TRANSPORTATION RESEARCH RECORD 794

Household Activities and Consumer Perspectives

TRANSPORTATION RESEARCH BOARD

COMMISSION ON SOCIOTECHNICAL SYSTEMS
NATIONAL RESEARCH COUNCIL

NATIONAL ACADEMY OF SCIENCES
WASHINGTON, D.C. 1981

Transportation Research Record 794
Price $5.80
Edited for TRB by Mary McLaughlin

modes
1 highway transportation
2 public transit

subject areas
12 planning
13 forecasting

Library of Congress Cataloging in Publication Data
National Research Council. Transportation Research Board.
Household activities and consumer perspectives.

(Transportation research record; 794)
1. Choice of transportation–Research–Addresses, essays, lectures. 2. Transportation–Social aspects–Addresses, essays, lectures. I. National Research Council (U.S.). Transportation Research Board. II. Series.
TE7.H5 no. 794 [HE336.C5] 380.5s 81-11051
ISBN 0-309-03208-3 ISSN 0361-1981 [388.4] AACR2

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Some Recent Developments in Activity-Travel Analysis and Modeling

M.I. CLARKE, M.C. DIX, P.M. JONES, AND I.G. HEGGIE

The Transport Studies Unit at Oxford University has been working on a project that has contributed to many of the ideas and techniques involved in the activity approach to the study of travel behavior. The research itself is briefly described, and some of the major findings of interest to transportation planners are highlighted. The topics covered include the application of the activity approach to the data-collection, data-analysis, and modeling phases of transportation planning, and emphasis is laid throughout not only on the study results themselves but also on the research style. The research approach combines qualitative social-science interviewing techniques with more formal quantitative surveys and analysis, and the result is that each approach complements the other and the combination of both gives insights that are not obtainable when either technique is used in isolation.

The main objective of this five-year study (1) was to obtain a better understanding of household travel behavior and to develop an analytic and modeling capability that would enable this knowledge to be applied in transportation research and planning. The motive for initiating such a line of research was the growing dissatisfaction with the more traditional techniques of modeling transportation demand--techniques that, it was realized, were lacking in behavioral content (2) and were therefore unable to give relevant predictions of response to change.

Traditional approaches to the problem make a number of basic assumptions about the nature of travel decisions that rigidly structure the way in which the subject is viewed. In order to avoid similar constraints on this project, it was decided that an exploratory research design should be adopted by approaching the problem with as few preconceived ideas as possible.

ORGANIZATION OF THE RESEARCH

The approach adopted in the initial stages was to talk to travelers about travel in everyday terms. A number of specific interviewing frameworks were introduced within otherwise undirected household interview sessions, and comparisons were made of the "behavioral relevance" of each framework. It was found that recall and description associated with trip-based frameworks were imperfect, unconnected, and acausal. A framework in which participants discussed travel within the context of activities was found to have a closer apparent correspondence with the conscious planning and organization of travel behavior (an empirical investigation of this qualitative finding is described later in this paper).

Further exploratory studies using the activity framework revealed insights into the character of travel decisions. Individual respondents' emphasis on making travel decisions within the context of household plans or behavior led to our choice of the household as the basic descriptive and sampling unit. Respondents' continual concerns with timing--scheduling activities over the course of the day--stressed the importance of interdependencies, both within the pattern of trips made by individuals and between individuals. Time constraints within the environment (such as fixed and limited shop opening times) were stressed as much as, or more than, distances and travel costs. The importance of synchronizing time spent at home for shared family activities (such as meals and child care) led us to include in-home activity in our later diary surveys.

The results of these exploratory studies (3) enabled us to develop the conceptual framework that shaped the design of the main survey. The latter took the form of a two-stage data-collection exercise in which detailed seven-day activity diaries were collected from all members of 196 households in Banbury, Oxfordshire, and follow-up in-depth interviews were conducted with a subset of those households. The analysis of the results of both qualitative and quantitative aspects of the surveys is also described later in this paper.

The diary survey collected very detailed information about the way in which each respondent spent his or her time over the seven days (each discrete activity was recorded whether in or out of the home). In addition, a considerable quantity of data was collected that described the environment (both spatial and temporal) in which the respondents were operating. Thus, the location and opening hours of every potential activity location were recorded, along with details of the supply of transportation, so that opportunities for alternative activity programs could be assessed. Although it was felt that such detailed data should be collected for this research project, it is shown later in the paper that there is no need to go to these lengths in practical applications of the approach.

Up to this point in the project, we had tended to concentrate on static descriptions of travel behavior. The next phase focused more specifically on the dynamics of adaptation, in a series of supplementary surveys that examined how households adjusted their activity patterns in response to changes in the environment. This topic was also approached by conducting in-depth interviews with households but, since in this case we were asking hypothetical questions (How would you react if...?), it was necessary to impose some logical discipline on the responses. This was achieved by using an interview aid--the Household Activity Travel Simulator (HATS)--which was developed as part of the current project (4). When using HATS, each household member builds a representation of his or her activity schedule on a display board using colored blocks, and changes to that schedule can be simulated by rearranging those blocks. Since HATS embodies, in physical analog terms, the logic of the activity framework, a large degree of realism is introduced to the respondents' hypothetical reactions.

Four such studies were carried out during the project, and these led to a number of generalizations about households' response to change. The range of responses observed was very great but could be understood better if viewed as the adaptation of existing activity schedules. Changes in trip making emerged as a direct result of the new activity patterns. At the simplest level, minor retimings might be applied to the existing activity set, resulting in little or no change in trip making. In more extreme cases, major changes might be made, including altering the set of activities undertaken, their locations, or the method of travel between them. What kind of response is made in a particular case was found to depend on the severity of the imposed change (in particular on whether it required or merely invited a response from the household) and on the structure of the particular family. Households with older children, for example, have more free time and fewer space-time or interpersonal linkages than families with young children and so can more readily absorb certain types of change without major reorganization.

The picture to emerge, then, from the study of dynamic response to change was one of discontinuous and asymmetric forms of adaptation shaped by family structure and space-time constraints. The final phase of the project investigated the feasibility of developing a mathematical model capable of reproducing such responses. This is described in the final section of this paper.

Having described the content of the project in general terms, we now go on to discuss in rather more detail some specific findings that have particular relevance for transportation planning.

COLLECTION OF TRAVEL-SURVEY DATA

The comparisons of the performance of different types of activity diaries led to one particularly important finding: that an activity diary is likely to capture more trip making than the equivalent travel diary. The Banbury survey was timed to follow exactly 12 months after a conventional household travel survey in the same town and was designed to be equivalent in all other important respects, in order to allow comparisons. The activity-diary survey found 4.4 reported trips/respondent, of 66-min total duration, in comparison with the travel survey's figures of 3.9 trips/respondent and 57 min (increases of 13 and 16 percent, respectively).

A comparison of the travel-time results of the two types of surveys is given below (the differences for home-based work and home-based education trips are not significantly different from zero at the 95 percent confidence level):

Trip Category	Trips per Person per Day: Activity Survey	Travel Survey	Difference
All	4.37	3.86	0.51
Home-based			
Work	0.88	0.79	0.09
Education	0.54	0.55	-0.01
Other	2.16	1.93	0.23
Non-home-based	0.80	0.60	0.20

The table shows that this discrepancy is accounted for largely by differences in the trip rates reported for discretionary purposes--other and non-home-based--while the compulsory trip purposes show no significant difference (comparisons of travel times by purpose show similar differences).

Clearly, there are a number of possible sources for this observed discrepancy, and so differences between the two surveys in target populations, selected samples, definitions, and seasonal or other temporal variations were checked. But most of the effects were finally attributed to the diary types themselves. It is suggested that an activity diary is a more efficient way of collecting details on trip making, particularly for incidental trips that may be easily forgotten, because

1. At the recall stage, the activity framework enables respondents to adopt a more natural and efficient search strategy, which leads to a more complete recall of travel information;
2. At the recording stage, the activity format requires that time be continually accounted for, and this alerts respondents to forgotten activities and travel; and
3. At the coding and analysis stages, the activity format provides greater opportunity for checking logical consistency and completeness of each record (for example, each shift in location logically implies that a trip has been made).

Such results suggest that the possibility of adopting an activity diary might be considered for some kinds of travel surveys, although the extra accuracy obtained must of course be balanced against the extra cost of the more complex format of an activity survey. The subject is discussed further elsewhere (5).

ANALYSIS OF ACTIVITY DATA

Daily Patterns of Behavior

The main survey resulted in two types of information, neither of which is amenable to traditional techniques of transportation data analysis. The activity diaries give rise to a mass of very detailed quantitative data that describes how households organize their time but is difficult to present without sacrificing much of its detail. The in-depth interviews, on the other hand, result in a rich picture of the motives and mechanisms that underlie the activity patterns but do not lend themselves to other than a "journalistic" style of presentation. We adopted a dual approach to the analysis, in which the qualitative and quantitative assumed equal importance.

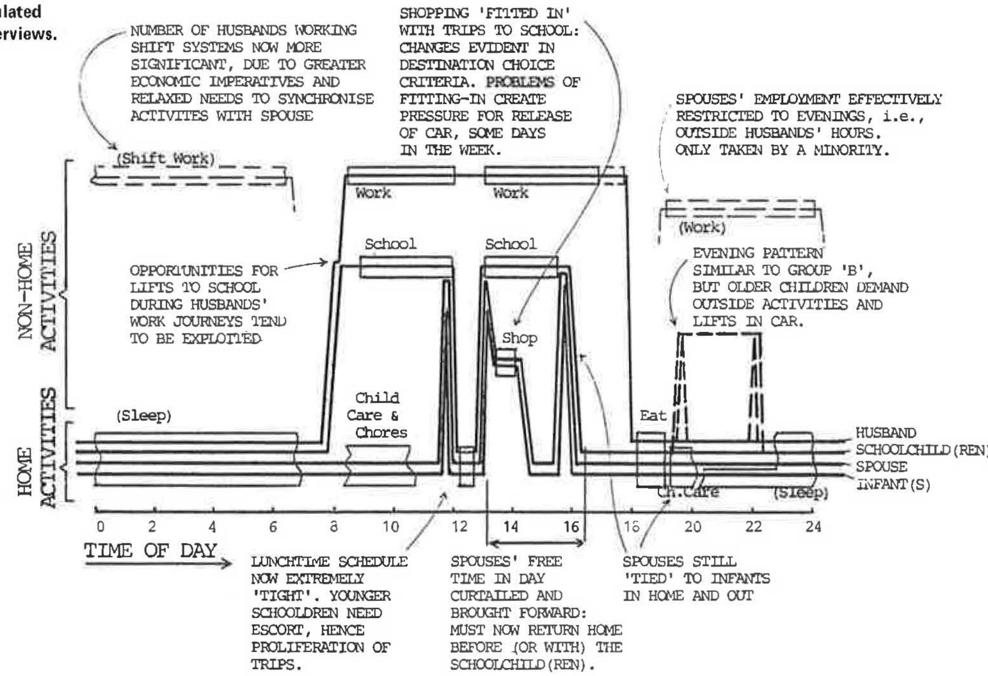
Our analysis involved the investigation of a theme that had emerged as being important during the exploratory studies--i.e., that household structure (in terms of the numbers and ages of children) is a major determinant of daily behavior and hence of travel. We therefore developed the following series of eight groups describing the stages in the family life cycle, among which all households could be allocated:

Life-Cycle Group	Description
A	Younger adults without children
B	Families with preschoolchildren
C	Families with preschoolchildren and young schoolchildren
D	Families with young schoolchildren
E	Families with older schoolchildren
F	Families of adults, all of working age
G	Older adults, no children in household
H	Retired persons

For each of these stages, profiles of typical daily family behavior were constructed from the two data sources independently. In the case of the qualitative data (see Figure 1), this was done by noticing any constraints on behavior that emerged from the interviews and building a typical schedule around them (an example might be that in group A, where both members of a household would tend to be employed full time and any shopping must be done either at lunchtime or on the way home). For the quantitative data (see Figure 2), the job can be done analytically, by calculating from the observed data the proportion of respondents of a particular type who are engaging in a particular activity at a particular time.

Comparison of the results showed encouraging correspondence between the profiles derived from the two sources of data. But each type of data has its

Figure 1. Activity patterns postulated for group C households from interviews.



own contribution to make to the study. The qualitative data allow anecdotal suggestions to be made as to why various features of the pattern appear in the way they do, and the quantitative analysis shows not just "typical" behavior but also the spread of behavior about that mean. In Figure 2, for example, it can be seen that, although few mothers in this group work (because they have young children to look after), those that do so must arrange to work part time either during times when their young children are at a nursery school (the correspondence between the plot for young children at school and mothers working is striking) or in the evening when the father is available to babysit. None of them are at work between 4:00 and 5:30 p.m., when the older children are returning from school.

Analytic Comparisons Between Life-Cycle Groups

We continued our analysis with a comparison of household behavior that used a simpler description of behavior: activity time budgets. This approach ignores the exact timing and sequencing of activities and concentrates instead on the way in which individuals share out the time available to them between different classes of activity. We calculated a time budget for each household as the mean of those of the two main adult members of the family, the budgets being in terms of time spent on each of 26 groups of activities per average weekday.

Differences between the household activity budget of families from different life-cycle groups were investigated by means of a multivariate discriminant analysis. Although the discriminant functions that best explained the variance between the budgets of households in different life-cycle groups are linear combinations of time spent on several activities, they can be interpreted at a simple level as being measures of time spent on child-care activities and in formal work. The first function (child care) explains 62 percent of the between-group variance, and the second (work) explains a further 23 percent.

In Figure 3, each household is plotted against axes that represent the two discriminant functions on one of eight graphs (one graph for each life-cycle group). The households from particular life-cycle groups do indeed tend to lie in clusters, which implies that they behave similarly. But, whereas groups A, B, C, and H are reasonably clearly defined, it is difficult to distinguish between groups D, E, F, and G. More formal analysis confirms the existence of these five fairly distinct clusters.

In Figure 4, we have plotted merely the centroids of the cluster of households that make up each life-cycle group. This representation brings out the idea of a classic path through the life-cycle groups for a typical household. Starting as a young married couple at A, they change their activity patterns drastically with the arrival of the first child and move to point B. As the family develops, they follow the path through points C, D, and E until the change between groups F and G (families with adult children and older couples with no children) is negligible. Retirement brings another major change in activities, represented by the move to point H. There are, of course, other paths for people who adopt alternative life-styles (6).

