destination class 1 choice on any occasion and that this p value reflects the individual's distinctive preferences for class 1 and class 0 destinations. Finally, to allow for group heterogeneity, we assume the individual's p is a random sample from a distribution of p values (preferences, utilities) over the population. This distribution can be described by the density function f(p). Given these assumptions,

1. b(p/i) is the posterior distribution of p for the individual, after a given sequence of choices i and equals

$$\frac{\ell(i/p) \cdot f(p)}{\int_0^1 \ell(i/p) \cdot f(p) \cdot dp}$$

where $\ell(i/p)$ is the likelihood of the trip history (by Bayes theorem); and

2. The expected probability that any individual with a given past sequence of destination choices i will choose destination 1 next is

$$\int_0^1 p \cdot b(p/i) \cdot dp$$

It can be shown that, with the increase in size of a group of individuals who have the same past history i but different p values, the probability that the group will choose a destination class 1 next equals the posterior expectation of p or

$$\int_0^1 p \cdot b(p/i) \cdot dp$$

This is the same as for the individual in 2 above.

The predictions for groups and individuals can be interpreted in behavioral terms, for example, as the outcome of the effects of so many interacting and influential variables that choices appear to behave like a random variable over time. Other formulations and interpretations are possible; for example, Jones (53) derives individual and group probabilities as the outcome of different Bernoulli, Markov, and linear learning processes in which next destination choice probabilities are affected by last destination choice in different ways.

However, the use of probability theory presents some problems for future research. First, extensions of mathematical theory are required to predict choices of individuals and groups over more than 2 classes of destination. Second, there is little evidence or theory to suggest which, if any, of the standard probability distributions (normal, gamma, beta) should be used to define f(p), the density function that describes the different preference and utility ratings of a population for any destination class. Some specification of f(p) is necessary to produce accurate destination choice predictions for models of this kind. This seems an area for future empirical research.

Finally, there is another aspect of the aggregation problem besides that of aggregation over individuals in different locations. To provide operational models of spatial choice decisions, the custom is to group at least some of the choice set alternatives (e.g., shopping places for a particular good) into classes. In effect, this is aggregating possible choice states of the individual and group. For example, in studies of destination choice, activities, origins, and destinations may be grouped into classes by zone (8), by kind of land use (40, 76), or by locational characteristics (75). Little consideration has been given to the effects of choice state aggregation (27). For example, if travel decision-making is not identical with respect to each member of a destination class (for example, each kind of retail establishment in a commercial zone), then what does a model of decision-making with respect to the class of alternatives mean? Examining the effects of choice state aggregation on predictive accuracy and meaning appears to be an important area for research.

Although models predicting travel for every possible member of a spatial choice set are not analytically inconceivable, they would scarcely be operational for a large area with many activities, origins, destinations, and routes. Two crucial problems arise, therefore. The first is defining what constitutes similarity of alternatives for disaggregate, behavioral models of spatial choice. The second is specifying classes of similar alternatives for choice sets. Rushton (75) has initiated work in these directions. However, he works with a priori assumptions about the criteria (size, distance) that individuals use to define destination classes. The question as to how decision-makers themselves perceive groups of alternatives remains unanswered. Appropriate general specifications of similar alternatives for modeling purposes can only be made after this problem is resolved through empirical research.

Problem of Choice Set Definition

Next, there is the problem of bounding choice sets for disaggregate, behavioral models of spatial choice. At present, aggregative and many disaggregative trip distribution models assume that all individuals in a city share a common set of destination and route alternatives (6, 8, 55, 60, 97, 98). For example, gravity, entropy, and utility models of interzonal trip distribution assume that each individual within a given zone can and does consider every other zone in the city as a potential destination. Some destinations are more likely to be used than others, but only because of variations in attractions and distance impedance. It does not matter whether the trip is undifferentiated by purpose (8, 97, 98) or whether it is specifically for shopping or some other kind of travel (9, 22, 23, 55, 57, 60).

However, the assumption that every individual selects from the same citywide choice set seems most implausible. This contention is supported by recent work on the individual's cognition (33, 35), information field (12, 41), and activity and action spaces (48, 86, 95). At best, individuals in the same neighborhood and socioeconomic class may share some members of their sets of spatial alternatives for different activities (47). However, it is likely that these sets will be different for different activities, that they will be restricted to one part of a city (41), and that they will vary as alterations in the neighborhood occur and as individuals learn more about their area (33, 35, 36, 78). As well as varying with the individual's activity and socioeconomic status and length of residence, the number and locations of spatial alternatives that a person considers seem likely to change with distance and direction from his or her origin (41, 86), with the complexity of alternatives, with the legibility and ease of pathfinding that different kinds of city structure afford (101), and with the base (home, work) from which the person is to travel.

Hence, choice sets are not at all easy to define for disaggregate models of spatial choice behavior. Nor will sets be the same at different levels of aggregation, for example, for residents at neighborhood, city sector, and citywide scales. This contrasts with the position in mode-choice modeling, where a small number of alternatives can usually be clearly defined and remain the same for individuals and groups at most levels of aggregation. Accordingly, much more empirical work needs to be done on methods of delineating route and destination choice sets shared in common by individuals for different activities (41). Until the problem is resolved, disaggregate, behavioral models of spatial choice will lack an operational definition that makes sense, and they cannot be expected to make good predictions of travel decisions other than mode choice.

Problems of Including Attitudinal and Perceptual Variables

Even if choice sets can be defined, questions remain as to how route or destination alternatives are perceived, experienced, or cognized by individuals and how cognition affects evaluation, selection, and overt travel behavior. Similar questions have recently been addressed by Hartgen (44) and others (11, 28, 37, 66) with respect to alternative modes. It is clear that travel decision processes may be influenced somehow by age (4, 61), income (26, 46), occupation (49), race (67), and other socioeconomic characteristics (50, 65, 99). However, such characteristics may not be highly correlated with cognition, preference formation, and overt choice behavior (44; 63, pp. 55-57). Moreover, correlation does not imply direct causation, and hence the use of socioeconomic variables as surrogate predictors may lead to inferior explanations, predictions, and forecasts of destination and route choice. There is considerable evidence from learning theory in psychology that the direct causes of choice decisions may not be the socioeconomic characteristics of persons per se, but the subjective preferences they form for different imperfectly known attributes of alternatives (5, 38, especially chapters on concept identification, judgment, and choice).

Because normal household descriptors may not yield good predictions of travel decisions of individuals and groups, variables must be incorporated in disaggregate, behavioral models to specifically test the effects of individuals' perceptions of, and attitudes toward, route, destination, or mode alternatives. Surrogate indicators of psychological and personality traits, such as apathy and fantasy-proneness, also cannot be used. Although Golledge (34, p. 418), Myers (63, pp. 52-56), Stone (81), and LeBoulanger (56) indicate that psychological variables may be highly correlated with mental processes in travel decision-making, they are exceedingly difficult to define and measure. Moreover, the same problems of model misspecification arise with the use of these surrogates as with the use of socioeconomic surrogates.