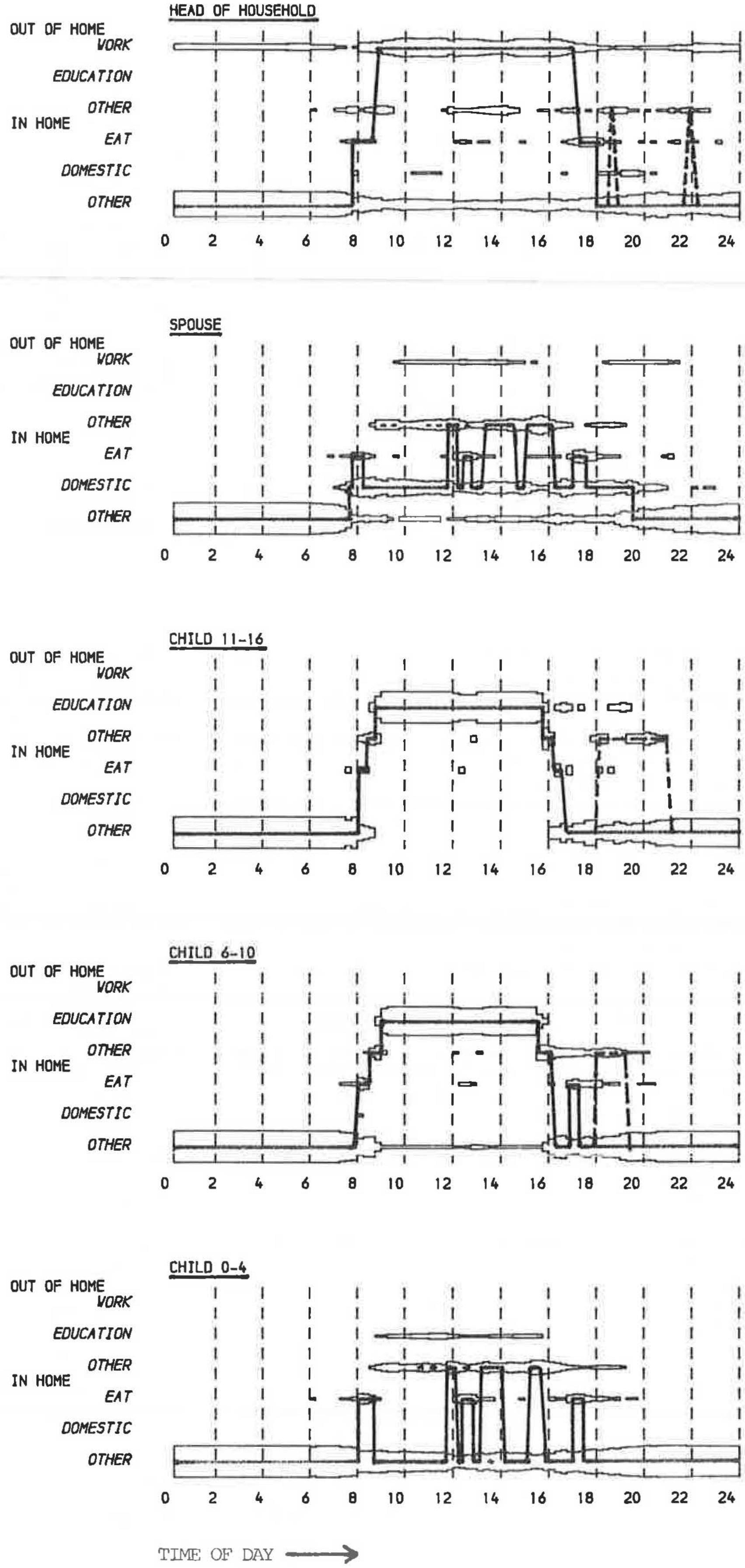
Relations Between Activities and Travel

Finally, in our analysis of behavior patterns we look at the impact on travel of the differences in activity patterns across life-cycle groups. An analysis of trip "circuits"--sequences of trips that start and end at home--reveals basic differences between the travel patterns of families from different life-cycle groups, particularly in terms of the complexity of the travel arrangements made (see Table 1).

In group A, since both members of the households tend to be employed, most of the nonwork activities take place as part of a work circuit. In fact, more than half of the spouses' work circuits also involve shopping.

In group B, the arrival of the first child has the expected effects. Most obviously, the wife now makes very few journeys involving work and, since she is now at home during the day, she can do much of the family shopping (30 percent of her circuits

Figure 2. Measured activity patterns for group C households (Thursday).



are simply home-shop-home). The husband no longer needs to do so much shopping in conjunction with work, and a marked reduction in their proportion of serve-passenger circuits reflects the reduced opportunity for lift-sharing to and from work.

The major characteristic of group C is the large proportion of circuits that include serve passenger. More than half of the wife's circuits involve this activity, and more than a quarter involve no other. The husband is also heavily involved in lift-giving in conjunction with work and in simple circuits with no other activity. The complexity of the activity patterns among families that have both schoolchildren and infants clearly manifests itself in these figures.

The proportion of circuits that involve providing lifts declines for the wife as the family grows up through groups D, E, and F. For the husband, however, the commitment to providing lifts remains constant as long as the children are in school.

In the final life-cycle group, the retired, almost all of the wife's circuits are simple ones. This is because there is now no need for the complex arrangements required to meet the needs of a family as in earlier groups. The same trend is not apparent for husbands; their simplest travel patterns occur in group G. Both wives and husbands show a local maximum in the proportion of simple circuits at life-cycle group B--after the necessity of fitting in activities around work in group A and before the complications of a growing family set in in later groups.

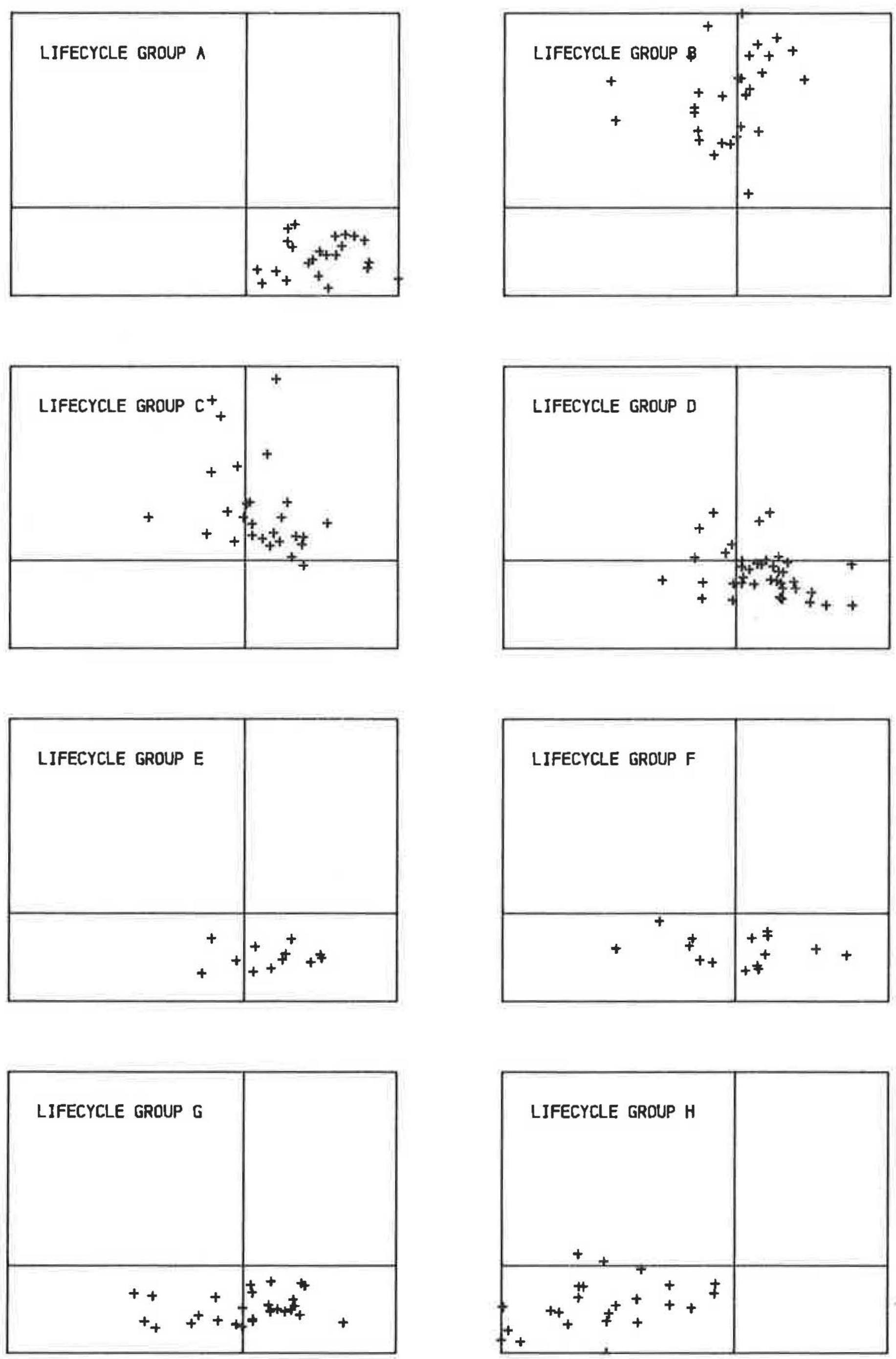


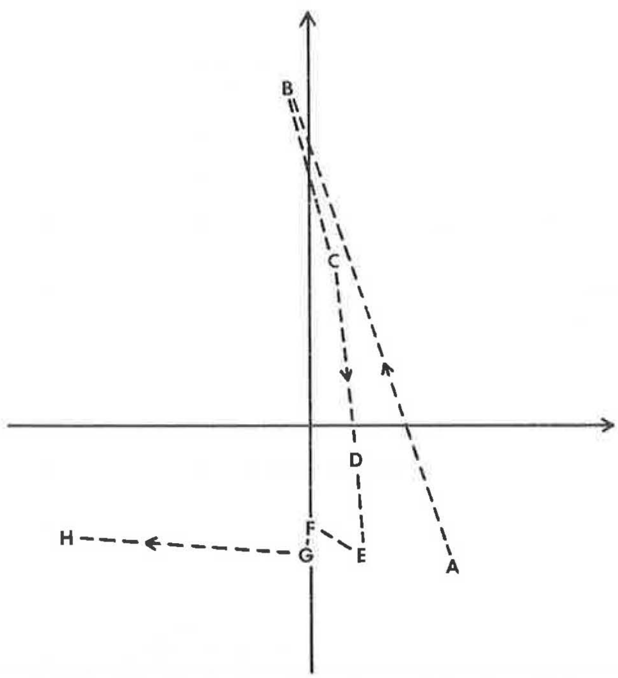
Figure 3. Surveyed households plotted in terms of activity and time budgets.

Reanalysis of Conventional Data Sets

Although the above analysis of trip circuits was performed from the detailed activity survey, it could just as easily have used conventional travel data. Whether one thinks of the analysis in terms of trip chains or activity chains is to some extent arbitrary. Travel data are in fact just a special case of activity data, providing no detail on multiple activities at any one location.

It follows that much analysis in terms of activities does not require expensive, detailed activity data, and we have produced activity schedules of the type shown in Figure 2 from conventional travel-data sources (7). Nevertheless, activity data provide an added level of detail that, particularly in a research context, allows examination of the linkages caused by, for example, family meal times.

Figure 4. Typical path of a household through life-cycle stages.



ACTIVITY-BASED BEHAVIORAL MODEL

Most conventional travel models are quite incompatible with the ideas developed in this study. They make little or no provision for the spatial and temporal constraints and linkages between household members that these surveys have suggested are instrumental in shaping the responses of households. We have therefore developed a model structure that takes explicit account of these features and is formulated in terms of activity patterns rather than trips (8,9).

The model is made up of a series of modules, each of which represents a possible response that a household may make when faced by an external stimulus. The model predicts changes in a household's activity schedule; resulting changes in travel patterns follow automatically.

The model is applied to individual households incrementally so that the first module only allows the household to make adjustments to the timing and sequence of the set of activities that they undertook before the application of the stimulus. If this process fails to reveal any feasible options, then other modules are invoked that represent more complex responses, such as changing the activity set or the location of activities.

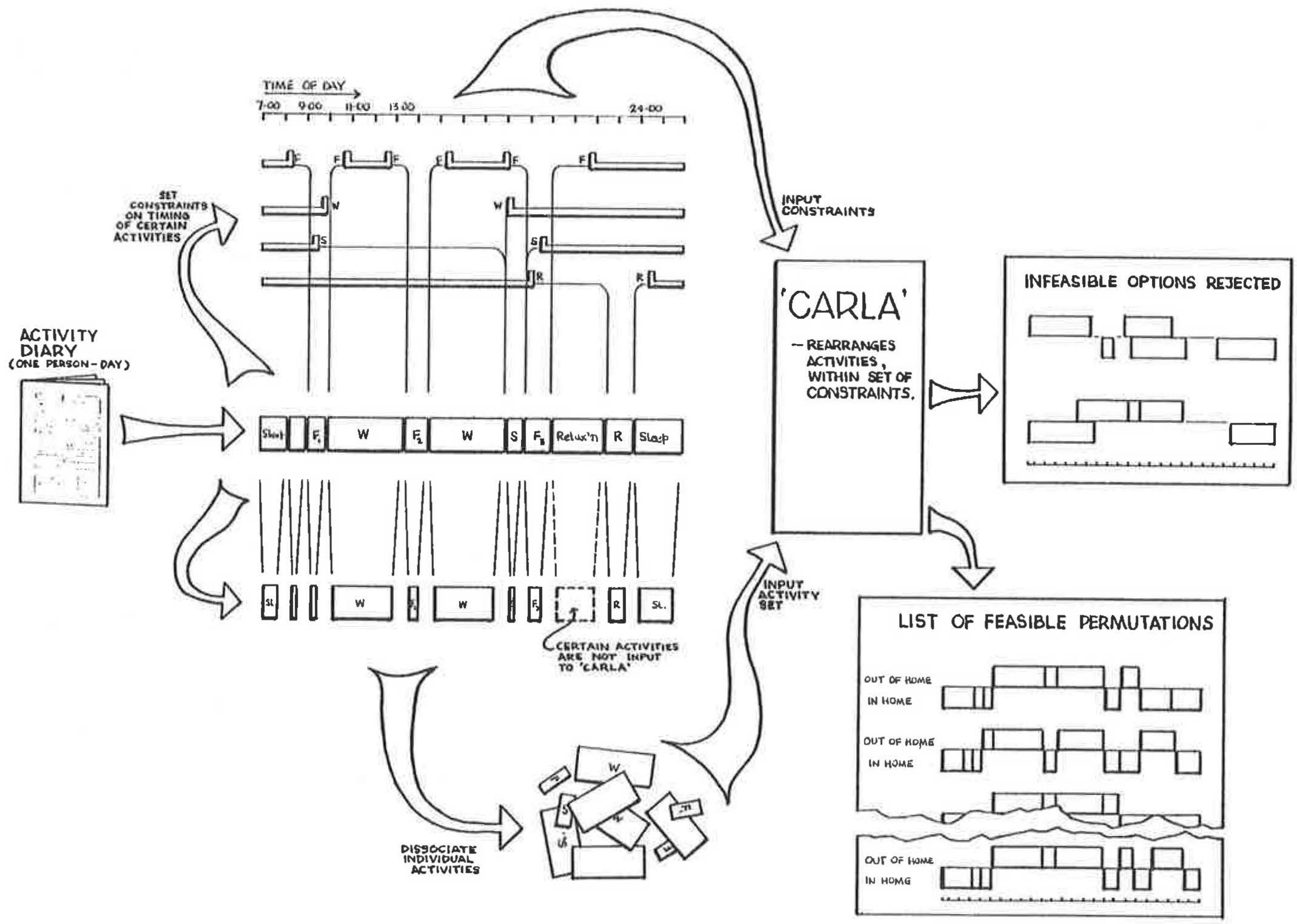
By feasible options we mean activity schedules that obey a particular set of rules. These rules represent logical constraints on activity patterns, land use limitations in both temporal and spatial dimensions, and behavioral aspects such as the existence of linkages between members of the household. Such rules were observed to be in operation when households rearranged their real activity schedule in the course of our surveys.

The core of the model, then, is a submodel

Table 1. Weekday trip circuits of household heads and spouses by family life-cycle group.

Purpose	Household Member	Percentage of Trip Circuits by Life-Cycle Group A	B	C	D	E	F	G	H
Work	Head	56	50	55	45	44	59	48	18
	Spouse	53	8	12	35	45	42	28	8
Shopping	Head	26	24	17	23	23	21	18	39
	Spouse	46	49	40	37	40	45	39	51
Serve passenger	Head	15	6	31	28	32	18	6	7
	Spouse	7	17	52	28	4	4	7	0
Other	Head	39	43	27	29	28	29	37	47
	Spouse	50	50	40	37	29	29	45	51
Work and shop	Head	14	6	4	6	6	7	2	2
	Spouse	31	2	6	11	10	10	9	4
Work and serve passenger	Head	12	3	12	6	12	13	1	0
	Spouse	2	0	7	6	3	0	3	0
Work and other	Head	9	8	9	4	9	5	2	1
	Spouse	18	0	5	5	1	2	1	0
Shop and serve passenger	Head	5	2	5	5	5	1	1	1
	Spouse	0	5	18	9	1	2	2	0
Shop and other	Head	5	9	4	5	6	4	3	10
	Spouse	13	14	12	11	4	5	6	7
Serve passenger and other	Head	5	2	6	5	8	5	2	1
	Spouse	4	6	13	6	1	2	2	0
Simple circuits (one stop)	Head	69	79	72	78	69	67	89	79
	Spouse	58	78	67	66	81	81	81	81

Figure 5. Schematic representation of use of CARLA activity scheduling model to produce feasible activity programs.



(CARLA) that produces rearrangements of a set of activities subject to the various rules. This submodel is shown in Figure 5, where it can be seen that an individual's activity diary gives rise to two sets of information: (a) the individual activities that make up the diary and (b) a set of constraints that represent the times between which each activity may take place.

The constraints are an essential part of the process, since they are the representation of both supply constraints (e.g., shops are only open at certain times) and behavioral rules (e.g., families are unlikely to wish to reschedule their meal times by more than a certain amount of time). These constraints are exogenous to the model itself and may therefore be defined as necessary for a particular application.

The algorithm produces all logical permutations of the activities subject to the temporal constraints, and the resulting set of feasible options corresponds to the household's choice set. The actual choice process is handled by an objective function that is able to point to the "best" option. Study of actual household reactions observed in our surveys showed that a simple function such as "minimizing change" was not sufficient. Rather, it was decided that a two-stage function should be developed to reflect the fact that change will be resisted if at all possible but that, once a change is forced on a household, then a new schedule is chosen so as to maximize some function of free time (measured in various ways) and to minimize travel disutility.

Then there is the question of aggregation. The model necessarily works at a highly disaggregate level, either on surveyed activity data or on hypothetical schedules generated for "prototypical" households of the kind described earlier in this paper in the discussion of daily behavior patterns. It is suggested that study of the modeled reaction of individual prototypical households is a very powerful research and policy tool, but there will of course be occasions when an aggregate prediction is required. For this we propose to use stochastic techniques to attach probabilities of adoption to the various options in the choice set of each of a number of generated households and to bring those probabilities to a gross level to produce a population prediction. We are therefore investigating the integration of the household-level activity model with sample enumeration techniques to provide aggregate prediction capabilities.

The model is still under development, but the rescheduling algorithm has been implemented, tested on real activity data, and found to be practicable. Even in this simple form, the model is capable of being used to investigate simple responses to policies. We have, for example, used it to examine the predicted response of a sample of schoolchildren to various levels of shift in school hours, and the results exhibit just the kind of discontinuous response that was apparent in the HATS interviews. Small changes in school hours can be dealt with by minor retimings of schedules, whereas more severe ones require a major rescheduling of activities and trips.

CONCLUSIONS

The topics discussed in this paper have shown the usefulness of the activity-based study of travel at the data-collection, analysis, and modeling stages of transportation planning. The work also has important implications for other aspects of planning, such as policy generation or evaluation. Although some of these techniques (particularly the modeling) are still in the development stage, others are operational and, most importantly, many can be applied to conventional data sources. Travel-survey data contain much information about the timing, sequencing, and linking of major out-of-home activities rarely used in conventional analyses.

The importance of linkages between household members leads to another immediately practicable theme: use of the stage in the family life cycle as a classificatory variable. That this variable accounts for real differences in travel between households has been demonstrated by our (and other) analyses. Moreover, the variable has a dynamic aspect (one can think of cohorts of the population moving between life-cycle groups over time) that lends itself to predictive modeling applications (6).

ACKNOWLEDGMENT

The support of the U.K. Social Science Research Council in funding the work described in this paper is gratefully acknowledged. We also wish to thank the Oxfordshire County Council for making available the results of the Banbury travel survey.

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Basic Properties of Urban Time-Space Paths: Empirical Tests

RYUICHI KITAMURA, LIDIA P. KOSTYNIUK, AND MICHAEL J. UYENO

Temporal and spatial characteristics of urban travel behavior as a time-space path are explored. An abstract model that integrates Hagerstrand's prism, the concept of trip linkage, and the intervening-opportunities concept of trip distribution is developed as a tool for this exploration. Empirical examination of hypotheses derived from the abstract model indicates that the probability of permanently returning home is a function of the time when, and the location where, the trip maker's last sojourn (or stop at an activity site) is completed; that the average duration of a sojourn is negatively correlated with the number of sojourns in the path; and that the spatial distribution of sojourn locations depends on the number of sojourns.

The dominance of the work trip in the development of models aimed at understanding and predicting travel behavior has led to the suppression of the space-time element in these models. The temporal component (time of day) of the work trip is basically constant, as is the spatial aspect in terms of destinations. Travel for other purposes is characterized by countless possibilities of destinations, frequencies, time scheduling, and combinations with other purposes. Only limited research has been devoted to this type of travel behavior because its importance to the planning of roads and highways was not of the highest order and also because it was considered complex.

Recently, however, the importance of considering this type of travel became more obvious when the response to the energy crises of 1973-1974 and the spring of 1979 included travel rescheduling or foregoing discretionary activities and combining trips (1,2). One approach to such aspects of travel behavior is to analyze the behavior in its entirety as a "path" (3) in the time-space dimension. Clearly, an understanding of time-space elements and interactions in travel behavior would be invaluable. Yet currently available analysis methods fail to provide an adequate framework for dealing with the complexity of travel behavior, which is becoming increasingly important.

Research in this field is in the stage of seeking analytic structures, examining alternative hypotheses, and attempting to develop a theoretical framework. Accordingly, the space-time characteristics of travel behavior as a path have been largely unexplored. It appears that the accumulation of relevant empirical observations of the behavior would also be extremely valuable. Such an effort should provide appropriate bases for the model-building effort, just as empirical observations of trip-length distributions, accumulated over decades, have added to researchers' understanding of urban travel patterns.

This paper summarizes the results of a research effort that explored some of the basic characteristics of urban travel behavior represented as time-space paths. The objective of the study is to hypothesize several macroscopically observable properties of the time-space path and statistically examine these hypotheses on an empirical data set. The goal of the effort is to identify a set of fundamental properties of travel behavior with the anticipation that the empirically supported properties would offer guidance for model-building efforts related to complex travel behavior.

As a tool for this exploration, the study developed a simple abstract model of travel behavior that integrates three well-known concepts and frequently practiced approaches: Hagerstrand's prism (3), the concept of trip linkage (4), and the intervening-opportunities concept of trip distribution (5, p. 111). Although highly hypothetical in its nature, the abstract model offers a framework from which certain properties of the time-space path can be inferred. Those inferred properties constitute a set of statistically testable hypotheses. Furthermore, as the assumptions of the simple model are relaxed, these properties can serve as acceptable limits for testing more realistic models.

Since there is no standard terminology on the subject (6,7), we define some key terms used in this study. A (time-space) path is defined as an individual's trajectory in the time-space dimension over a study period. This study deals only with those closed paths that originate and terminate at the home within the study period (a day). The study is abstract in the sense that it focuses on the spatial and temporal aspects of the path while suppressing attributes such as types of activities or modes of travel. Consider a site where a trip maker can pursue one or more out-of-home activities. A site may be a complex of more than one facility in close proximity. A stop made at such a site is called a sojourn, and the site where a sojourn is made is called a sojourn location. A trip is defined as the movement between two successive sojourn locations or between a sojourn location and home. A chain is defined as a series of connected trips that originates and terminates at home. A path can have one or more chains in a day, and a chain can have one or more sojourns in it.

REVIEW OF SPACE-TIME TREATMENT IN PREVIOUS MODELS

Several research efforts have recently been devoted to the development of a fundamental and coherent framework for analysis of travel behavior, including several analyses of trip linkages (7-12) and time allocation among daily activities (13,14). Although, conceptually, these approaches are not new (4,15-17), they show the promise of overcoming weaknesses that exist in the analytic framework of urban travel demand analysis.

In spite of these developments, relatively little is known of general space-time characteristics of travel behavior presumably because of the absence of simple analytic structures that capture this behavior. Empirical spatial and/or temporal distributions of linked trips have been reported (17-20), but these aggregate observations are not precisely suited to the exploration of individual path characteristics. Many studies of trip linkages or chaining used Markovian models in condensing the abundant information on observed behavior. The Markovian time-homogeneity and history-independence assumptions of those models, however, are clearly too restrictive to be useful if they are applied as a framework for understanding and describing the very fundamental space-time aspects of urban travel behavior [empirical examples of their irrelevance can be found in a report by Kondo (15) as well as in later sections of this study].

The state of the art of utilitarian analysis of travel behavior, on the other hand, appears to be overwhelmed by the complexity of the decision process [perhaps not to the decision maker (10) but certainly to the researcher] as well as the extensiveness and stochastic nature of contributing factors and the large number of possible alternatives involved. Only a few utilitarian analyses have considered travel as a path through space and/or time. A discrete choice analysis of travel patterns by Adler and Ben-Akiva (7) assumed that each path has a certain utility associated with it that could be expressed as a linear function of scheduling convenience, travel expenditure, and destination attributes. The time element, however, was totally implicit in the model; and the scheduling-convenience variable, which could involve certain time factors, was constructed only from the number of activities and from the number of activities per chain. Presumably because of its emphasis on policy analysis, the main concern of the study was the macroscopic description of travel patterns, aggregated over time and space as well as across individual households.

A different type of model was developed by Horowitz (8,11) that may be described as a hybrid of a discrete-choice model and a stochastic-process model. The model development starts with a time-dependent utility of destination location j when visited from location i by mode m. The history dependence of the behavior is incorporated by a parameter that represents the number of trips made up to the time point of concern. The household is the behavioral unit of the study, as in the study by Adler and Ben-Akiva (7). The temporal continuity condition, however, is not apparent in the model. The activity duration is not a component of the utility function, at least in an explicit form. The temporal characteristics of the behavior are again deemphasized, and it is difficult to identify space-time properties of the path from the model.

Although the traditional trip-distribution analysis has completely left out the temporal aspect of travel behavior and the continuity condition of trips, time-budget analyses (16,17) have not meaningfully incorporated the spatial aspect. Although effort has been made to represent the continuity condition, the main emphasis of recent developments is still placed on the atemporal distribution of trips. In spite of Hagerstrand's conceptualization of time-space paths, it appears that no effort has been devoted to exploring the space-time aspect of urban travel behavior.

ABSTRACT MODEL OF THE TIME-SPACE PATH

An abstract model that integrates Hagerstrand's prism, the concept of trip linkage, and the intervening-opportunities concept of trip distribution was developed as a tool for extracting space-time properties of time-space paths. The basic assumptions of the model are as follows:

1. The movement of people is one-dimensional, or the study area can be represented as a linear city;
2. Opportunities are homogeneously distributed in the linear city at a constant density; and

3. The speed of travel is invariant regardless of time and location.

These assumptions, similar to those found in Burns (21), offer the ideal situation where the Hagerstrand's prism represents the domain of possible trajectories that one can follow given an origin coupling constraint that one cannot leave home until a certain time of day (21) and a destination coupling constraint that one must return home by a certain time of day.

The abstract model involves another assumption regarding the distribution of trips or sojourn locations: The trip maker pursues out-of-home activities whenever there are acceptable opportunities within the feasible region of the time-space coordinates. The probability of acceptance of an opportunity is assumed to be constant.

Thus, the model depicts activity linkage in a probabilistic manner that may well replicate observed behavior. The behavioral implications of the model, however, are rather limited. The activity decision is assumed to be sequential, as opposed to simultaneous activity planning where most of the activities for the day are prescheduled (12). Certain aspects of the behavior are thus not represented by the model. For example, the model does not represent the empirically observed interdependency (13) in temporal scheduling of activities. However, the purpose of the model is not to replicate travel and activity choice behavior, and the model is kept intentionally simple for this reason. In its present form, the model does not incorporate the type of activities or the time when the trip maker leaves home. No assumptions are imposed regarding the duration of out-of-home activities. It should be emphasized, however, that the model is not intended to be descriptive or predictive. Rather, it is developed as a conceptual framework to extract in an abstract manner some specific aspects of travel behavior. Its possible behavioral weakness is acceptable as long as the model serves this purpose.

FORMULATION OF HYPOTHESES

Four basic hypothetical properties of the time-space path that can be immediately inferred from the abstract model are discussed here. Most of the discussion is limited to the one-chain path--i.e., the path that involves only one closed series of trips that originates and terminates at home. Some generalizations are discussed later in this paper. As is apparent from the model development, the model is directly applicable to the paths that consist of discretionary sojourns.

The first property of the path derived from the model, or hypothesis 1, is as follows: The conditional probability of returning home, given that a sojourn is completed at time t at a given location, is an increasing function of time. As a special case, suppose that the probability of making another sojourn depends only on the acceptability of reachable opportunities. Then the conditional probability exponentially increases with time.

The number of reachable opportunities decreases linearly as time proceeds (21). Then, if one applies the intervening-opportunities concept, the conditional probability of not finding an acceptable activity location within the prism is given by

$$P(t) = \alpha \exp(\ell\gamma v t) \quad 0 \leqslant t \leqslant T \tag{1}$$

where

α = a constant = $\exp(-\ell\gamma vT)$,
γ = density of opportunities,
v = speed of travel,
ℓ = constant acceptability parameter of the opportunity model, and
T = time component of the destination coupling constraint (the origin coupling constraint is expressed as $t = 0$).

One can expect that, if the trip maker does not find a location for an activity within the prism, he or she will return home. This gives the rationale for the second half of the hypothesis. In spite of the simplicity of the underlying discussion, the above result has important implications for the modeling effort, specifically the implied rejection of the Markovian time-independent properties.

Next, consider a generalization to the case where there exists some minimum time requirement for engaging in out-of-home activities. Attention is paid here to the possible case in which a trip maker may not have enough time left to engage in an activity even when an acceptable opportunity is reachable. If that is the case, one would expect the trip maker to return home. Let t^m be the minimum time required for an activity (this is generally different from the activity duration and varies depending on the nature of the activity and possibly on the attributes of the trip maker). Thus, it would be appropriate to assume some distribution function for t^m. Let $F(t^m)$ be the distribution function of the minimum time for the activity. Then the probability of being engaged in this activity is the joint probability of finding an acceptable opportunity within the reachable opportunity volume and having sufficient time left for the activity at that location. The probability of returning home, in turn, is expressed as

$$P^h(t,x) = 1 - F(T - t - x/v) + e^{-\ell\gamma v(T-t)} \int_0^{T-t-x/v} e^{\ell\gamma v t^m}\, dF(t^m) \quad 0 \leqslant t \leqslant T - x/v \tag{2}$$

where x represents the location of the trip maker at time t in terms of the distance from home. Examination of the above equation shows that $P^h(t,x)$ is an increasing function of t regardless of the distribution of t^m.

The formulation of Equation 2 also provides the second hypothesis: Suppose that the minimum time duration for an activity can be represented by a random variable from a distribution $F(t^m)$. Then, given that a sojourn is completed at time t and location x, the conditional probability of returning home increases with x, the distance from home, as well as with time t.

This can be seen by taking the partial derivative of Equation 2 with respect to x:

$$\partial P^h(t,x)/\partial x = (1/v)(1 - e^{-\ell\gamma x})[dF(u)/du]\Big|_{u=T-t-x/v} \geqslant 0 \quad x > 0 \tag{3}$$

for any distribution function F and any t. The probability of returning home is affected by both the time when, and the location where, the transition to the next sojourn occurs. The temporal and spatial dependency of this probability appears to be a critical element in the analysis of time-space paths.

Knowing that the conditional probability of returning home is an increasing function of time, one also obtains hypothesis 3: The average per sojourn of the sum of travel time and sojourn duration decreases as the number of sojourns in the path increases.

Proving fully this empirically observed (22) property requires an involved analysis of the process. Since this paper is concerned with the qualitative characterization of the time-space path, however, the following simplified illustration will serve the purpose.

Suppose that a trip maker who left home at time t = 0 has completed the first sojourn at location x. Let s_1 be the sum of the first travel time and sojourn duration. Since the probability of pursuing another activity decreases with time (hypothesis 1), the probability of pursuing another activity decreases as s_1 increases. Therefore, the expectation is that s_1 will be larger when the trip maker returns home after the first sojourn than in the case where he or she continues on.

One can apply the same logic to conclude that the sum of the first n trip times and the sojourn durations is larger when the out-of-home path terminates after the nth sojourn, compared with the case where it extends to pursue another activity or more. Then, introducing the assumption that the unconditional distribution of sojourn durations does not depend on t, or that at least its mean does not increase with t as suggested by empirical observations (23), leads to the statement given in hypothesis 3.