There are, however, conceptual and measurement problems in including perceptual and attitudinal variables in models of spatial travel decisions in future research. First, there is the question of identifying what perceived attributes of alternatives (such as shopping places, recreational areas) are important. It cannot be assumed a priori that travel time, scale of facilities, environmental amenity, travel costs, or any other factor is significant. Maybe, for example, perceived money cost and perceived travel time are linked in a "cost of the trip" dimension in travelers' minds, and alternatives are perceived and evaluated in terms of this rather complex criterion. Indeed, recent studies of the perception of shopping places (17, 30, 96) indicate that individuals may use only a few complex attributes to assess alternatives (e.g., the amenities of the environment in the case of destinations). Moreover, these perceived attributes apparently bear no clear relation to the size and distance variables that traditional spatial choice models have assumed to be important [as, for example, the gravity or central place models of destination choice (7, 10, 16, 51, 55)].

Recent developments in models of the mind, and associated multidimensional scaling (MDS) measurement techniques, have in a few cases been used to identify the attributes of spatial alternatives that are significant to individuals (17, 43, 77, 90). However, MDS procedures are expensive and difficult to administer; they can often be used only with small samples, and the naming of discovered attributes is difficult. Nonetheless, MDS procedures offer the most rigorous way of defining attitudinal and perception variables for disaggregate, behavioral models of spatial choice. They do not require necessarily any prenomination of possibly significant attributes of destinations or routes by the researcher for individuals to score or identify; these may be uncovered indirectly through the use of MDS algorithms. Consequently, considerable application of MDS procedures to identify the perceived characteristics of destinations or routes may be expected in the future.

Modern scaling procedures not only help define the dimensions of alternatives that are important to individuals but also yield (a) diagrams of the individual's mental positioning of alternatives with respect to each dimension (that is, scores of alternatives for each attitudinal-perceptual variable) and (b) measures of individual and group preferences for each alternative [see Burnett (17) and Downs (30) for the case of destinations]. This paves the way for building models that link, first, functions describing individual and group perceptions of alternatives; second, group and individual subjective preference functions; third, the probability of a group or individual choosing each alternative; and, fourth, the relative frequency of trips by individuals and groups to each member of a choice set. One model of this kind has already been developed and tested for spatial choice and demonstrates a direction for future research using MDS theory and techniques.

$$P(A_j/A_j, \ldots, A_k) = \sum_{i=1}^{m} \frac{V_{ij}}{\sum_{x=1}^{k} V_{ix}} \Big/ m$$

$$= 1 \left[\sum_{i=1}^{m} U_{ij} \Big/ m \right]^{h}$$

$$= \hat{1} \left[\sum_{i=1}^{m} D_{ij} \Big/ m \right]^{\hat{h}}$$

$$= \hat{1} \left[\sum_{i=1}^{m} (d^r_{ij1} + d^r_{ij2} + \ldots + d^r_{ijn})^{1/r} \Big/ m \right]^{\hat{h}}$$

$$\log P(A_j/A_j, \ldots, A_k) = L + \hat{h} \log \left[\sum_{i=1}^{m} D_{ij} \Big/ m \right]$$

$$= L + \hat{h} \log \left[\sum_{i=1}^{m} (d^r_{ij1} + d^r_{ij2} + \ldots + d^r_{ijn})^{1/r} \Big/ m \right]$$

where

$P(A_j/A_j, \ldots, A_k)$ = probability of decision-makers' choosing spatial alternative j out of a set of k alternatives;

$\frac{V_{ij}}{\sum V_{ix}}$ = response strength of decision-maker i (or measure of his degree of preference) for alternative j relative to the strength of his response for all other alternatives;

U_{ij} = decision-maker i's judgment of the magnitude of his preference for alternative j (this judgment lies behind the preference rank he will assign the alternative to provide data for a non-metric-MDS procedure);

D_{ij} = estimate of U_{ij} (it is recovered by the nonmetric MDS of decision-maker i's rank order data);

$d_{ij1}, d_{ij2}, d_{ij3}, \ldots, d_{ijn}$ = set of recovered distances of alternative j from decision-maker i's ideal alternative along each of the n dimensions used for assessment;

r = the recovered constant used to combine the distances and otherwise known as the Minkowski metric number (this is the decision-makers' perception of alternatives);

m = total number of decision-makers in a homogeneous sample, that is, in a sample with only random differences between the decision-makers' relative response strengths and judgments;

k, l, L, and h = constants; and

$\hat{l}$ and $\hat{h}$ = recovered estimates of l and h (17).

One problem with this kind of model is that there is little evidence or theory to suggest the appropriate forms of mathematical expression to relate perception and preference functions and choice probabilities. In the model above, as in other subjective utility models of spatial choice so far developed (9, 13, 57), continuous, additive functions form the starting point of model building. As Harman and Betak suggest (43), MDS procedures can also be used to see whether individuals have discontinuous, nonadditive, and nonlinear functions relating cognition, preference, and choice.

Another problem that should be considered is that the number and kinds of attitudinal and perceptual variables that individuals use to make choices may be different for different people and will certainly vary for the same person over time. Burnett (17) has shown that the significant attributes and ratings of shopping places by individuals vary with their stage of learning about their neighborhood. This is consistent with other work on spatial learning and information, for example, by Bowlby (12), Golledge (33, 34, 35), Golledge and Rivizzigno (36), and Hanson (41). Consequently, it seems important to develop process models to describe how spatial learning occurs and how this affects route, destination, and mode choice by individuals and groups over time. The use of stochastic process theory or psychological learning models for this purpose has been shown to be possible (18, 34, 78). These comments also suggest that some modification of behavioral mode-choice models may be required, where it is standard practice to assume that the attributes of modes and their importance to different population groups remain constant over time, that is, reflect stable preference structures and stable subjective utility functions. In a mode or spatial choice environment that is constantly changing, this assumption cannot be made.

However, even if the changing perceived characteristics of travel alternatives can be identified, measured, and included in models, no assistance will be provided to policy-makers unless they are linked with the manipulatable, objective design characteristics of routes, destinations, and modes. Perceived characteristics of alternatives may be related to objective counterparts in accordance with psychophysical laws of judgment (14). That is

$$0 = kP^n$$

or

$$\log 0 = K + h \log P$$

where P stands for a perceptual characteristic (like psychological distance), 0 stands for the matching objective one (like distance in miles), and k, K, and h are constants and may vary with the individual's position in space and time. Much more work needs to be done to verify that this kind of relation holds in travel decision-making and to look for spatial and temporal invariance or trends in the parameters relating objective and perceived characteristics. If such relations are discovered, then models of response to future systems can be developed based on individual and group perceptions of system characteristics.

By far the most serious difficulties for the development of disaggregate, behavioral models of travel stem from the dubious status of the mind as an object of scientific inquiry. Perceptions, attitudes, preferences, and decisions are mental events and are, hence, nonobservable and unverifiable. For example, Hanson (39) follows behaviorist thinking by arguing that words describing mental processes are alternative words for overt behavior. Consequently, studies of perceptions, attitudes, and preferences may not be analysis of the causes of overt behavior, like movement, as commonly supposed, but rather be alternative ways of describing movement itself. Perceptual and attitudinal studies may therefore be tautologous and scientifically barren. Other philosophies of mind besides the behaviorist example cited, and their consequences for the explanation of spatial behavior, are examined in another paper (21).