The property reflects one aspect of the intricate interrelationships among several attributes of the path--i.e., the number of activities, activity durations, travel cost, and spatial distribution of activity locations. In the utilitarian analysis of the path, each of these attributes will enter into the utility function in an interactive manner. This hypothesis depicts a trade-off that may exist among those elements.

These hypotheses suggest that the spatial distribution of sojourn locations may also vary depending on the number of sojourns. From Hagerstrand's prism concept, it can immediately be seen that the distance to the farthest location that can be visited in a path is negatively correlated with the sum of out-of-home sojourn durations. That maximum distance, under the assumptions postulated here, can be expressed as a linear function of the total out-of-home sojourn duration. Now, one can reasonably assume that the total sojourn duration is positively--but not necessarily linearly (hypothesis 3)--correlated with the number of sojourns in the path. Therefore, the distance to the farthest location that can be visited in a path is negatively correlated with the number of out-of-home sojourns and also with the total sojourn duration. One may interpret the property as an expression of the trade-off between space utility and time utility.

The additional restriction on the feasible region of the path will naturally affect the distribution of activity locations. The following inference can be drawn from this: The larger the number of sojourns in the path, the more concentrated the sojourn locations generally tend to be. The discussion below illustrates this for a simplified case.

In addition to the assumptions stated earlier, suppose that the sojourn duration is a constant rather than a random variable. If one applies the intervening-opportunities model, the spatial distribution of the first sojourn location (x_1), given that one has left home, is expressed by a negative exponential function:

$$dF(x_1) = K\beta \exp(-\beta x_1) \quad 0 < X_1 \leqslant L(1) \tag{4}$$

where

$\beta = \ell\gamma$,

$K = 1 - \exp[-\beta L(1)]$,

$L(1)$ = maximum distance reachable when only one sojourn is made = $(T - d_1)v/2$, and

d_1 = duration of the first sojourn.

The probability of returning home after the first sojourn is expressed by using Equation 1 as a function of x_1:

$$P^h(x_1) = \begin{cases} \alpha \exp[\beta(x_1) + (d_1 + d_2)v] & 0 < x_1 \leqslant L(2) \\ 1 \quad L(2) < x_1 \leqslant L(1) \end{cases} \tag{5}$$

where α is as defined earlier, d_2 is the duration of the second sojourn, and $L(2) = (T - d_1 - d_2)v/2$. Then the distribution of the first sojourn location from which no further activities are pursued is

$$dF(x_1)P^h(x_1) = \begin{cases} K\alpha\beta \exp[\beta(d_1 + d_2)v] & 0 < x_1 \leqslant L(2) \\ K\beta \exp(-\beta x_1) \quad L(2) < x_1 \leqslant L(1) \end{cases} \tag{6}$$

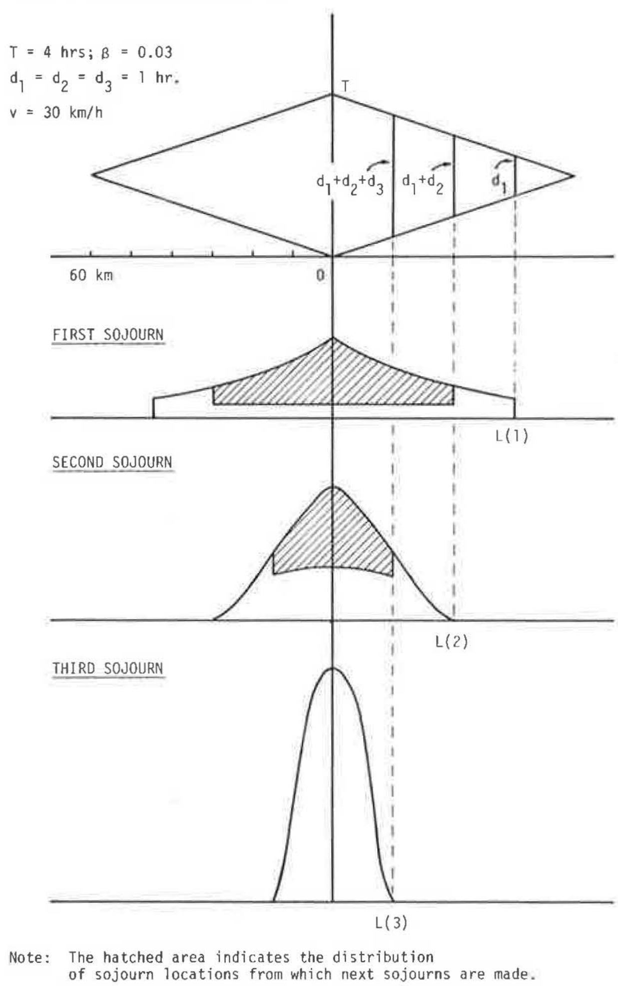
The distribution of the first sojourn location from which further activities are pursued is given as

$$dF(x_1)[1 - P^h(x_1)] = \begin{cases} K[\beta e^{-\beta x_1} - \alpha\beta e^{\beta(s_1+s_2)v}] & 0 < x_1 \leqslant L(2) \\ 0 \quad L(2) < x_1 \leqslant L(1) \end{cases} \tag{7}$$

These two distributions are shown in Figure 1.

The distribution of the first sojourn location varies depending on the number of sojourns--in this case, exactly one or more than one--and the locations are distributed closer to home in the latter case. After manipulating the distribution of the second activity location by using the intervening-opportunities concept, the same logic can be applied to show that the above tendency holds for the second

Figure 1. Distribution of sojourn locations in a hypothetical linear city.



Note: The hatched area indicates the distribution of sojourn locations from which next sojourns are made.

location or farther for the nth location in general. The figure illustrates this for up to n = 3.

This discussion is based on the assumption that the opportunities are homogeneously distributed. The conclusion that the distribution concentrates around home as the number of sojourns increases thus cannot be generalized. Therefore, more generally, hypothesis 4 can be stated as follows: The distribution of sojourn locations (or trip destinations) depends on the number of sojourns in the path. It should be noted that this hypothesis is derived for an extremely simplified case. More rigorous theoretical support of the hypothesis requires an involved analysis that is unwarranted in view of the study objective. The obvious dependence of a sojourn location on the previous sojourn location, however, suggests that the hypothesis applies to a more general case where the sojourn durations are random at least for relatively small n.

MULTIPLE-CHAIN PATHS

The above discussion assumed for illustrative simplicity that a path consists of a single home-based chain of trips. Since hypotheses 1-3 are induced on the basis of either the conditional probability of permanently returning home or the total number of out-of-home sojourns and their durations, they apply to multiple-chain paths without modifications. At the same time, this implies that the abstract model has not distinguished between single- and multiple-chain paths.

One approach to multiple-chain paths within the present framework is to assume the existence of additional constraints on the time-space path. Given that a certain set of locations is visited, travel cost almost always decreases by consolidating trips into one chain. As the earlier discussion has indicated, the volume of reachable opportunities keeps on decreasing as time proceeds. In light of these factors, it would seem more logical for a trip maker to make only one trip chain. Therefore, one can expect that, when a path involves more than one chain, there are certain constraints that prevent the consolidation of activities into a single chain; e.g., activities are available only during certain time periods or the trip maker must return home to perform some household tasks. Thus, one may conjecture that, given the number of out-of-home sojourns, the number of home-based chains in a path is positively correlated with the magnitude of constraints under which the trip maker acts. The conjecture follows after one introduces to the abstract model an additional assumption that a trip maker prefers less travel expenditure.

Consideration of travel behavior in a more realistic context, however, leads to additional statements regarding the number of chains in a path. Adler and Ben-Akiva (7) hypothesize that the utility of an activity would be greatest if it were pursued separately from other activities, since one can then select the best arrangement for the activities. The Adler and Ben-Akiva model has a structure that represents the trade-off between the increased utility of the activity and the increased travel expenditure. This utilitarian approach thus suggests that the number of chains is negatively correlated with the valuation of travel expenditure relative to the utility of activities perceived by the trip maker. Pursuing activities separately, at various times of the day, requires the constant availability of expedient transportation. From this, it follows that, for a given number of sojourns, the number of chains is positively correlated with the mobility of the trip maker [the discussion here is critically different from those by Bentley and others (6) and Hemmens (23) in that this study is concerned with trip consolidation given the number of sojourns to be made in the day]. These conjectures are more behavioral, and no clear-cut theoretical support can be obtained from the abstract model. The next section of this paper examines these conjectures together with the four hypotheses. After they are statistically tested, the abstract model can be extended to enrich its behavioral implications.

The introduction of additional coupling constraints, as suggested by the first conjecture, increases the number of prisms and reduces the feasible region of the path, as is often illustrated (3,21). Hypotheses 1-4 still apply to the multiple-prism case, with slight modifications, as long as all prisms originate and terminate at the home base. The feasible region of a path that involves nondiscretionary activities such as work and school is defined by applying a prism to each discretionary segment of the path (3,21). The hypotheses presented above, therefore, apply to each prism of those paths as well. New aspects are the non-home-based chain (e.g., office-based chain during the lunch break) and prisms that originate and terminate at different locations. This calls for modification of the hypotheses, especially hypothesis 4, if the statements are to be made for the entire path. For practical purposes, however, dealing with respective prisms would be sufficient.

Before the findings of the empirical analysis are presented, some limitations must be discussed. The first problem is that the prism is not observable. In the review of previous travel-behavior models presented earlier in this paper, it was assumed that the origin and destination coupling constraints are known constants. Of course, this is not the case in empirical data analysis. A trip maker may have several prisms that restrain his or her path even when he or she does not pursue activities that are obviously nondiscretionary. The distribution of opportunities, another determinant of the path, is not incorporated in the analysis. In addition, this study does not explore the behavioral distinctiveness of trip makers. Although the results presented in the next section generally strongly support the hypotheses, these limitations must be kept in mind.

EMPIRICAL RESULT

The empirical analysis of this study was conducted by using the 1965 Detroit Area Transportation and Land Use Study (TALUS) data set. The characteristics of the area are discussed elsewhere (24). The data set consists of a household sample of trip records that include information on the entire set of trips made by each member of the household on the survey day and socioeconomic information on the individual and the household. In this study, approximately 10 percent (32 100) of the original trip records were sampled according to residential locations. The sampling used nine geographic areas, selected to represent a wide spectrum of socioeconomic status. The only individuals used in the analysis were those who (a) pursued at least one out-of-home activity on the survey day, (b) had a closed home-based path, (c) had at least one car available to the household, (d) held a driver's license, (e) were at least 18 years old, (f) made the trips by car (either as a driver or a passenger), and (g) made all trips within the three-county-wide study area. Such aspects as mode choice are not explored in this study. The sample includes 4736 individuals who satisfy all these conditions, and unless otherwise mentioned the results presented below are for the 1806 trip makers whose paths do not contain work trips. Eighty-one percent of those individuals were not in the labor force. A one-day period starting at 2:30 a.m. and ending at 2:29 a.m. is used as the study period.

An overview of the data set is presented in Table 1 in terms of the number of chains and the number of sojourns on the survey day. Whereas approximately one-third of the 1806 individuals made only one nonwork, out-of-home sojourn, about 45 percent of the sample made three or more sojourns. The multiple-sojourn chain is a quite common phenomenon among this sample of 1806 individuals: Among those who made more than one sojourn, 78 percent (or 936 trip makers) had at least one multiple-sojourn chain. Other overall statistics of interest are as follows: Average number of trips per trip maker = 4.51, average number of sojourns per trip maker = 2.85, average number of chains per trip maker = 1.66, and average number of sojourns per chain = 1.72.

There is no notable difference in Table 1 between the aggregate statistics for trip makers who made no work trips and the 2930 trip makers who made work trips. The marginal distribution of the number of chains, however, shows a significant difference between the two groups. The group with no work trips has a higher representation of paths with larger numbers of chains (three or more), whereas the second group has a higher-than-expected frequency of two-chain paths. This is intuitively agreeable, since one can expect that the second, nonwork activity is quite often pursued separately, after the trip maker returns home from work. The contingency table formed by the two column-total rows is highly significant (χ^2 = 82.2 with 3 df). No notable difference was found in the distribution of the number of sojourns between the two groups. Overall statistics for the second group are as follows: Average number of trips per trip maker = 4.40, average number of sojourns per trip maker = 2.82 (1.39 when work is excluded), average number of chains per trip maker = 1.57, and average number of sojourns per chain = 1.79.

Figure 2 shows the relative frequency of returning home permanently for the day, given that a sojourn is completed outside the home base within respective 1-h time periods. The observed relative frequency serves as an estimate of the conditional probability of returning home, a critical element in stochastic analysis of the path. In general, the figure, with its clearly increasing frequency of returning home as time proceeds, supports hypothesis 1. The increasing tendency shown in the figure was tested by weighted least-squares regression using logit, which is defined as $\ell n(f_i/f_i')$ where f_i is the observed frequency of returning home during time period i and f_i' is the observed frequency of not returning home. The result naturally yielded a highly significant positive coefficient of time (t-statistic = 3473 with 18 df).

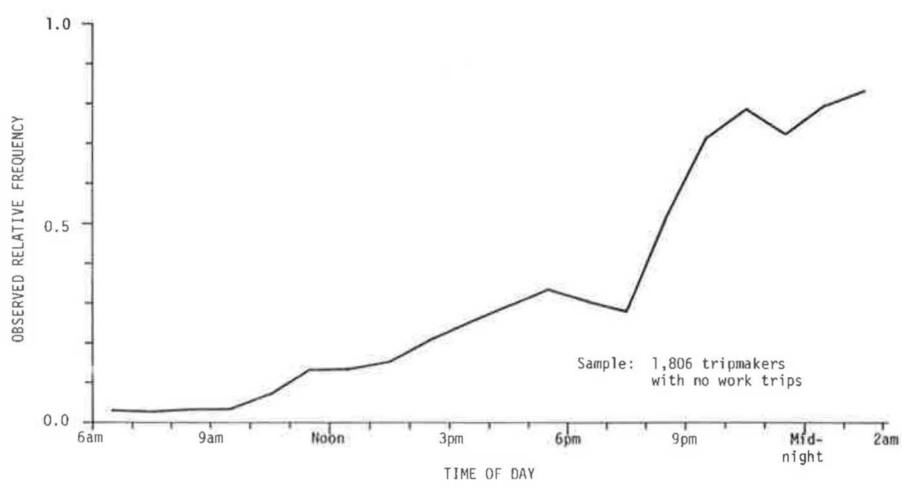
A "dip" in the early evening periods, however, is notable. This is presumably a result of after-dinner activities such as social visits and shopping. As Damm (13) noted, human activity can be allocated by considering several time periods of the day, each of which is perceived to have distinguishable characteristics and to be appropriate for a particular set of activities. The model used here is obviously too abstract to represent such an aspect of human behavior, although some immediate modifications, such as time-dependent opportunity density, would replicate the observation. However, the central focus of hypothesis 1--that the relative frequency of returning home is a function of time--is clearly indicated in the result. It demonstrates explicitly, yet simply, the temporal dependency of the behavior, expanding the body of empirical evidence (17,23). The result also indirectly supports the assumption used by Nystuen in the development of his simulation model (25): that the utility of returning home increases as time proceeds.

Figure 3 shows a spatial, as well as temporal, dependency of the probability of returning home.

Table 1. Distribution of trip makers by number of chains and sojourns in path.

Number of Sojourns	Number of Trip Chains 1	2	3	≥4	Total
Trip Makers Making No Work Trips					
1	611				611
2	219	180			399
3	98	132	59		289
4	52	78	50	13	193
5	27	39	28	15	109
≥6	28	57	56	64	205
Total	1035	486	193	92	1806
Trip Makers Making Work Trips					
1	966				966
2	212	506			718
3	218	206	69		493
4	75	139	46	12	272
5	52	76	36	9	173
≥6	76	135	58	39	308
Total	1599	1062	209	60	2930

Figure 2. Time variations in relative frequencies of returning home permanently for the day.