Even apart from philosophical debates, to make sense of the "mental" components of disaggregate, behavioral models of travel decisions is difficult. What, for example, are the units of measurement of perceptual time, comfort, or convenience? How will we ever know if the units used by different individuals are comparable? How in these circumstances can we make sense of aggregating the perceptual scales of individuals to help predict group travel? At the moment, perhaps we must treat models with perceptual-attitudinal variables just as plausible, convenient constructs for the prediction of destination, route, or mode choice. One undesirable consequence is the weakening of any claim that this kind of model identifies the causal mechanisms behind travel decisions. It does not, however, follow that disaggregate behavioral models will not make better predictions than aggregate models. This can obviously only be validated (or invalidated) by developing and testing models of both kinds.

SUMMARY AND CONCLUSION

This paper collates and reviews current work on urban travel decisions other than mode choice. Its aim is to assist with the development of disaggregate, behavioral models that have applications in the trip generation, trip distribution, and route assignment phases of urban transportation planning. Particular attention has been concentrated on the theory of individual spatial choice behavior and applications to route choice and destination choice in shopping, recreational, and social travel.

Three problems have been selected as requiring the focus of attention in future research: the aggregation problem, the problem of delineating choice sets, and problems of including attitudinal and perceptual variables in model building. These problems were selected because they are already claiming attention as the cutting edge of present work and also because 2 of them (the first and third) are not unique to modeling travel decisions other than mode choice.

Nonetheless, some important issues have clearly been left aside:

1. How to model interactions between changes in urban land use and transport networks and changes in route and destination choice over time;
2. How to handle the sequencing of different kinds of travel decision (time of day, purpose, route, mode, destination) in a general model of travel behavior (9, 13, 22, 24, 57, 96, 98); and
3. How to model the connections between changes in spatial travel and transportation demands and possible social change over the short and the long term [e.g., the provision of increased access to peripheral city work opportunities and residential and other amenities by the inner-city poor (45) and modeling the social impacts of new transport links (20)].

Despite the fact that these questions have been left aside, it is hoped that this paper has raised and clarified some fundamental issues in the disaggregate, behavioral modeling of urban travel and spatial choice.

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REFERENCES

1. Aaker, D. A., and Jones, J. M. Modelling Store Choice Behavior. Journal of Marketing Research, Vol. 8, 1971, pp. 38-42.
2. Allen, W. B., and Boyce, D. E. Transportation Research: Problems, Prospects and Possibilities. Regional Science Department, Univ. of Pennsylvania, Philadelphia, draft manuscript, 1974.
3. Anderson, J. Space-Time Budgets and Activity Studies in Urban Geography and Planning. Environment and Planning, Vol. 3, 1971, pp. 353-368.
4. Ashford, N., and Holloway, F. H. Variations of Urban Travel Characteristics With Age. Transportation Engineering Journal, ASCE, Vol. 98, 1972, pp. 715-732.
5. Atkinson, R. C., Bower, G. H., and Crothers, E. J. An Introduction to Mathematical Learning Theory. Wiley, New York, 1968, pp. 135-186.
6. Bacon, R. W. An Approach to the Theory of Consumer Shopping Behavior. Urban Studies, Vol. 8, 1971, pp. 55-64.
7. Barton, R. F. Daily Consumer Shopping Under Probabilistic Gravitation. Center for Regional Studies, Univ. of Kansas, Lawrence, 1967.
8. Beckmann, M. J., and Golob, T. F. A Critique of Entropy and Gravity in Travel Forecasting. In Theory of Traffic Flow and Transportation, American Elsevier, New York, 1972, pp. 109-119.
9. Ben-Akiva, M. Structure of Passenger Demand Models. Highway Research Record 526, 1974.
10. Berry, B. J. L., and Pred, A. Central Place Studies: A Bibliography of Theory and Applications. Regional Science Research Institute, Philadelphia, Bibliography Series 1, 1965, Sections 1, 6, 9, 10, 11, 16.
11. Betak, J., and Betak, C. Urban Modal Choice: A Critical Review of the Role of Behavioral Decision Variables. Transportation Center, Northwestern Univ., Evanston, Ill., Res. Rept., 1969.
12. Bowlby, S. R. Spatial Variation in Consumers' Information Levels. Transportation Center, Northwestern Univ., Evanston, Ill., Res. Rept. 4, 1972.
13. Brand, D. Separable Versus Simultaneous Travel Choice Behavior. Paper in this Spec. Rept.
14. Briggs, R. On the Relationship Between Cognitive and Objective Distance. Paper presented at Fourth International EDRA Conference, Blacksburg, Va., April 17, 1973.
15. Brush, J. E., and Gauthier, H. L. Service Centers and Consumer Trips. Department of Geography, Univ. of Chicago, Res. Paper 113, 1968.
16. Bucklin, L. P. Trade Area Boundaries. Some Issues in Theory and Methodology.

Journal of Marketing Research, Vol. 8, 1971, pp. 30-37.
17. Burnett, K. P. The Dimensions of Alternatives in Spatial Choice Processes. Geographical Analysis, Vol. 5, 1973, pp. 181-204.
18. Burnett, K. P. A Three-State Markov Model of Choice Behavior Within Spatial Structures. Geographical Analysis, Vol. 6, 1974.
19. Burnett, K. P. Bernoulli Model of Destination Choice. Highway Research Record 527, 1974.
20. Burnett, K. P. Decision Processes and Innovations: A Transportation Example. Economic Geography, 1974.
21. Burnett, K. P. Behavioral Geography and Models of the Mind. In Essays on Multidimensional Analysis of Perceptions and Preferences (Golledge, R. G., and Rushton, G., eds.), Ohio State Univ. Press, Columbus, 1974.
22. A Disaggregated Behavioral Model of Travel Demand. Charles River and Associates, Inc., 1972.
23. Cole, H. S. D. A Computer Model for the Comparison of Alternative Foodstuffs Shopping Environments. Socio-Economic Planning Sciences, Vol. 6, 1972, pp. 329-348.
24. Cullen, I. G. Space-Time Budgets and Activity Studies in Urban Geography and Planning. Environment and Planning, Vol. 3, 1971, pp. 353-368.
25. Curry, L. The Geography of Service Centres Within Towns. Lund Studies in Geography, Series C, Vol. 24, 1962, pp. 31-53.
26. Davies, R. L. Effects of Consumer Income Differences on Shopping Movement Behavior. Tijdschrift Voor Economische en Sociale Geografie, Vol. 60, 1969, pp. 60-62.
27. Dickey, J. W., Horton, F. H., and Thomas, E. N. Areal Aggregation and Forecasting Precision in Urban Transportation Studies. Tijdschrift Voor Economische en Social Geografie, Vol. 60, 1969, pp. 60-62.
28. Dobson, R., Golob, T. F., and Gustafson, R. L. Multidimensional Scaling of Consumer Preferences for a Possible Transportation System: An Application of Two Approaches. Transportation Research Department, General Motors Corp., Warren, Mich., Publ. GMR-1368, 1973.
29. Dobson, R., and Kehoe, J. Disaggregated Behavioral Views of Transportation Attributes. Highway Research Record 527, 1974.
30. Downs, R. M. The Cognitive Structure of an Urban Shopping Centre. Environment and Behaviour, Vol. 2, 1970, pp. 13-39.
31. Garrison, W. L., and Worrall, R. D. Monitoring Urban Travel. Transportation Center, Northwestern Univ., Evanston, Ill., 1966.
32. Gilbert, G. Recreational Travel Behavior: The Case for Disaggregate, Probabilistic Models. Paper in this Spec. Rept.
33. Golledge, R. G. The Geographical Relevance of Some Learning Theories. In Behavioral Problems in Geography (Cox, K. R., and Golledge, R. G., eds.), Department of Geography, Northwestern Univ., Evanston, Ill., 1969, pp. 101-145.
34. Golledge, R. G. Some Equilibrium Models of Consumer Behavior. Economic Geography, Vol. 4, 1970, pp. 417-424.
35. Golledge, R. G., and Brown, L. A. Search, Learning and the Market Decision Process. Geografiska Annaler, Vol. 49, 1967, pp. 116-124.
36. Golledge, R. G., and Rivizzigno, V. L. Learning About a City: Analysis by Multidimensional Scaling. In Essays on Multidimensional Analysis of Perceptions and Preferences (Golledge, R. G., and Rushton, G., eds.), Ohio State Univ. Press, Columbus, 1974.
37. Golob, T. F., Canty, E. T., and Gustafson, R. L. An Analysis of Consumer Preferences for a Public Transportation System. Transportation Research, Vol. 6, 1972, pp. 81-102.
38. Greeno, J. G. Elementary Theoretical Psychology. Addison-Wesley, Reading, Mass., 1968.
39. Hanson, N. R. Mental Events Yet Again: Retrospect on Some Old Arguments. In What I Do Not Believe and Other Essays (Tuolmin, S., and Woolf, H., eds.), Rendel, Dordrecht, Holland, 1971, pp. 190-214.