The figure is based on the tabulation of travel records for the 783 trip makers from Warren, Michigan, a suburban middle-income community, by developing a set of five rings for the area and by tabulating sojourn locations according to those rings [a similar set of rings was also developed for the city of Birmingham, Michigan (see Figure 4)]. Since the frequency of trips to ring 5 in the data set was extremely small, rings 4 and 5 were merged and will hereafter be referred to as ring 4. Rings 2, 3, and 4 are approximately 5, 10, and 15 km from the community center, respectively. The tabulation is for trip makers who did not make work trips.

A temporal tendency similar to that in Figure 2 can be found in Figure 3. It also exhibits spatial dependency of the behavior. The observed relative frequency of returning home, given that a sojourn is completed outside the home within respective time periods, generally increases as the distance from home increases. Although a few exceptions can be noted, the figure is strongly supportive of hypothesis 2.

The statistical significance of the spatial and temporal effects shown in Figure 3 was examined by

Figure 3. Space-time dependence of relative frequencies of permanently returning home for the day.

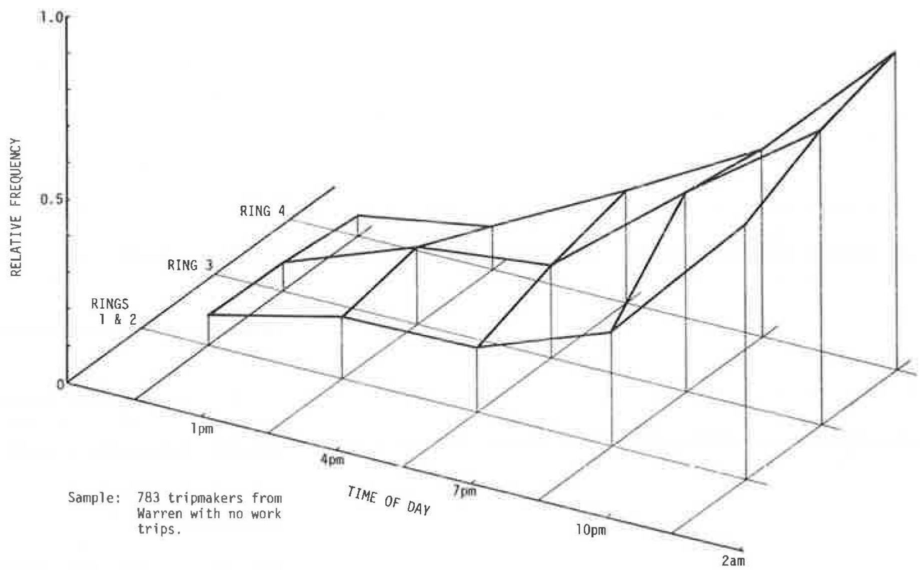
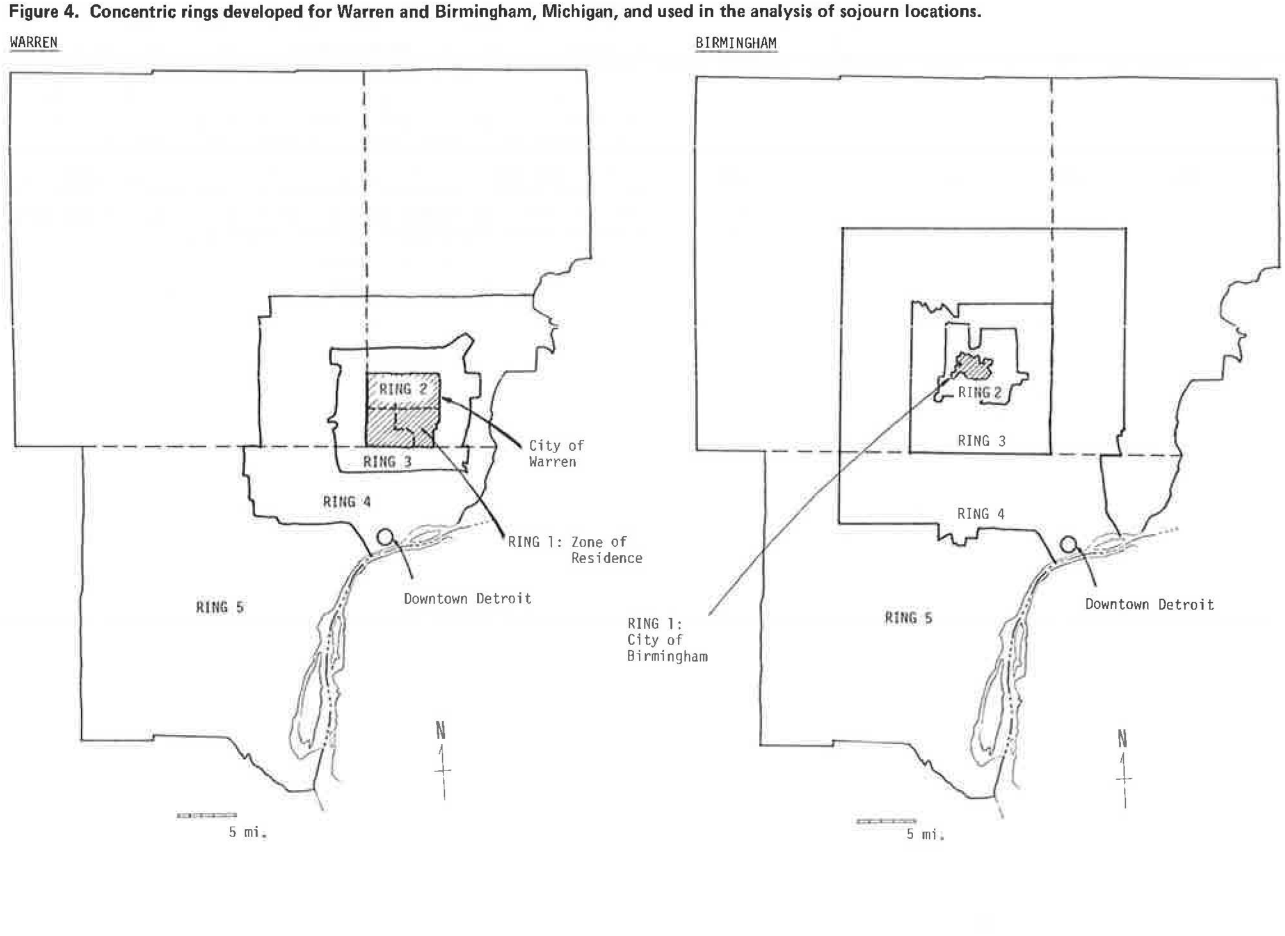


Figure 4. Concentric rings developed for Warren and Birmingham, Michigan, and used in the analysis of sojourn locations.



using logit multiple classification analysis (26). The result indicated that the independent effects of time and location are both significant at α = 0.001 (with, respectively, χ^2 = 285.5, df = 4; and χ^2 = 15.5, df = 2). The time-location interaction terms were found to be significant at α = 0.01 (χ^2 = 24.7, df = 8).

An immediate implication is that spatial interaction patterns vary depending on time. The intensity of the interaction is also a function of the distance from the trip maker's home to the present location as well as the spatial separation between the present and the next locations. The result implies that one cannot apply a single trip matrix to represent trip makers' movements in general. Each trip maker has a unique trip matrix that depends on the location of his or her residence. The elements of the matrix vary as a function of time, and their rate of change possibly varies depending on the distance from home. The result indicates that, in addition to the cost of travel to a destination location and its attributes, the utility of the destination is also a function of the time of day and the distance from home. The result suggests a new, dynamic approach to spatial interaction analysis [a closely related discussion can be found elsewhere (27)].

Figure 5. Average sojourn and travel durations by number of sojourns in the path for trip makers making no work trips.

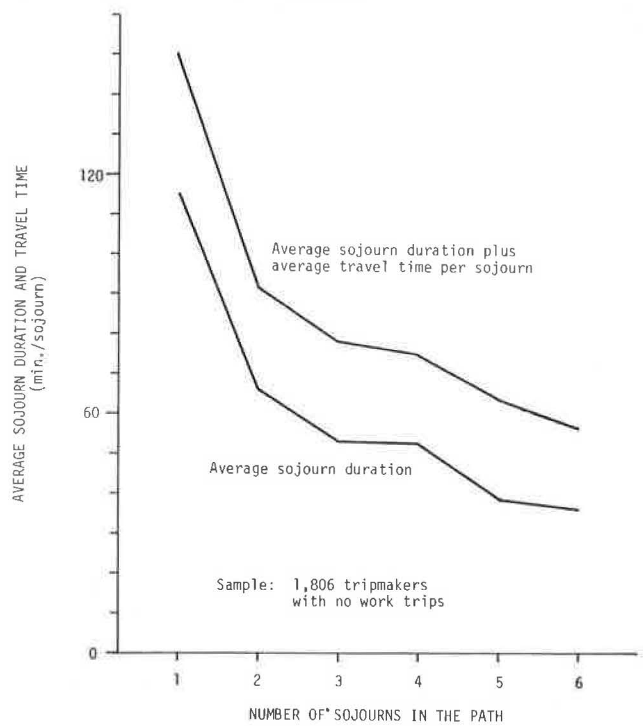


Table 2. Average travel time spent per sojourn by number of sojourns and chains in the path.

Number of Trip Chains	Time per Sojourn by Number of Sojourns (min/activity)				
	1	2	3	4	≥5
1	34.0	22.3	21.8	19.6	20.4
2		30.3	25.5	23.4	19.1
3			28.7	23.4	18.8
4				18.8	20.2
Overall	34.0	25.9	24.9	22.0	19.5

Note: Sample = 1806 trip makers who made no work trips.

Another temporal aspect of the time-space path is the duration of sojourns. Figure 5 shows the average travel time per sojourn and the average sojourn duration by the number of sojourns in the path (for the 1806 trip makers with no work trips). The average travel time per sojourn is defined as the total travel time divided by the number of sojourns in the path. Figure 5 supports hypothesis 3 by showing a steady decline in (a) average duration per sojourn and (b) average travel time plus average sojourn duration per sojourn as the number of sojourns increases. Using a Dutch data set, Vidakovic (22) reported a similar result. This tendency is found in the present study regardless of the number of trip chains.

The result can be interpreted as an indication of the trade-off between the number of activities and the time that can be spent for respective activities. This may provide a guideline in formulating a utility function for utilitarian analyses of the time-space path. At the same time, the result offers strong evidence for rejecting the Markovian model structure, where the sojourn duration is essentially independent of the number of sojourns.

Table 2 gives the average travel time spent per sojourn by the number of out-of-home sojourns and by the number of trip chains in the path. The table provides support for the assertion that a path is more efficient, in terms of travel cost, when more trips are consolidated into a chain. The table shows that, given the number of chains, the average travel time spent per sojourn decreases as the number of sojourns (or number of trips) increases. The table also shows the general tendency that, given the number of sojourns, the average travel time increases with the number of chains or decreases as the degree of trip consolidation increases. The tendency, however, is not clear when the number of sojourns is four or more, presumably because of the small sample size of trip makers with a large number of sojourns.

The table also offers support for hypothesis 4 regarding the correlation between the spatial distribution of sojourn locations and the number of sojourns. When the number of sojourns equals the number of chains (diagonal elements of the table), the average travel time presented in the table represents the average length of home-based trips. A clear tendency found in the table is that the average length of trips to sojourn locations decreases as the number of sojourns increases. Thus, for this special case, the spatial distribution of sojourn locations depends on the number of sojourns in a manner that is compatible with the earlier discussion. The differences among the four average travel times are generally significant.

Hypothesis 4 is more directly examined by using sample subsets that represent both areas for which rings were developed: Birmingham, a high-income community, and Warren, a middle-income community (Figure 4). Figure 6 shows the result. It should be noted that the present result is an extension of previous empirical observations of spatial distributions of sojourn locations (18-20) in that it involves an additional dimension, the relation between the distribution of sojourn locations and the number of sojourns in the path or chain.

Figure 6a is obtained from the 439 sojourn records of 168 trip makers from Birmingham. The significance of the difference in the relative frequency between two adjacent numbers of sojourns is examined by using the difference in the logit and, when significant, is shown in the figure in terms of the level of significance. The overall tendency in the relative frequency is evaluated by a weighted least-squares regression of logit on the number of

Figure 6. Distribution of sojourn locations by number of sojourns in a day for trip makers making no work trips.

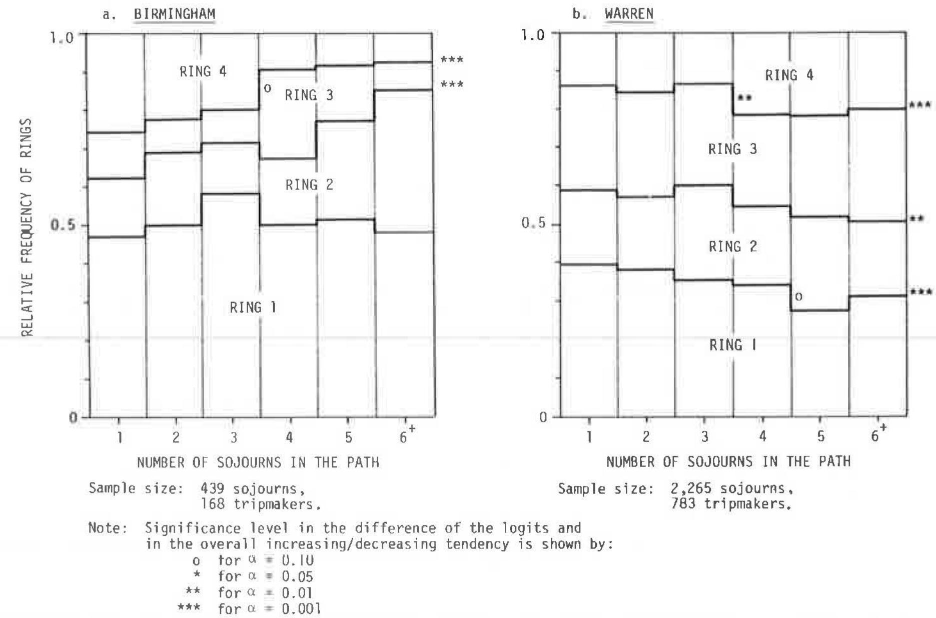
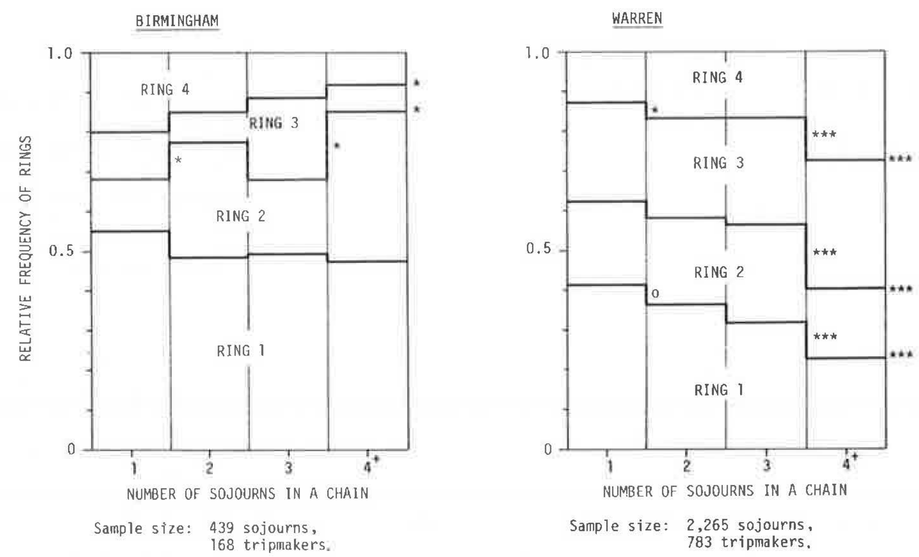


Figure 7. Distribution of sojourn locations by number of sojourns in a chain for trip makers making no work trips.



sojourns. The figure also shows the significance level of the slope.

Figure 6a clearly indicates that the relative frequency for ring 4, which is the farthest ring and includes downtown Detroit, decreases as the number of sojourns per day increases. The result is again consistent with the earlier discussion. The statistical significance of this decreasing tendency was tested by a rank-ordering method using the logit (28), and the tendency was found to be significant at α = 0.05. The weighted least-squares analysis also showed a significant slope (at α = 0.001).