40. Hanson, S. Intra-Urban Travel Linkages and the Spatial Organization of Urban Activities. Department of Geography, Northwestern Univ., Evanston, Ill., Res. Rept., 1970.
41. Hanson, S. Information Levels and the Intra-Urban Travel Patterns of Swedish Households. Transportation Center, Northwestern Univ., Evanston, Ill., Household Travel Behavior Study Res. Rept. 5, 1972.
42. Hanson, S., and Marble, D. F. A Preliminary Typology of Urban Travel Linkages. Department of Geography, Northwestern Univ., Evanston, Ill., Res. Rept. 57, 1970.
43. Harman, E. J., and Betak, J. F. Behavioral Geography, Multidimensional Scaling and the Human Mind. In Essays on Multidimensional Analysis of Perceptions and Preferences (Golledge, R. G., and Rushton, G., eds.), Ohio State Univ. Press, Columbus, 1974.
44. Hartgen, D. A Note on the Ability of Socio-Economic Variables to Explain Attitudinal Bias Towards Alternative Travel Modes. Planning and Research Bureau, New York State Department of Transportation, Albany, PRR 32, 1972.
45. Harvey, D. Society, the City and the Space Economy of Urbanism. Commission on College Geography, Association of American Geographers, Washington, D.C., Resource Paper 13, 1972.
46. Holly, B. P., and Wheeler, J. O. Patterns of Retail Location and the Shopping Trips of Low-Income Households. Urban Studies, Vol. 9, 1972, pp. 215-220.
47. Horton, F. E., and Reynolds, D. R. An Investigation of Individual Action Spaces: A Progress Report. Proc. Association of American Geographers, Vol. 1, 1969, pp. 70-74.
48. Horton, F. E., and Reynolds, D. R. Effects of Urban Spatial Structures of Individual Behavior. Economic Geography, Vol. 47, 1971, pp. 36-48.
49. Horton, F. E., and Wagner, W. E. A Markovian Analysis of Urban Travel Behavior: Pattern Response by Socioeconomic Occupational Groups. Highway Research Record 283, 1969, pp. 19-29.
50. Huff, D. L. A Topographical Model of Consumer Space Preferences. Proc., Regional Science Association, Vol. 6, 1960, pp. 159-173.
51. Huff, D. L. A Probabilistic Analysis of Shopping Centre Trade Areas. Land Economics, Vol. 31, 1963, pp. 81-89.
52. Isard, W., and Dacey, M. F. On the Projection of Individual Behavior: I and II. Journal of Regional Science, Vol. 4, 1962, pp. 1-34, 51-83.
53. Jones, J. M. A Composite Heterogeneous Model for Brand Choice Behavior. Management Science, Vol. 5, 1973, pp. 499-509.
54. Koppelman, F. S. Prediction With Disaggregate Models: The Aggregation Issue. Paper presented at HRB 53rd Annual Meeting, 1974.
55. Lakshmanan, T. R., and Hansen, N. G. A Retail Market Potential Model. Journal of American Institute of Planners, Vol. 31, 1965, pp. 134-143.
56. LeBoulanger, H. Research Into the Urban Traveler's Behavior. Transportation Research, Vol. 5, 1971, pp. 113-125.
57. Liou, P. S., and Talvitie, A. P. Disaggregate Access Mode and Station Selection Models for Rail Trips. Highway Research Record 526, 1974.
58. Marble, D. F. Residential Location and Household Travel Behavior. Highway Research Circular 12, 1965, pp. 11-16.
59. Marble, D. F. Three Papers on Individual Travel Behavior in the City. Transportation Center, Northwestern Univ., Evanston, Ill., 1967.
60. Marble, D. F., and Bowlby, S. R. Shopping Alternatives and Recurrent Travel Patterns. In Geographic Studies of Urban Transportation and Network Analysis (Horton, F., ed.), Department of Geography, Northwestern Univ., Evanston, Ill., 1968, pp. 42-75.
61. Marble, D. F., Hanson, P. O., and Hanson, S. E. Intra-Urban Mobility Patterns of Elderly Households: A Swedish Example. Paper presented at International Conference on Transportation Research, Brussels, June 1973.
62. Massy, W. F., Montgomery, D. B., and Morrison, D. G. Stochastic Models of Buying Behavior. M.I.T. Press, Cambridge, 1970.