Figure 6a shows that the relative frequency of trips to ring 2, the area immediately adjacent to Birmingham, tends to increase with the number of sojourns whereas that of Birmingham itself is relatively invariant. The indication is that, as the number of sojourns increases, the trajectories of trip makers' movements tend to contract into a relatively small area within and around the area of residence (rings 1 and 2 form approximately a rectangle of 13 by 11 km).

The result of the 783 trip makers and 2265 sojourns for Warren is also shown in Figure 6b. The tendency, however, is contrary to that found for Birmingham. The relative trip frequency for ring 4, which also includes downtown Detroit, increases as the number of sojourns increases (significant at α = 0.001). On the other hand, those for ring 1 (residence zone of the trip maker) and ring 1 plus ring 2 decrease with the number of sojourns (both significant at α = 0.01). It appears that this group of trip makers from Warren tends to make multisojourn trip chains that involve ring 4 [a similar observation can be found elsewhere (19)].

Figure 7 shows the spatial distribution of sojourn locations by the number of sojourns in each chain. The figure for Birmingham again shows the tendency that sojourn locations tend to concentrate around the area of residence as the number of sojourns in the chain increases (significant at α = 0.05). The tabulation for Warren, on the other hand, clearly indicates an increased relative frequency of visits to ring 4 when a chain involves a larger number of sojourns (significant at $\alpha = 0.001$).

The spatial distributions of opportunities relative to the two areas are, of course, substantially different. Since Warren is located closer to Detroit than Birmingham, its proximity to areas with high opportunity density may be the source of the above divergence between the two. The model of this study can easily be generalized to explain this (note that homogeneity in the opportunity distribution was assumed in the discussion leading to hypothesis 4). Overall, the result here confirms the hypothesis that the spatial distribution of sojourn locations varies depending on the number of sojourns in the path. The result at the same time suggests possible behavioral distinctiveness [e.g., difference in the perceived "action space" (29)] between the two areas, which, however, is not within the scope of the abstract model.

Similar tabulations of sojourn locations are shown in Figure 8 for those trip makers from the two areas whose paths involved work trips. These paths are constrained by more than one prism whose exact size and location in the time-space coordinates are unobservable. Figure 8, which shows the distribution of sojourn locations by the number of sojourns in the path, exhibits a clear tendency that indicates that ring 4, which includes downtown Detroit, gets an extremely large share of the trips made by trip makers who pursue only one sojourn (work) a day. This is an obvious result, since the relative frequency in this case is identical to the distribution of the work locations of these trip makers. The reduced share of ring 4 thereafter (significant at $\alpha = 0.001$) indicates that the rest of the activities tend to be pursued in the relative vicinity of the area of residence, presumably because sojourn locations are constrained by relatively small prisms, e.g., between work and home. Overall, the result again confirms the dependence of sojourn locations on the number of sojourns. No differences are notable between the two areas for those trip makers who had work trips in their paths.

Unlike the other hypotheses, the first conjecture regarding the number of chains in the path is not directly testable since no measurements are available that represent the magnitude and nature of constraints on the path. Many of the 1806 trip makers who did not make work trips are homemakers. Thus, it is expected that they may have been responsible for larger shares of household chores, especially child care. This would create various types of constraints on the trip maker's behavior (30,31). Therefore, the study took the approach of using the life-cycle stage as a proxy for the constraints and explored its relation with the number of chains. The latter is viewed as a characteristic of the path that represents the magnitude of constraints.

Figure 9 shows the distribution of the number of chains by five life-cycle categories conditioned on the number of sojourns per day (two, three, four, or more). The trip makers in households where the youngest child is between 5 and 17 years old (life-cycle category 3) have a very small frequency of making only one trip chain per day, especially when the number of sojourns is large. This is an expected result, since children of school age would create a larger magnitude of constraints for the caretaker, and it supports the finding of Jones and others (31).

A similar contingency analysis was conducted by using the number of cars available as a proxy for mobility and using income as a proxy for the valuation of travel expenditure. The results are shown in Figure 9, which indicates no clear tendency between income and the number of chains and suggests that the 1965 sample of the 1806 individuals was rather insensitive to the travel cost of intraurban nonwork trips. The tabulation for the number of cars available, on the other hand, exhibits a tendency that indicates that the number of chains in the path increases with the number of available cars. Although the indication is statistically weak, it points out another aspect of urban travel behavior as a time-space path.

CONCLUSIONS

After integrating several well-known concepts into an abstract model, this study has inferred and empirically examined several hypotheses that focus on the temporal and spatial aspects of urban travel patterns. The empirical results indicate that the relative frequency (or estimated conditional probability) of a trip maker returning home is, in general, an increasing function of the time when and the location where the transition occurs. Another temporal aspect of the path is the dependence of the average sojourn duration on the number of sojourns in the path. The results also showed the dependence of the spatial distribution of sojourn locations on the number of sojourns. A strong correlation was

Figure 8. Distribution of sojourn locations by number of sojourns in a day for trip makers making work trips.

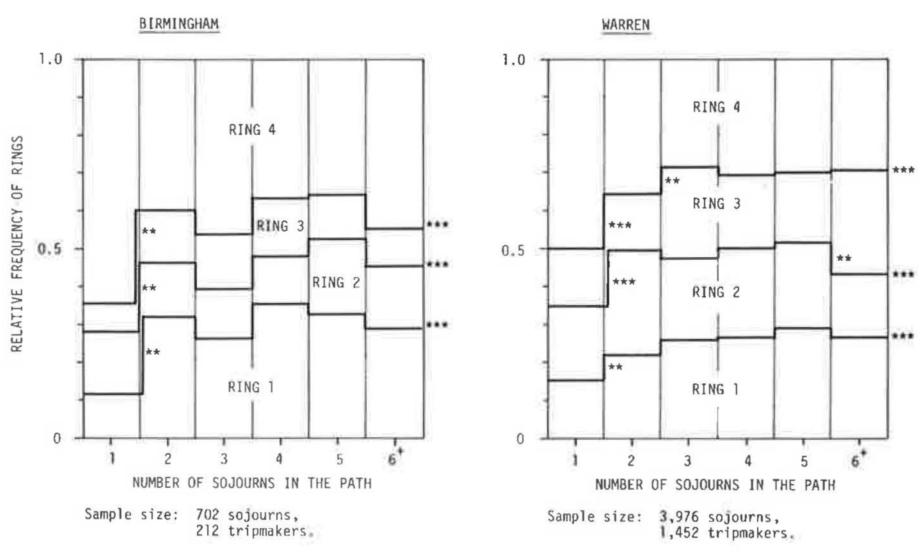
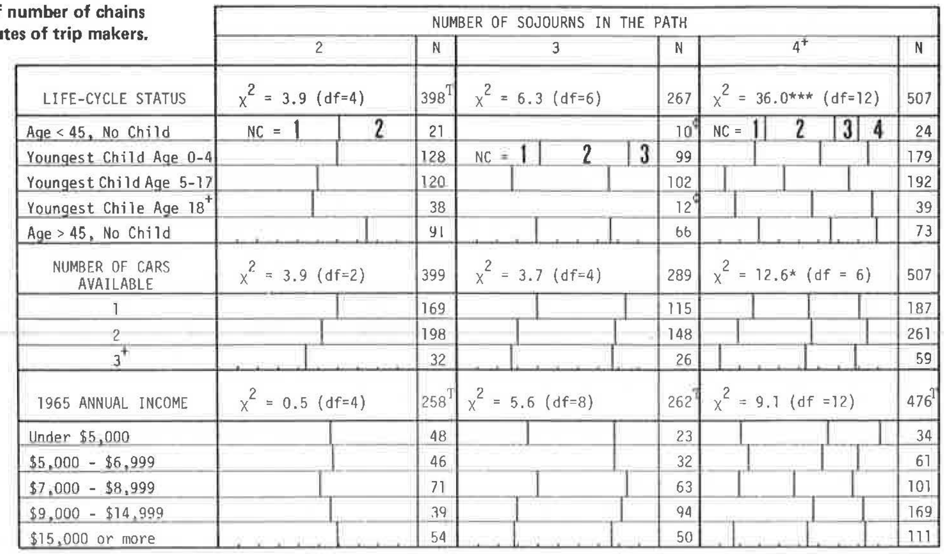


Figure 9. Distribution of number of chains by socioeconomic attributes of trip makers.



Sample: 1,195 tripmakers with no work trips and with more than one sojourn.

NC: Number of chains in the path.

TTripmakers with unknown socioeconomic attributes are eliminated.

ΦThe row is excluded from the analysis due to the extremely small sample size.

found between the number of chains and trip makers' life-cycle status, which suggests varying magnitudes of constraints under which those segments of the population act.

The model developed here can be classified as a stochastic-process model. Thus, the study's first implication is the explicit rejection of the Markovian assumptions often used in analyzing trip-changing behavior. The temporal-spatial dependence found above is not compatible with the Markovian time-homogeneity assumption. The dependence of spatial distributions of sojourn locations on the number of sojourns and the interrelationship between sojourn duration and the number of sojourns all imply that the Markovian history-independence assumption is inappropriate when applied to this behavior.

On the other hand, certain aspects of travel behavior may be well represented by a Markovian model. For example, an empirical tabulation presented by Bentley and others (6) indicates that the number of sojourns in a chain can be represented by a geometric distribution that assumes a Markovian decision process in trip making. Although our results do not support the application of the Markovian models in the time-space framework, further examination of travel behavior may find relevant and useful applications of those models. The above findings also indicate the direction in which the Markovian models can be modified for better representation of travel behavior.

The findings of the study also have certain implications for the utilitarian approach to the modeling of trip behavior. The negative correlation between the number of sojourns and the average sojourn duration is suggestive of a trade-off between these two factors, both of which would be important components of the utility function. The dependency on time and location of the transition frequencies to home indicates that the utility of an activity may be best specified as a function that involves those two factors. The temporal and spatial elements are probably key components of the utility function.

Spatial and temporal aspects of travel behavior are inseparable, perhaps simply because the path evolves in the time-space dimension. Patterns of spatial interaction will vary depending on time, whereas travel decisions will vary depending on the location where they are made. The spatial and temporal characteristics of a path also depend on other characteristics of the path, such as the number of sojourns. Obviously, many intricate relations are embedded in the observed time-space path.

This study has shown that a simple, abstract model can be used in unwinding these relations so that some may then become observable. The basic space-time characteristics illustrated in this study may guide further quantitative modeling efforts and delineate empirical analysis of the complexity of travel behavior.

ACKNOWLEDGMENT

Portions of this study were supported by a National Science Foundation grant to the University of California at Davis.

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Implications of the Travel-Time Budget for Urban Transportation Modeling in Canada

A. CHUMAK AND J.P. BRAAKSMA

The travel-time-budget concept, which examines regularities in the allocation of travel time in urban areas, is investigated. Previous analysis of three U.S. cities suggests that the daily travel-time budget is approximately 1.1 h/traveler. The objective of this research is to (a) verify the theory in Canada and (b) determine the practical implications for transportation planning. Analysis of home interview surveys in Calgary, Toronto, and Montreal supports the conclusions previously developed in the United States. A detailed analysis of the Calgary data indicates that the travel-time budget is not affected by such factors as mode of travel, trip purpose, automobile ownership, or location of residence with respect to the central business district. Several practical applications of the concept are developed, including a procedure for conducting an independent validity check of conventional travel forecasts. This process is very simple to conduct and allows forecasts to be verified by using a different model. The travel-time budget is also a useful tool for developing equilibrium travel forecasts. Equilibrium models relate travel demand to available capacity and may reduce the demand for nonessential trips during peak periods. Further research is recommended on the application of the travel-time budget to other aspects of urban travel forecasting, including traffic assignment, modal split, and evaluation of personal mobility.

Since the early 1950s, several transportation planners and economists have suggested that individuals allocate a certain budget for the purchase of transportation goods and services. Tanner (1) produced the first empirical evidence to support the hypothesis that households allocate a fixed portion of their income for transportation.

Subsequently, Zahavi (2) and Goodwin (3) have extended this theory to the other resource that individuals must expend for transportation: time. Zahavi published the first empirical evidence to suggest that in urban centers the average daily travel per individual traveler is approximately 1 h (2). At present, this theory is supported by the travel data of three U.S. cities: Washington, D.C., Minneapolis, and St. Louis. This new concept is not yet completely accepted by transportation planning professionals and may even be considered with a certain amount of skepticism. The primary objective of this paper is to analyze Canadian data and investigate the validity of the travel-time-budget concept in Canada. This analysis may be considered an expansion of the work of Zahavi.

The secondary objective of this paper is to assess the practical implications of the travel-time-budget concept for conventional transportation planning. If proved valid, this concept may be very useful as a means of conducting an independent check of travel forecasts developed through the conventional models of trip generation, trip distribution, and modal split. A methodology is presented for developing equilibrium travel forecasts by using the travel-time budget. Equilibrium travel forecasts relate the travel demand projected by the conventional model to the availability of transportation facilities and congestion.

PREVIOUS RESEARCH

The travel-time budget describes an urban phenomenon in which the average travel time per trip maker appears to remain stable. The first empirical data in support of this concept were presented by Zahavi in the 1970s (2,4). The following table gives the results of Zahavi's analysis for Washington, D.C., and the Twin Cities of Minneapolis-St. Paul as well as data from the 1970 Nationwide Personal Transportation Survey, which provides data on average travel behavior in the urban centers of the United States. Similar data developed for St. Louis by Bochner and Stuart (5) are also presented:

City	Year	Avg Daily Travel Time per Trip Maker (h)
Washington	1955	1.09
	1968	1.11
Twin Cities	1958	1.14
	1970	1.13
St. Louis	1976	1.04
All United States	1970	1.06

In all cases, the average travel time per trip maker remains stable at approximately 1.1 h/trip maker. The most interesting result of the table is that not only has the travel-time budget remained stable over a 20-year period but the concept is also valid for all cities analyzed regardless of population size. This consistency is not characteristic of conventional transportation planning models of trip generation and trip distribution, which often have to be recalibrated for each city every 10 years. It is most difficult to apply these models interchangeably between cities without considerable calibration.

The results of the table above represent arithmetic averages that are obtained by dividing the total daily travel time in the city by the total number of trip makers. The results should therefore be treated strictly as an empirical observation, and no interpretation should be made as to whether individuals consciously or subconsciously allocate 1 h for travel. Zahavi obtained the estimates of the total daily travel time of trip makers through a special computer analysis of home interview surveys in each of the cities. The estimate of daily travel time, expressed as person hours of travel, includes travel by all modes and is obtained through a direct summation of all trip times reported by the survey respondents. It is important to note that this analysis is based on the travel times reported in the home interview surveys, which represent "door-to-door" travel times as perceived by the traveler. A trip maker is defined as an individual who makes at least one mechanized trip per day. Because an estimate of the number of trip makers is not readily available from the transportation data banks used in most cities, a separate computer analysis is required to estimate the number of people who report at least one mechanized trip. The ratio of trip makers to population varies considerably from city to city as a function of car ownership and household size. Accordingly, the estimate of travel time per capita may vary even though the travel time per trip maker remains stable. The need to conduct a separate computer analysis for each city accounts for the fact that more data are not currently available.

Recently, Zahavi (6,7) has published data for several cities outside of North America, such as Munich, Nuremberg, Bogota, and Singapore.

TRAVEL-TIME BUDGET AND CANADIAN CITIES

The principal results of the travel-time-budget analysis of Canadian cities are given below:

City	Year	Avg Daily Travel Time per Trip Maker (h)
Calgary	1971	1.11
Toronto	1964	1.09
Montreal	1971	1.18

The data indicate that travel patterns in Montreal, Calgary, and Toronto clearly confirm the previous research of Zahavi.

This paper analyzes the 1971 Calgary data in much greater detail in order to investigate the effect of such variables as mode, trip purpose, car ownership, and location of residence on the travel-time budget. It is anticipated that such an exercise will assist in understanding the basic underlying mechanisms of the travel-time-budget phenomenon. An attempt is also made to compare all observations and conclusions with the previous research of Zahavi.

Another objective of this detailed analysis of Calgary is to identify those socioeconomic conditions under which the travel-time budget is not valid. It is proposed that, if the theory is able to successfully withstand this rigorous testing, then the overall validity and acceptance of the theory will be considerably enhanced.

Mode of Travel

Table 1 (8) summarizes the analysis of the travel-time-budget concept for trip makers in Calgary who use a variety of transportation modes. The average travel time for all trip makers by all modes was 66 min, whereas those who traveled only by automobile or transit each had a budget of 61 min. As mentioned earlier, these figures represent perceived door-to-door travel time. All estimates are within the 95 percent confidence interval.

These data also reveal the interaction between trip rate and length that occurs along with the travel-time budget. There appears to be an inverse relation between trip time and trip rate. Trip

Table 1. Travel-time budget and mode of transportation (Calgary).

Mode	Trips per Trip Maker	Time per Trip (min)	Daily Travel Time per Trip Maker (min)	Ratio of Mean to Median
All mechanized	3.76	17.7	66.3	1.22
Car only	3.72	16.4	61.0	1.22
Transit only	2.09	29.0	60.6	1.02
Transit and car	3.92	21.3	83.5	1.18
Car driver	4.02	16.9	68.0	1.13

Figure 1. Distribution of daily travel time in Calgary for travelers by all mechanized modes.

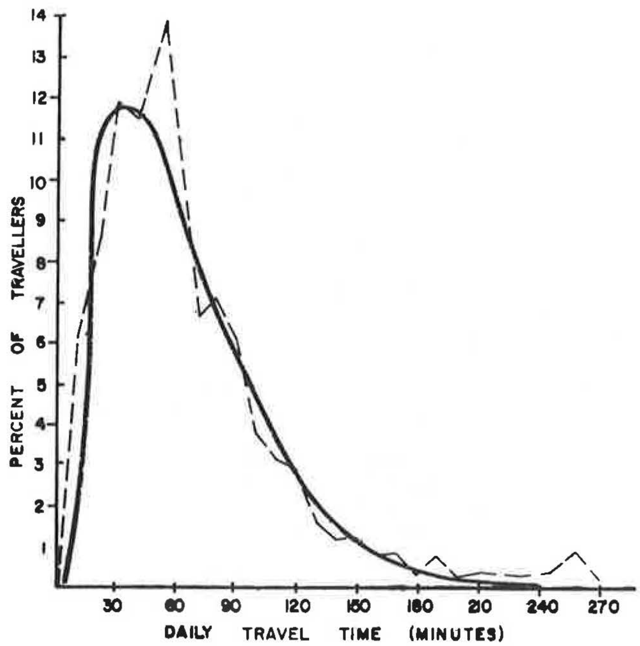
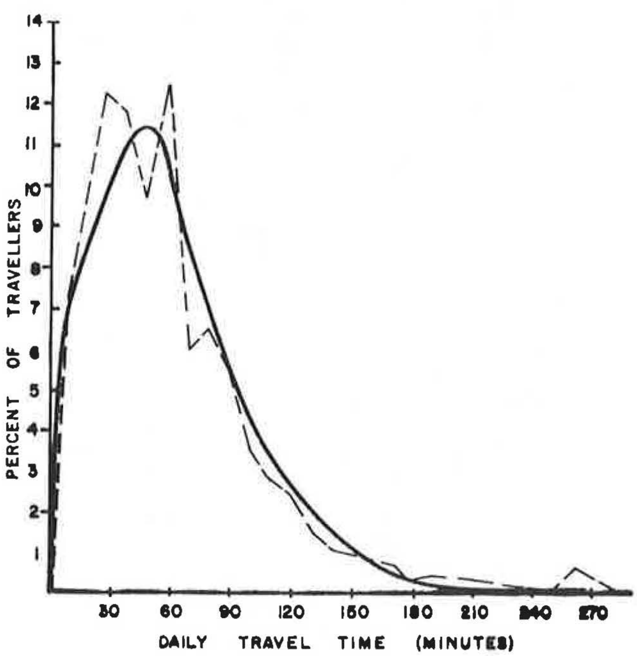


Figure 2. Distribution of daily travel time in Calgary for automobile-only travelers.



makers who use only transit have considerably longer trip times because of lower overall travel speeds, and these travelers can therefore accommodate only two trips within the daily travel-time budget. The overall mobility of these travelers, the ability to make mechanized trips, is therefore restricted to slightly more than the two trips usually required for work travel. Conversely, travelers whose only mode is the automobile have the shortest trip times and are quite willing to increase their trip generation rate to 4.0 trips/traveler in order to fully expend the travel-time budget. Although travelers who use the other modes have intermediate rates of trip generation and trip length, the basic inverse relation between the two variables continues to apply. Zahavi (4) identified a similar inverse relation in his analysis of Washington, D.C., and the Twin Cities.

It is also interesting to note that in Calgary as well as in the U.S. cities the group of travelers who consistently exceed the travel-time budget are those who use both transit and car. These travelers are partly restricted by low transit speeds. Their average trip time is 21.3 min compared with 16.4 min for automobile-only trip makers. This group, however, also has a very high trip generation rate, which may result from psychologically associating different modes with different purposes. After taking the two mandatory transit work trips, the individual still has a desire to make use of his or her car, which is available. As will be shown later, this is the only socioeconomic group identified in the analysis that exceeds the travel-time budget.

Figures 1 and 2 show the frequency distributions of daily travel time for trip makers by mode. These diagrams can be drawn by two methods. The travel times reported in the home interview surveys have many discontinuities, primarily because people tend to perceive their trip time to the nearest 10 min and therefore there is no smooth continuum for the data points on the time axis. It may be argued that the continuous curve interpolated between the data points is a more accurate representation of the actual travel-time distribution in a city. Both the "perceived" and "actual", or smoothed-out, travel-time distributions are shown in Figures 1 and 2.

The "actual" travel-time frequency distribution for automobile-only trip makers (Figure 2) shows a rather sharp peak at 50 min. The "perceived" plot indicates that this peak actually appears to consist of two peaks at 30 and 60 min. This 30-min peak was not expected, and the underlying reasons for it are investigated later in this paper. One hypothesis is that the 30-min peak is caused by trip makers who do not travel to work and that this second peak consists primarily of shopping and sociorecreation trips.

In the distribution of travel times for travelers by all modes (Figure 1), the perceived distribution has only one peak at 60 min, and the actual distribution peaks at 40 min. Similar distributions exist for travel by other modes, including automobile (drivers) and transit.

Trip Purpose

The objective of this analysis is to determine what effect trip purpose, particularly the need for the two daily work trips, has on the travel-time budget. Figures 3 and 4 and Table 2 (8) analyze travel time for workers and nonworkers, which can be directly compared with the daily travel time of the entire population presented in Table 1 and Figures 1 and 2. Those making nonwork trips have daily travel

Figure 3. Distribution of daily travel time in Calgary for nonwork travelers by all mechanized modes.

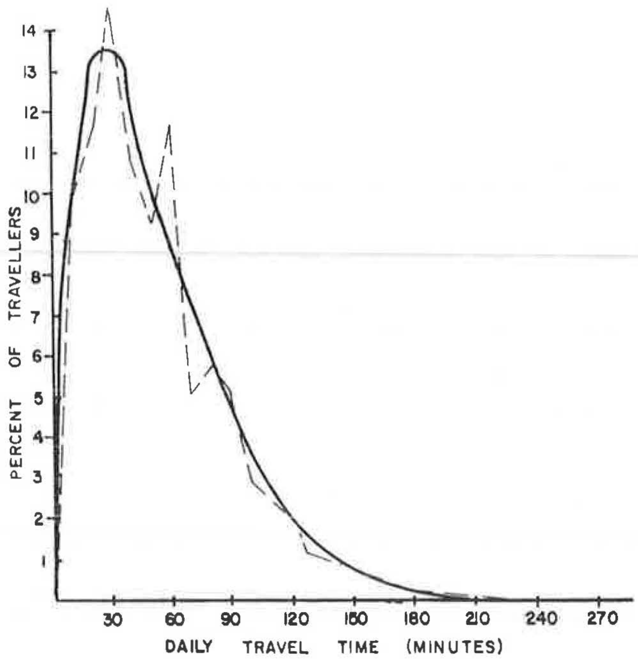


Figure 4. Distribution of daily travel time in Calgary for nonwork automobile-only travelers.

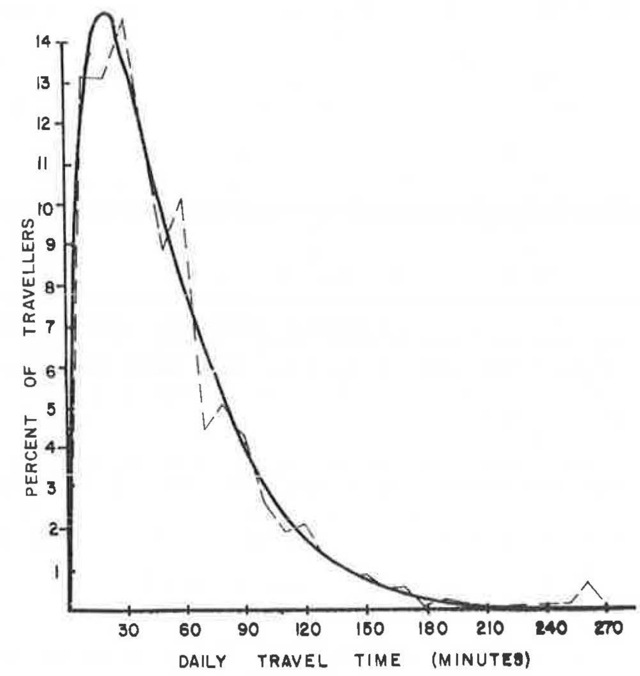


Table 2. Travel-time budget and trip purpose (Calgary).

Mode	Trip Purpose	Trips per Trip Maker	Time per Trip (min)	Daily Travel Time per Trip Maker (min)	Ratio of Mean to Median
All mechanized modes	Nonwork	3.23	17.1	55.2	1.22
	Work	3.76	17.65	66.3	1.22
Automobile	Nonwork	3.43	15.2	52.1	1.3

times of 55 min by all mechanized modes and 52 min by automobile only. The daily travel time of nonworkers is approximately 20 percent lower than that of the entire Calgary population or that of workers; both these populations have a daily travel time of 66 min. The major reason for this decrease is a reduction in the trip rate of nonworkers from 3.8 to 3.2 trips/trip maker. Trip times have remained similar.

The most interesting feature of Figure 3 is that the travel-time frequency distribution for nonwork travelers shows a pronounced peak at the 30-min mark. It may be reasonable to assume, therefore, that it is the nonwork travelers who are responsible for the secondary 30-min peaks in the travel-time frequency distribution of automobile-only trip makers shown in Figure 2.

Location of Residence

Now that the underlying mechanisms of the travel-time-budget concept are understood, it would be valuable to analyze separate groups of trip makers who have different socioeconomic characteristics. This analysis will determine whether the budget concept truly applies to the entire urban population or is valid only for certain identifiable socioeconomic groups.

Two factors that could have a strong influence on the travel-time budget are income and distance of residence from the central business district (CBD). The Calgary travel survey records include the traffic zone in which the residence is located. From a city traffic-zone map, it is possible to identify the zones that fall within a given radius from the downtown core. The appropriate zones are aggregated to calculate the daily travel time for trip makers who live 1.5, 1.5-3, 3-6, 6-9, and more than 9 km from the downtown core. The results are summarized in Table 3.

There appears to be very little variation in daily travel time between those trip makers who live in the downtown core through to those who live in the outskirts. Average trip rate and average trip time also appear to remain stable with increased distance from the CBD.

These results are again similar to those previously obtained by Zahavi (7), who analyzed two Washington, D.C., corridors to examine the relation between daily travel time and distance of residence from the CBD. In both corridors, the perceived daily travel time per trip maker remained constant at about 1.1 h as the distance between residence location and the CBD increased from 0 to 14 km.

Automobile Ownership

Other variables that may be expectd to strongly influence the daily travel-time budget are income and automobile ownership. Unfortunately, income data were not collected in the 1971 Calgary travel survey. It may be argued, however, that the number of cars owned per household is a surrogate measure of income for medium income ranges. Table 4 analyzes the effect of automobile ownership on the travel-time budget in Calgary (8). For comparison, travel-time-budget data for Washington, D.C. (4), are also included. It should be noted that the results of Table 4 refer to travel by automobile only.

The daily travel time of trip makers in non-car-owning households is 0.7 h and increases rather quickly to 1.06 h when a household acquires a car. This sudden increase in travel associated with the acquisition of a car is also exhibited in the data for Washington, D.C. The travel time among trip makers whose households own from one to three cars remains constant; the actual difference is less than 10 percent, in both Calgary and Washington, D.C.

Automobile Travel-Time Budget

The theory of the personal travel budget considers travel by all modes in the city. Zahavi (4) has developed an additional corollary that applies only to automobile travel. His analysis of 22 of the world's cities (see Table 5) reveals that automobiles are used for approximately 0.8 h (48 min) each day. The consistency of this relation is very strong, since the standard deviation is 0.08 or only 10 percent of the mean. A broad spectrum of urban areas was analyzed, including the Tri-State Region of New York.

This relation does not apply to cities in developing countries, which are defined as those where the rate of automobile ownership is less than 0.1 cars/person. In these cities, significantly higher daily automobile travel time is found. This increase may be partly explained by the lower speeds made necessary by a higher level of congestion. In these cities, the rate of car use is also considerably higher. Many different individuals may use the same car during the course of the day.

The automobile travel-time budget is calculated as the average of the daily interzonal vehicle hours of travel in the city divided by the number of personal vehicles. The estimate of vehicle hours of travel is directly available from the conventional traffic model assignment of traffic on the network and represents interzonal travel time with no access or egress time. This definition of travel time is considerably different from the perceived door-to-door travel time used to analyze the personal travel-time budget.

It is important to understand the underlying mechanisms that are responsible for the constancy of the travel-time budget. These mechanisms are best illustrated graphically in Figure 5 (4,8). It has been proved in several studies (4) that the average automobile trip distance is roughly proportional to the square root of the population, as indicated in Figure 5. The automobile trip rate, however, is inversely proportional to the average trip length, distance, or time. It is this complementary decrease in trip rate, as trip lengths increase, that is responsible for the constancy of the travel-time budget. If trip lengths become very long, as is the case in the New York Tri-State Region, the trip rate appears to decrease asymptotically to a basic 3 trips/car. (A similar inverse relation between trip rate and trip time was identified for the personal travel-time budget in the preceding discussion of travel mode.)

Table 6 (8) summarizes daily automobile travel times for the Canadian cities of Calgary, Toronto, and Montreal. Additional Canadian data are not available, since the other cities have not conducted 24-h travel surveys. The average daily travel time per car in these cities is 0.86 h, which is similar to the results of Zahavi's analysis. It is important to note, however, that the dispersion of the Canadian data is much greater. The automobile travel-time budget as identified by Zahavi clearly applied to Calgary both in 1964 and 1971 as well as to Montreal in 1971. The budget is slightly

Table 3. Travel-time budget and location of residence (Calgary).

Distance of Residence from CBD (km)	Trips per Trip Maker	Time per Trip (min)	Daily Travel Time per Trip Maker (min)
0-1.5	3.73	18.0	67.0
1.5-3	3.46	18.0	62.6
3-6	3.79	17.6	66.8
6-9	3.86	17.2	66.5
>9	3.63	18.3	66.4

Table 4. Travel-time budget and automobile ownership (Calgary).

Automobiles per Household	Trips per Trip Maker	Time per Trip (min)	Daily Travel Time for Automobile Trip Makers (h)	
			Calgary	Washington, D.C.
0	2.62	16.0	0.70	0.9
1	3.87	16.5	1.07	1.12
2	4.26	15.9	1.13	1.12
≥3	4.11	17.1	1.17	1.11

Table 5. Analysis of vehicle travel-time budget for various world cities.