63. Myers, J. G. Consumer Image and Attitude. Institute of Business and Economic Research, Univ. of California, Berkeley, 1972.
64. Morrill, R. L., and Schultz, R. The Transportation Problem and Patient Travel to Physicians and Hospitals. Western Regional Science Association Annals of Regional Science, June 1971, pp. 11-24.
65. Nader, G. A. Socio-Economic Status and Consumer Behavior. Urban Studies, Vol. 6, 1969, pp. 235-245.
66. Nicholaidis, G. C. Quantification of the Comfort Variable for Use in Disaggregate Mode Choice Models. Transportation Research Department, General Motors Corp., Warren, Mich., 1973.
67. Notess, C. B. Shopping and Work Trips in the Black Ghetto. Journal of the Urban Planning and Development Division, ASCE, Vol. 98, 1972, pp. 71-83.
68. Nystuen, J. D. A Theory and Simulation of Intraurban Travel. In Quantitative Geography: Part I—Economic and Cultural Topics (Garrison, W. L., and Marble, D. F., eds.), Department of Geography, Northwestern Univ., Evanston, Ill., Studies in Geography 13, 1967, pp. 54-83.
69. Paine, F. T. Consumer Attitudes Towards Auto Versus Public Transport Alternatives. Journal of Applied Psychology, Vol. 53, 1969, pp. 472-480.
70. Pershing, J. J., Jr. Spatial Patterns of Urban Travel. Paper presented at Northeast Regional Science Association Conference, New Brunswick, N.J., April 1974.
71. Pipkin, J. S. A Probabilistic Model of the Choice Process in Multi-Purpose Urban Travel. Department of Geography, Northwestern Univ., Evanston, Ill., Res. Rept., 1972.
72. Quandt, R. E., and Baumol, W. J. Abstract Mode Model: Theory and Measurement. Journal of Regional Science, Vol. 6, 1966, pp. 13-27.
73. Ratcliffe, E. P. A Comparison of Drivers' Route Choice Criteria and Those Used in Current Assignment Processes. Traffic Engineering and Control, Vol. 13, 1972, pp. 526-529.
74. Rushton, G. The Scaling of Location Preferences. In Behavioral Problems in Geography (Cox, K. R., and Golledge, R. G., eds.), Department of Geography, Northwestern Univ., Evanston, Ill., 1969, pp. 199-237.
75. Rushton, G. Behavioral Correlates of Urban Spatial Structure. Economic Geography, Vol. 47, 1971, pp. 49-58.
76. Sasaki, T. Estimation of Person Trip Patterns Through Markov Chains. In Theory of Traffic Flow and Transportation, American Elsevier, New York, 1972, pp. 119-130.
77. Shepard, R. N., Romney, A. K., and Nerlove, S. B. Multidimensional Scaling, Theory and Applications in the Behavioral Sciences. Seminar Press, New York, Vols. 1 and 2, 1972.
78. Silk, J. Search Behavior: General Characterization and Review of Literature in the Behavioral Sciences. Department of Geography, Univ. of Reading, Penn., Geographical Paper 7, 1971.
79. Smith, R. W. Attitudes Towards Route Choice in Urban Transportation Systems. Proc., Canadian Good Roads Association Meeting, 1970, pp. 588-608.
80. Spence, P. S. Orderliness in the Journey to Shop. Tijdschrift Voor Economische en Sociale Geografie, Vol. 62, 1971, pp. 22-34.
81. Stone, G. P. City Shoppers and Urban Identification: Observations on the Social Psychology of City Life. American Journal of Sociology, Vol. 60, 1954, pp. 36-45.
82. Stopher, P. R. A Probability Model of Travel Mode Choice for the Work Journey. Highway Research Record 283, 1969, pp. 57-65.
83. Stopher, P. R. Urban Models. The author, Hamilton, Ontario, 1970.
84. Stopher, P. R., and Lisco, T. Modelling Travel Demand: A Disaggregate Behavioral Approach. Transportation Research Forum, 1970, pp. 195-214.
85. Stopher, P. R., Spear, B. D., and Sucher, P. O. Towards the Development of Measures of Convenience for Travel Modes. Highway Research Record 527, 1974.
86. Stutz, F. P. Distance and Network Effects on Urban Social Travel Fields. Economic Geography, Vol. 49, 1973.

87. Talvitie, A. P. Comparison of Probabilistic Modal Choice Models: Estimation Methods and Systems Inputs. Highway Research Record 392, 1972, pp. 111-120.
88. Talvitie, A. P. Aggregate Travel Demand Analysis With Disaggregate Travel Demand Models. Transportation Research Forum, 1973.
89. Thorpe, D., and Nader, G. A. Customer Movement and Shopping Center Structure: A Study of a Central Place System in North Durham. Regional Studies, Vol. 1, 1968, pp. 173-191.
90. Tuite, C. J., and Betak, J. F. A Personal Construct Approach to Urban Neighborhood Cognition. Department of Geography, McMaster Univ., Hamilton, Ontario, draft paper.
91. Vickerman, R. The Demand for Non-Work Travel. Journal of Transport Economics and Policy, Vol. 6, 1972, pp. 176-210.
92. Vidakovic, V. A Study of Individual Journey Series: An Integrated Interpretation of the Transportation Process. In Theory of Traffic Flow and Transportation, American Elsevier, New York, 1972, pp. 57-70.
93. Wachs, M. Relationships Between Drivers' Attitudes Towards Alternative Routes and Driver and Route Characteristics. Highway Research Record 197, 1967, pp. 90-97.
94. Westlius, O. The Individual's Pattern of Travel in an Urban Area. Statens Institute for Byggnadsforskning, Sweden, 1972.
95. Wheeler, J. O., and Stutz, F. P. Spatial Dimensions of Urban Social Travel. Annals of Association of American Geographers, Vol. 61, 1971, pp. 371-386.
96. Wilhelmson, B. The Destination, Mode and Route Choice of Individuals: A Discussion of Their Interrelationships and Their Impact on an Aggregated Behavioral Model. In Urban Traffic Model Research, Planning and Transportation and Computation Company, London, 1971, pp. 153-156.
97. Wilson, A. G. Statistical Theory of Spatial Distribution Models. In The Demand for Travel: Theory and Measurement (Quandt, R. E., ed.), Heath, Lexington, Ky., 1970, pp. 55-82.
98. Wilson, A. G. Entropy in Urban and Regional Modelling. Pion, London, 1970.
99. Wong, S. T. A Multivariate Analysis of Urban Travel Behavior in Chicago. Transportation Research, Vol. 3, 1969, pp. 345-363.
100. Worrall, R. D. A Longitudinal Analysis of Household Travel. Transportation Center, Northwestern Univ., Evanston, Ill., Res. Rept.
101. Zannaras, G. An Analysis of Cognitive and Objective Characteristics of the City: Their Influence on Movements to the City Center. Ohio State Univ., Department of Geography, PhD dissertation, 1973.
102. Survey Findings. Chicago Area Transportation Study, Vol. 1, 1959.
103. Study Findings. Pittsburgh Area Transportation Study, Vol. 1, 1961.

Recreational Travel Behavior: The Case for Disaggregate, Probabilistic Models

Gorman Gilbert, Department of City and Regional Planning, University of North Carolina at Chapel Hill

Increasing attention has focused recently on the advantages and properties of disaggregate, probabilistic transportation models (26, 27). These models consider the individual traveler rather than an aggregation of households within zones and use statistical tools such as discriminant analysis, probit analysis, and logit analysis to assign a probability to a traveler that he or she will make a certain travel decision. Aggregation usually occurs by using these probabilities to compute the expected number of travelers who will make this travel decision.

Although considerable experience has been gained in using disaggregate models, this experience has been almost entirely devoted to urban work trips and to the mode-choice decision in particular (28, 30). [Stopher and Reichman (26) reviewed the earlier empirical work on the use of these models.] Yet in a recent review of 46 urban transportation studies, Sajovec (23) found that 63 percent of the trips were not home-based work trips. Furthermore, as leisure time and personal income continue to increase, nonwork travel will no doubt continue to gain in importance. It is clear, therefore, that the ultimate value of disaggregate, probabilistic models depends not only on how well they represent work trips but also on how well they represent nonwork trips.

In many ways, nonwork trips represent a much tougher test of disaggregate models than do work trips. Nonwork trips are less regular both in time and space than work trips. Also, they involve a wider range of trip purposes. Yet the primary difficulty in modeling such trips lies in the fact that they are less economically motivated and more psychologically motivated. For example, inclement weather and crowded highways do not deter a person from traveling to work, yet a cloudy sky may dissuade a person from making a shopping trip or a trip to visit friends.

Among types of nonwork trips, recreational trips in particular are both interesting and challenging to model. They are perhaps the most dependent on psychological motivations, and they sometimes show a strong disregard for distance. [Burch (1) examined the psychological motivations underlying recreation, and Wolfe (33) showed distance to vary drastically in importance among different types of recreational trips.] Witness, for example, trips of several hundred miles to experience solitude in remote wilderness areas. Yet, recreational trips are vitally important as a generator of economic prosperity, traffic congestion, and environmental exploitation. For example, in New Hampshire tourism contributes more than $300 million annually to the state's economy and at the same time adds almost enough overnight guests to double the state's population (13)! Given such economic and traffic consequences, it is imperative that transportation (and recreation) planners be able to predict recreational travel behavior.

In the remainder of this paper the use of disaggregate, probabilistic models will be examined in the context of recreational travel behavior. The requirements of recreational models and the previous research in this area will be assessed. A strategy will then be proposed for using disaggregate, stochastic models to represent recreational travel behavior. Finally, a research program will be suggested for a disaggregate, stochastic recreational travel model.

RECREATIONAL TRAVEL MODELING

Model Criteria

To develop or analyze any modeling effort first requires a determination of what it is that the model should do. What policy questions should be answered by the model? What output quantities are needed? What operational criteria should the model meet? For the case of a recreational travel model, answers to these questions are given below.

Policy Questions
1. What effects on recreational travel and usage will result from changes in either transportation or recreational facilities?
2. What changes will result from changing public tastes (e.g., increased public environmental awareness)?
3. What changes will result from economic changes such as increased fuel cost, discriminatory pricing, or increased fees?
4. What changes will result from increased leisure (e.g., a 4-day work week)?

Model Outputs
1. Recreational usage (user-days) at a given recreation site
2. Recreation trips from origin i to recreation site j

Model Parameters
1. Transportation facilities, recreation supply, recreation demand
2. User characteristics, desires, and perceptions
3. Intervening events (e.g., crowding, weather)

Model Characteristics
1. Predict travel for several time scales (annual, seasonal, weekend)
2. Represent competition among recreation sites
3. Account for multipurpose and multidestination journeys
4. Classify trips by purpose
5. Consider individual travelers

The policy issues reflect the broad societal importance of recreational travel. It is important not only to know the impact of tourism on highway traffic or on the park environment but also to have answers to social and economic questions. For example, what segments of the population use public park facilities and how can fair management policies be determined to avoid discrimination against user groups while preventing destructive overuse of an area? [That problem is now being faced in the Boundary Waters Canoe Area in Minnesota (10).] On a more pecuniary level is the question of how rising fuel costs will affect recreational incomes, a question recently addressed by the New Hampshire House of Representatives and perhaps by other state governments.

Previous Research

Recreational travel research has focused on 2 major topics: predicting the demand for recreation (trip generation) and predicting where a recreationist will go (trip distribution). Although the analogy to urban transportation planning is apparently strong, such is not necessarily the case. Much of the demand analysis research has been done by recreation planners and social scientists concerned with the use of a particular site or with population participation characteristics and not with the resulting highway traffic.

Recreational demand research may be divided into 2 categories: site specific and user specific. The former is very common; it may involve a single location (16, 24) or a group of locations (5, 12). Many state recreation plans are in the latter classification. [Chubb (2) provides a review of the methodologies used in many state recreation plans.] Often, site-specific demand research is mathematically simple and involves extrapolation techniques or regression of attendance against time and perhaps other independent variables. The objective of this research has sometimes been to estimate the benefits of a recreational site (4, 15, 25), but commonly the objective has been to predict future consumption of recreation at the site. This point is important in that the word "demand" has often been used mistakenly; for, as Tadros and Kalter (29) point out, projections are often made without knowing the effects of costs on the projections. A notable exception to this tendency has been the approach of Clawson and Knetsch in using travel costs to develop demand curves.

User-specific demand research followed primarily from 2 national recreation surveys: the Outdoor Recreation Resources Review Commission survey in 1960-61 and the Bureau of Outdoor Recreation survey in 1965. After these surveys, a number of analyses were performed to develop methods of predicting recreational demand. These analyses show income and age to be the primary variables in explaining recreational participation. Pertinent to the disaggregate, probabilistic model described in the next section of this paper is the fact that recent analyses of these survey data have yielded a 2-equation demand prediction method. The first equation estimates the probability that a person participates in a given recreational activity, and the second estimates the amount of time he or she will participate. A thorough review of this national survey-based research is presented by Cicchetti (3). Examples of other user-specific demand prediction efforts include Ungar's (31) "activity index" for state park campers, Vickerman's (32) non-work-trip generation models, and LaPage's (17) and Hoffman and Romsa's (14) analyses of private campground users.

The distribution of recreational trips has been less common than the prediction of recreational demand. A few studies have used models such as regression analysis (9), cross classification (6), and linear programming (29), but most studies have used the gravity model (8, 31, 34), the intervening opportunities model (22), or an electrical analog model called the systems theory model (2, 7, 8, 11). For each of these latter 3 types of models, the modeling approach is essentially the same: Total trips emanating from origins (often counties) are estimated; a highway network is coded; and the attraction of each possible recreation site is estimated. The trip generation step follows directly from the demand analysis already described. However, the attractiveness of a recreational site is more difficult to determine. Most attempts at measuring attractiveness have used an attractiveness index, that is, a score given to a site depending on the facilities it offers. The methods used in determining these scores have often been subjective (2, 7), although some indexes have resulted from careful analyses of user preferences for facilities (8, 31).

These trip distribution models marked a significant advance in recreational planning methodology. As Chubb (2) demonstrates in his review of state recreation plans, most recreation planning has been done without consideration of the transportation network that connects recreation sites with the problem demanding recreation opportunities. Thus, these distribution models for the first time considered simultaneously and explicitly the 3 factors determining recreational travel: recreational supply and demand and the highway network connecting them.

Yet, the models have many deficiencies. Notwithstanding the need to measure attractiveness and the fact that the time scale used is a year or a season, the models treat user characteristics only implicitly by categorizing trip types and by using demand analysis research results to predict trip generation. Thus, just as in modeling urban work trips, aggregation poses a problem. However, in recreation travel models it might be argued that aggregation is even more deleterious. For example, Chubb modeled boaters in Michigan; yet it has been shown that even in a single recreation area boaters vary considerably. [Research by Lucas (18) in the Boundary Waters Canoe Area showed that motorboaters, canoeists, and motorcanoeists display significantly different travel behavior.] Moreover, the increased importance of noneconomic motives in recreational travel decisions suggests that these decisions are even more personalized than those of work trips. By not explicitly considering user characteristics and preferences, the models are unable to deal with factors such as weather, crowding, price and cost changes, and changes in user preferences and perceptions.

DISAGGREGATE APPROACH

The restrictions and requirements of a recreational travel model and the experience with more traditional trip distribution models may cause one to wonder whether disaggregate, probabilistic models offer significant improvements in recreational modeling. To answer this question, we must first determine how such models can be applied to recreational trip-making. What follows is one approach for developing such a disaggregate recreational model.

Proposed Model

Consider the case of extraurban recreational trips to recreational facilities in a region. Initially, consider the seasonal flows of such trips; short-term recreational trips, such as those on weekends, will be discussed later.

It may be argued that recreationists make explicitly or implicitly at least 3 travel decisions: to participate in a given type of extraurban recreation; to engage in this activity with a certain degree of intensity (i.e., numbers of trips); and to choose the sites at which to engage in this activity. For trips outside of a region, mode choice would also be an important decision, but for regional recreation trips the choice of mode is usually more restricted. The discretionary nature of recreation travel is apparent in the second travel decision: Knowing that a person is a skier does not tell how often he travels to ski areas. Thus, the prediction of seasonal recreational trips demands that the number of trips made by a person be explicitly modeled.

A disaggregate, probabilistic recreational travel model may be simply constructed as a multiplicative combination of 3 probabilistic terms. Let $X(i)$, $N_{ij}(n)$, and $D_{ij}(k)$ be defined as follows:

$X(i)$ = probability that a person participates in recreation activity i;
$N_{ij}(n)$ = probability a person makes n annual activity I trips given that he or she participates in activity i; and
$D_{ij}(k)$ = probability a person from city j chooses site k given that he or she undertakes an activity i trip.

In mathematical terms, these definitions become

$$X(i) = P\{X = i\}$$

$$N_{ij}(n) = P\{N_j = n \mid X = i\}$$

$$D_{ij}(k) = P\{D_j = k \mid X = i\}$$

For a resident in city j, these probabilities multiplied together yield the probability that the resident will make n seasonal activity i trips to site k. Thus, the expected number of such trips made in a season t_{ijk} is given by

$$t_{ijk} = X(i)\,D_{ij}(k)\sum_{n} n\,N_{ij}(n) \tag{1}$$

Equation 1 illustrates the disaggregate nature of the model. The 3 travel decisions are each treated in a disaggregate fashion and combined to yield predictions of an individual's travel behavior.

Aggregation occurs by computing the expected value of the seasonal trips made by all city j residents to site k. To compute this quantity, however, one must alter the probability X(i) by making it city specific. That is, X(i) is the probability that a person with given age, income, and other characteristics will participate in activity i. What is needed is the probability that any resident of city j will participate in that activity. Let $X_j(i)$ represent this probability. The expected number of seasonal trips to site k by all city j residents T_{ijk} is given by

$$T_{ijk} = D_{ij}(k)X_j(i)P_j \sum_n nN_{ij}(n) \tag{2}$$

where P_j is the population of city j. Thus, seasonal flows from city j to site k can be predicted if the 3 probabilities $X_j(i)$, $N_{ij}(n)$, and $D_{ij}(k)$ can first be estimated.

Short-term recreational trip-making, such as that during a specific weekend, is much more difficult to model. Although only 2 travel decisions are important in this case (how many trips to take is no longer a relevant decision), the factors influencing these decisions are complex. For example, the decision to undertake a trip on a specific weekend—or on a specific day—depends on factors such as weather, anticipated crowding, distance to available recreation site, the person's previous experience with and commitment to the recreation activity, and his or her socioeconomic characteristics. Thus, trips on specific weekends may be predicted in 1 of 2 ways: Relate the decisions of individuals to these many variables or relate the proportion of seasonal trips that occur on a weekend to the intervening variables such as weather and time of year. Clearly the latter of these methods is the easier, and, although it is not disaggregate in that it does not model individual decisions at a particular point in time, it does rely on the seasonal travel predictions for individuals (Eqs. 1 and 2).

Parameter Estimation

The validity of the model depends, of course, on its ability to relate the 3 input probabilities to demand, supply, transportation, and user characteristics. If the model is to improve on existing models, then these factors must be explicitly incorporated into the process by which these probabilities are estimated.

The $X_j(i)$ probabilities may be derived from the user-specific demand analyses based on the national recreation surveys. The procedure is straightforward. Analyses of these data relate probability of participating in an activity X(i) to socioeconomic data, particularly income and age. Data from these variables for a specific urban area are used to estimate city-specific probabilities $X_j(i)$.

The other 2 probabilities, $N_{ij}(n)$ and $D_{ij}(k)$, are more difficult to estimate. Each of these probabilities refers to choices made among more than 2 alternatives (i.e., number of trips and choice of destinations). These probabilities can be estimated by the use of a multidimensional logit model (21). Clearly, however, the problem of estimating probabilities for a large set of destinations—which may not all be among the choice sets of individual travelers—requires further research.

However, the complexity of recreational travel decision-making is represented not just in the estimation methods chosen but also in the specification of variables to be included in the estimation process. The $N_{ij}(n)$ probability illustrates this point. This probability, which relates to the number of seasonal trips a recreationist makes, is dependent on a number of factors, including the socioeconomic characteristics of the person and the availability of recreational opportunities. Availability may be denoted by travel times to recreation sites for an activity and a variable denoting the supply of sites for this activity. For example, if the activity were camping, the total number of camping places in an area may be included as a variable. This is the procedure followed in the Rutgers University demand analysis that uses national survey data (3). Or both supply and travel time may be combined by constructing concentric rings around a city, summing the facilities in each ring, multiplying by the inverse of travel time to this ring, and summing the products. This procedure produces a weighted recreational accessibility index.

The user characteristics that might be included are numerous. Here the user-specific demand research is helpful in that it has shown age and income to be important indicators of recreation participation. However, these variables are not causal and are not able to represent the psychological motivations underlying recreational travel decisions. One of many ways in which such motivations and perceptions can be included in the model is by measuring a person's "environmental disposition" (19). Environmental disposition is a composite set of scores on environmental factors obtained from a questionnaire called the environmental response inventory. Its use in measuring environmental perceptions has been shown to be valuable in the case of wilderness recreationists (20). It has not yet been used as a variable to explain demand for recreational activities, but it does offer the capability for dealing with policy questions relating to changes in user preferences and perceptions.

The probability $D_{ij}(k)$ requires more variables to describe recreational facilities. The hypothesis in this case is that one site, say, a park, is chosen over another because of park facilities, park location, and user characteristics. However, the inclusion of park facilities immediately raises the question inherent to the trip distribution models already described: How does one measure attractiveness? Many answers are possible depending on the particular activity in question, but data needs will be minimized by using the results of factor analyses of recreational sites, such as those performed by Ellis (7).

Several types of data are required to estimate these 3 probabilities. Origin-destination data describing recreational trips are needed just as they are in the case of other recreational travel models. Also, user characteristics such as age, sex, and environmental disposition are required. Finally site characteristics are needed. This last type of data is already available in many states in the form of state recreational inventories.

CONCLUSION AND RESEARCH RECOMMENDATIONS

Several difficulties with existing recreational trip models have been discussed in this paper. Many of these exist also in the disaggregate probabilities model developed here. For example, neither type of model adequately deals with traffic peaking or multipurpose or multidestination journeys. Also, both models require some measures of recreational facility characteristics or attractiveness.

Yet there are 2 ways in which the disaggregate, probabilistic model offers potentially significant improvements over the existing models. One of these results from the fact that the model is disaggregate. Probabilities are determined for individuals and then aggregated to yield expected trip movements for an entire population. The model is, therefore, at least conceptually able to represent more realistically the variety of recreational trip motivations.

The second advantage relates also to the disaggregate nature of the model. Existing models are unable to incorporate user tastes and perceptions and thus are particularly limited in their predictive value for recreational travel. The disaggregate model, however, can incorporate these factors by including user perceptions such as those represented by a user's environmental disposition. By using this or other measures of user attitudes, one can measure changes in user travel motives and thus predict the resulting effects on recreational travel.

This last point suggests what research is needed to achieve improved predictive capability in recreational travel modeling. One of these steps, of course, is to test the model by estimating the 3 input probabilities; travel data for a variety of recreational activities are used. Just as the exponent in the gravity model varies considerably, as Wolfe (33) discovered, with recreational trip type, the input probabilities in the disaggregate model vary with trip type and experience is needed to determine how they vary. Also, research is needed to determine how best to incorporate the user characteristics and perceptions. What attitude measures are most useful, and how should they be included in the model? Stopher and Lavender (28) show that for mode choice for urban work trips user stratification is the best way to incorporate user characteristics. However, with the additional complexity of trip classification and user attitudes, such stratification may require unreasonable amounts of data.

A second and related research endeavor is also indicated. In the proposed model, probabilities must be estimated for 2 travel decisions made from n-dimensional choice sets. As already mentioned, these estimations encounter both data restrictions and conceptual difficulties resulting from a lack of choice sets common to all recreational travelers. These problems—which are common to the extension of disaggregate models to many other travel decisions as well—require considerable research attention.

Nonetheless, disaggregate models are a welcome and potentially useful addition to recreational travel modeling. What these models represent is a more rational approach to modeling a complex and highly psychologically motivated set of recreational travel decisions. But also, the models present a means of integrating research on user trip patterns, perceptions of recreational environments, and satisfactions with these environments. By so doing, the models will lead to increased capability for dealing with the many complex policy questions facing recreational planning.

REFERENCES

1. Burch, W. R., Jr. The Play World of Camping: Research Into the Social Meaning of Outdoor Recreation. American Journal of Sociology, Vol. 70, 1965, pp. 604-612.
2. Chubb, M. Outdoor Recreation Planning in Michigan by a Systems Analysis Approach. Michigan State Resource Planning Program, Technical Rept. 12, 1967.
3. Cicchetti, C. J. A Review of the Empirical Analyses That Have Been Based Upon the National Recreation Surveys. Journal of Leisure Research, Vol. 4, 1972, p. 90.
4. Clawson, M., and Knetsch, J. L. The Economics of Outdoor Recreation. Johns Hopkins Press, Baltimore, 1966.
5. Crevo, C. C. Characteristics of Summer Weekend Recreational Travel. Highway Research Record 41, 1963, pp. 51-60.
6. Deacon, J. A., Pigman, J. G., and Dean, R. C. Travel to Outdoor Recreation Areas in Kentucky. Journal of Leisure Research, Vol. 4, pp. 312-332.
7. Ellis, J. B. A Systems Model for Recreational Travel in Ontario: A Progress Report. Ontario Department of Highways, Rept. RR126, 1967.
8. Ellis, J. B., and VanDoren, C. S. A Comparative Evaluation of Gravity and System Theory Models for Statewide Recreational Traffic Flows. Journal of Regional Science, Vol. 6, No. 2, 1966, pp. 57-70.
9. Elsner, G. H. A Regression Method for Estimating the Level of Use and Market Area of a Proposed Large Ski Resort. Journal of Leisure Research, Vol. 3, 1971, pp. 160-167.
10. Gilbert, G., Peterson, G. L., and Lime, D. W. Toward a Model of Travel Behavior in the Boundary Waters Canoe Area. Environment and Behavior, Vol. 4, No. 2, 1972, pp. 131-157.
11. Gyamfi, P. A Model for Allocating Recreational Travel Demand to National Forests. Highway Research Record 408, 1972, pp. 50-61.
12. Hanis, E. H. Demand Analysis of State Park Utilization and Other Outdoor Recreation Activities in Maine. Public Affairs Research Center, Bowdoin College, Brunswick, Me., 1970.
13. Hendrich, P. The Impact of Recreation, Vacation, and Travel on New Hampshire—1954, 1958, 1963, 1967, and 1970. Office of State Planning, Concord, N.H., 1971.
14. Hoffman, W. L., and Romsa, G. H. Some Factors Influencing Attendance at Commercial Campgrounds: A Case Study. Land Economics, Vol. 48, No. 2, 1972.
15. Jansen, E. F., Ching, C. T. K., Frick, G. E., and Chandler, C. W. Economic Effects of Pawtuckaway State Park. Agricultural Exp. Station, Univ. of New Hampshire, Durham, Res. Rept. 17, 1971.
16. King, D. A. Socioeconomic Variables Related to Campsite Use. Forest Science, Vol. 14, No. 1, 1968, pp. 45-54.

17. LaPage, W. F. The Role of Fees in Campers' Decisions. Northeast Forest Exp. Station, U.S. Forest Service, Res. Paper NE-118, 1968.
18. Lucas, R. C. Wilderness Perception and Use: The Example of the Boundary Waters Canoe Area. Natural Resources Journal, pp. 394-411, Jan. 1964.
19. McKechnie, G. E. Measuring Environmental Dispositions With the Environmental Response Inventory. Proc., 2nd Annual Environmental Design Research Association Conference, 1970, pp. 320-326.
20. Peterson, G. L. Motivations, Perceptions, Satisfactions, and Environmental Dispositions of Boundary Waters Canoe Area Users and Managers. The Technological Institute, Northwestern Univ., Evanston, Ill., 1971.
21. Rassam, P. R., Ellis, R. H., and Bennett, J. C. The n-Dimensional Logit Model: Development and Application. Highway Research Record 369, 1971, pp. 135-147.
22. Sullivan, E. C. Models for Recreation Traffic Estimation Within a National Forest. Highway Research Record 408, 1972, pp. 38-49.
23. Sajovec, J. Travel Patterns. Dept. of Civil Engineering, Northwestern Univ., unpublished, 1971.
24. Shafer, E. L., Jr., and Thompson, R. C. Models That Describe Use of Adirondack Campgrounds. Forest Science, Vol. 14, No. 4, 1968, pp. 383-391.
25. Smith, R. J. The Evaluation of Recreation Benefits: The Clawson Method in Practice. Urban Studies, Vol. 8, 1971, pp. 89-102.
26. Stopher, P. R., and Reichman, S. Disaggregate Stochastic Models of Travel-Mode Choice. Highway Research Record 369, 1971, pp. 91-103.
27. Stopher, P. R., and Lisco, T. E. Modelling Travel Demand: A Disaggregate Behavioral Approach—Issues and Applications. Transportation Research Forum, 1970, pp. 195-214.
28. Stopher, P. R., and Lavender, J. O. Disaggregate, Behavioral Travel Demand Models: Empirical Tests of Three Hypotheses. Transportation Research Forum, 1972, pp. 321-336.
29. Tadros, M., and Kalter, R. Spatial Allocation Model for Projected Water-Based Recreational Demand. Water Resources Research, Vol. 7, No. 4, 1971, pp. 798-811.
30. Talvitie, A. Comparison of Probabilistic Modal-Choice Models: Estimation Methods and System Inputs. Highway Research Record 392, 1972, pp. 111-120.
31. Ungar, A. Traffic Attraction of Rural Outdoor Recreation Areas. NCHRP Rept. 44, 1967.
32. Vickerman, R. Demand for Non-Work Travel. Journal of Transport Economics and Policy, Vol. 6, No. 2, 1972, pp. 176-210.
33. Wolfe, R. I. Parameters of Recreational Travel in Ontario: A Progress Report. Ontario Department of Highways, Rept. 111, 1966.
34. Wolfe, R. I. Communications. Journal of Leisure Research, Vol. 2, No. 1, 1970, pp. 85-87.

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