City	Year	Population	Cars per Capita	Daily Travel Time (h)	Trips per Day	Trip Time (min)	Speed (km/h)	Trip Distance (km)	Daily Travel Distance (km/car)
Athens	1962	1 900 000	0.0205	1.38	7.79	10.6			
Bogota	1969	2 339 560	0.0235	1.37	4.55	18.0	21.7	6.6	30.0
Singapore	1968	1 536 000	0.0485	1.10	5.03	12.7	31.7	6.7	33.7
Bangkok	1972	4 067 000	0.0430	1.27	3.50	22.8	18.4	7.0	24.5
San Jose	1973	656 670	0.0464	1.27	3.81	20.0			
Tel Aviv	1965	817 000	0.0485	1.10	7.28	9.1	25.1	3.8	27.7
Kuala Lumpur	1973	912 490	0.0717	1.40	6.78	12.4	24.7	5.1	34.6
Caracas	1966	1 719 030	0.0878	1.21	4.90	14.8			
Hull[a]	1967	344 890	0.125	0.72	6.25	6.9			
Belfast[a]	1966	504 520	0.128	0.81	5.63	8.6			
London[a]	1961	8 826 620	0.141	0.75	3.27	13.7			
West Midland[a]	1964	2 529 010	0.154	0.62	3.59	10.3			
Copenhagen[a]	1967	1 707 000	0.201	0.74	4.21	10.5			
Tri-State[a]	1964	16 303 000	0.257	0.97	2.89	20.1	47.1	15.8	45.7
Baltimore[a]	1962	1 607 980	0.272	0.67	3.26	12.3	45.4	9.3	30.3
Monroe[a]	1965	96 530	0.328	0.71	5.79	7.3	37.0	4.5	26.1
Cincinnati[a]	1965	1 391 870	0.348	0.83	3.63	13.7	38.5	8.8	31.9
Orlando[a]	1965	355 620	0.386	0.70	4.33	9.7	42.7	6.9	29.9
Washington[a]	1968	2 562 030	0.398	0.85	3.28	15.6	40.8	10.5	34.4
Los Angeles[a]	1960	7 595 830	0.411	0.80	3.66	13.1	60.0	13.1	48.0
Twin Cities[a]	1970	1 874 380		0.86	4.12	12.5	37.4	7.8	32.1
Philadelphia[a]	1968	2 558 100			3.96			7.5	29.7

[a]Average daily travel time = 0.86; standard deviation = 0.24.

Figure 5. Mechanisms of automobile travel-time budget for U.S. and Canadian cities.

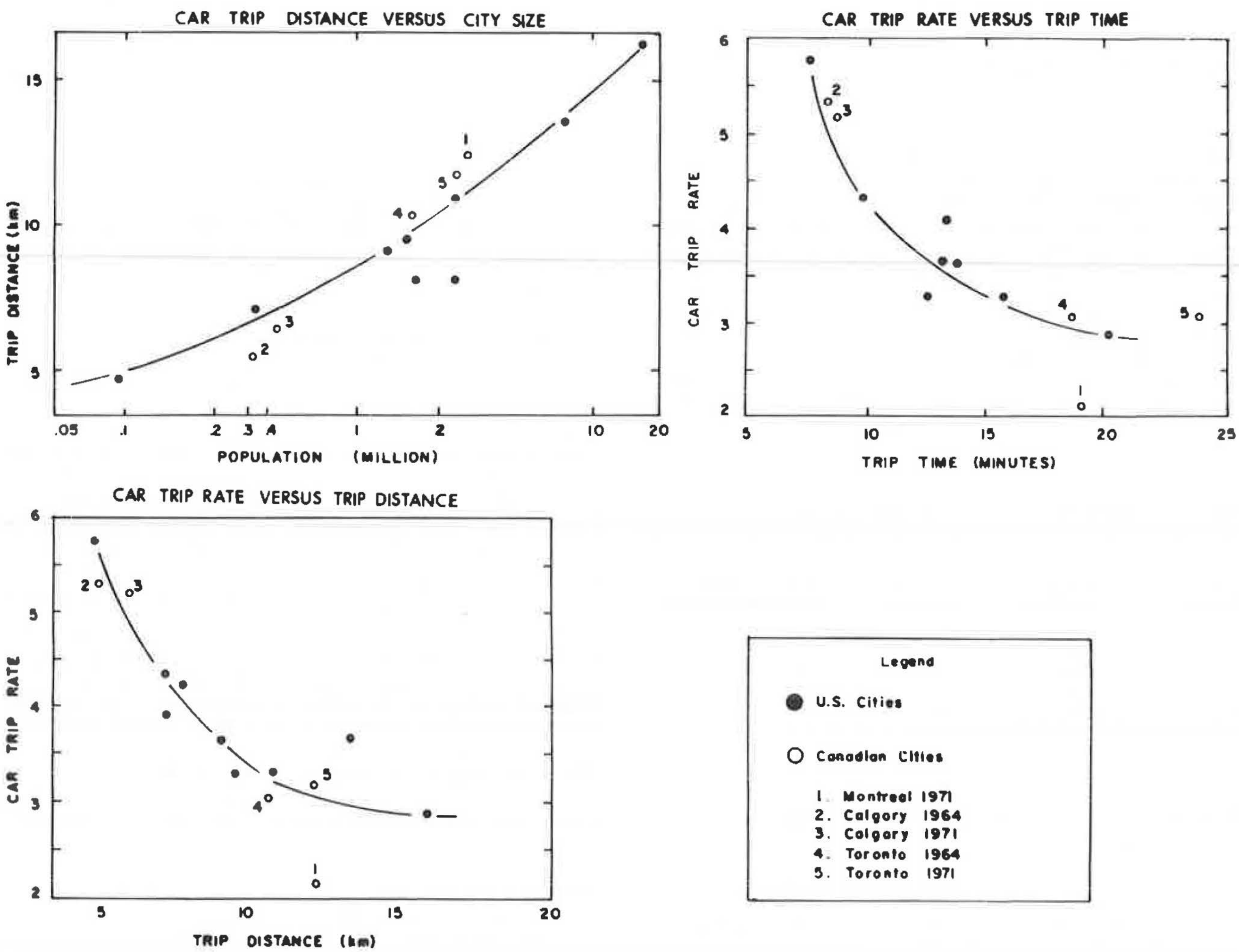


Table 6. Analysis of vehicle travel-time budget for Canadian cities.

City	Year	Population	Cars per Capita	Daily Travel Time (h)	Trips per Day	Trip Time (min)	Speed (km/h)	Trip Distance (km)	Daily Travel Distance (km/car)
Montreal	1971	2 484 462	0.25	0.62	2.03	18.4	41.4	12.7	25.8
Calgary	1964	304 065	0.34	0.75	4.5	9.1	33.6	5.1	27.3
	1971	408 000	0.37	0.76	4.6	9.4	38.2	6.0	31.5
Toronto	1964	1 774 570	0.26	0.93	3.02	18.5	33.4	10.3	31.1
	1971	2 096 920	0.33	1.25	3.17	23.6	30.8	12.1	38.4

Note: Average daily travel time = 0.86; standard deviation = 0.24.

exceeded in Toronto in 1964, but the discrepancy becomes much larger by 1971.

In the case of Toronto, the city grew quite rapidly from 1964 to 1971. Table 6 indicates that one of the main impacts of this rapid growth on transportation has been a deterioration in travel speeds, from 33 km/h in 1964 to 31 km/h in 1971. Throughout this period of rapid growth, travel behavior still adhered to the basic mechanisms of the automobile travel-time budget as indicated in Figure 5. Actually, Toronto is very similar to Washington, D.C. (Table 5), with respect to many travel characteristics such as population, trip rate, and trip length. The only major difference is that in 1971 Toronto travel speeds decreased to 31 km/h in comparison with speeds of 40 km/h in Washington, D.C. As a result, the average trip time in Toronto increased to 23.6 min versus 15.6 min in Washington, D.C., even though the average trip length in both cities is approximately 10-12 km. Since trip generation rates in both cities are rather similar, it appears that it is the deterioration in travel speeds that is responsible for the travel-time budget being exceeded in Toronto in 1971.

By 1971, the city of Calgary was also experiencing a growth rate similar to that of Toronto. In spite of this growth, however, Calgary has actually been able to improve travel speed through continuing expansion of the transportation system. As a result, the automobile travel-time budget has continued to apply in Calgary.

Montreal is a particularly interesting example because it is much less dependent on the automobile than any other Canadian city. The city's 24-h modal share for transit, approximately 30 percent, is one of the highest in North America. The automobile travel-time budget is also somewhat lower, primarily because of a low automobile trip rate of 2 trips/car. This low trip rate may be a result of people in Montreal relying much more heavily on transit for trip making. It is encouraging to note that when transit travel is included in the analysis, as it was in the personal travel-time budget, then the travel-time budget applies to Montreal.

The analysis suggests that the automobile travel-time budget exists in all of the Canadian cities analyzed except Toronto in 1971. Even in Toronto the trend exists, since it appears that the principal reason that the budget is exceeded is lower travel speed caused by an increase in congestion. This imbalance, however, may be of a temporary nature, and the travel-time budget may once again be adhered to in Toronto once travel speeds approach a more reasonable level of 35-40 km/h, as in Calgary and Washington, D.C.

Validity of Personal Travel-Time Budget in Canada

The personal travel-time budget is now supported by nine data points. It should also be noted that this analysis has included all the available data and that evidence to contradict the theory of the personal travel-time budget has yet to be established. The validity of the theory is further enhanced since it withstood a rigorous analysis that attempted to identify under which socioeconomic conditions the theory did not apply. In addition, it appears that there is an overall trend for an automobile travel-time budget in Canada, although the data are not as conclusive as those in support of the personal travel-time budget. It is suggested that the automobile travel-time budget be validated for each individual city before it is used for travel analysis.

The travel-time budget has some interesting and practical implications for the traditional transportation planning process. These implications are discussed in the following section and should be considered by the transportation planning profession in view of the above evidence in support of the theory.

IMPLICATIONS OF TRAVEL-TIME BUDGET FOR TRANSPORTATION PLANNING

The concept of the travel-time budget is not just an interesting phenomenon of urban travel behavior but also has some very practical applications for transportation planning. The two applications of the travel-time budget discussed in this section are (a) to perform an independent check on conventional travel forecasts and (b) to ensure that conventional traffic forecasts reflect an equilibrium between demand for travel and supply of transportation facilities. These applications of the budget concept can be used in direct conjunction with the transportation planning process and require a minimal amount of calculation.

Checking the Validity of Conventional Travel Forecasts

The basis of today's transportation planning process is a survey of individual households to measure such basic travel characteristics as trip generation. Traffic flows are then simulated by models such as the gravity model, which is calibrated to existing traffic counts.

Although these models are very effective at simulating existing travel patterns, forecasts of future travel should be considered very cautiously. Any forecast assumes a priori that present-day trip-making and trip distribution propensities, as measured in the surveys, will remain stable in the future. Trip-making characteristics may be forced to change because of changes in socioeconomic conditions. It is relatively easy to foresee socioeconomic changes such as reduced availability of gasoline, higher income levels, and increased leisure time. These factors could significantly affect trip-making characteristics.

In addition, travel forecasts developed today are unconstrained by the physical capacity of the transportation infrastructure. In many cities, there is now a policy to reduce roadway construction, especially facilities with limited access. If cities continue to grow and congestion is allowed to increase, residents may be forced to transfer nonessential trips to off-peak periods. The transportation planning process, as practiced today, does not recognize the effects of increased congestion and clearly overestimates travel under such circumstances.

The data currently available indicate that the travel-time budget is a much more stable indicator of urban travel behavior. The travel-time budget not only has remained consistent over a considerable period of time--more than 10 years in Washington, D.C., and the Twin Cities--but also is valid for a number of cities that have different population sizes and traffic problems. It would be very useful, therefore, to use the budget theory in order to perform an independent check of conventional travel forecasts, especially with changing socioeconomic conditions.

Conventional transportation planning models estimate not only traffic volumes on the various links of the urban network but also total vehicle and person hours of travel. It is very simple to use the travel-time-budget concept as a way of checking the validity of these forecasts of total vehicle and person hours.

Table 7 summarizes the travel forecasts developed for the city of Calgary for 1986 and 1996 along with forecasts developed through the budget concepts. As indicated in Table 6, the average interzonal travel time per personal vehicle in Calgary in 1971 may be estimated as 0.76 h. Given the population forecast, the number of vehicles can be calculated by assuming a saturation level of 0.5 personal vehicles per capita. If one combines these two variables, the daily vehicle travel time can be estimated as follows: For 1986, 0.76 (hours/vehicles) x 308 950

Table 7. Travel forecasts for Calgary.

	Conventional Forecast		Budget-Concept Forecast	
Item	1986	1996	1986	1996
Population	617 900	806 000	617 900	806 000
Number of cars[a]	308 950	403 000	308 950	403 000
Number of trip makers[b]	432 530	564 200	432 530	564 200
Vehicle hours of travel	259 518	338 100	234 800	306 300
Person hours of travel	NA	467 400	NA	507 780

[a] Assuming vehicle ownership will reach a saturation level of 0.5 personal vehicles per capita.

[b] Zahavi (4) has developed a regression equation to estimate the ratio of trip makers to population.

vehicles = 234 800 h; for 1996, 0.76 (hours/vehicles) x 403 000 vehicles = 306 300 h. The budget-based forecasts differ from the conventional ones by only 9 percent.

A similar verification can be conducted through the trip-maker travel-time budget. By 1996, the ratio of trip makers to population in Calgary is estimated at 0.7. The 1996 population will therefore generate 564 200 trip makers. A travel-time budget of 1.1 h cannot be directly applied, since this figure represents the door-to-door travel time perceived by the survey respondents. A detailed analysis of the Calgary data indicates that the actual interzonal travel time per trip maker based on network assignment is 0.9 h. This difference between actual and perceived travel time has yet to be thoroughly researched, and therefore each city must be analyzed on an individual basis.

The 1996 person hours of travel may therefore be calculated as follows: 564 200 trip makers x (0.9 h/trip maker) = 507 780 h. This figure can then be compared with the estimate of person hours of travel available from the traffic model. Once again, the difference between the conventional and budget-based forecasts is 8 percent.

This analysis considerably enhances the validity of the Calgary travel forecasts. The projections are now verified by another model that has a completely different theoretical base.

Equilibrium Travel Forecasts

The conventional transportation planning process assumes that trip generation rates will remain stable at existing levels regardless of increases in congestion. It appears reasonable to assume that if travel speeds deteriorate some trip makers would either transfer some trips to other, less congested periods of the day or possibly even forgo the trip.

There is an obvious need to relate trip generation to available travel speeds or other indicators of level of service. In other words, the demand for travel is expected to increase as speeds improve. Similarly, for a given transportation system, there is a physical limit to the volume of traffic that can be transported at a given speed. There must exist a state of equilibrium at which the volume of trips demanded equals the volume that can be accommodated by the facility. This equilibrium speed will also be the travel speed on that particular network. Of course, this concept is identical to the concept of price theory used in microeconomics, which states that at an equilibrium price the quantity of goods demanded equals the quantity that can be supplied.

The travel-time budget can be used to examine the relation between speed and travel demand. Through this procedure, it is possible to compare the speed associated with travel demand with the speed available through the transportation system and develop a truly equilibrium travel forecast. As an example, this procedure is now applied to the travel forecasts developed for the regional municipality of Ottawa-Carleton.

By the end of the century, the population of the Ottawa region is projected to grow from 620 000 to 1 400 000. The conventional traffic model forecasts 3 200 000 trips (10). According to the relation shown in Figure 3, the average trip length for a city of such size is 8.8 km. The number of vehicles is estimated to be 700 000, if we again assume a level of ownership of 0.5 vehicles/person. The vehicle travel-time budget may now be used to determine what speed of travel is actually implied by this travel demand forecast:

$$\text{Speed} = (3.2 \times 10^6 \text{ trips} \times 8.8 \text{ km/trip})/(0.7 \times 10^6 \text{ cars} \times 0.8 \text{ h/car}) = 50 \text{ km/h} \qquad (1)$$

Since existing travel speeds in Ottawa average only 32 km/h, this analysis implies that, if the forecast is to materialize, considerable road construction is necessary to increase travel speeds to 50 km/h. Such speeds are only achievable through an extensive freeway network such as that in Los Angeles. Even if the automobile travel-time budget does not apply and daily automobile travel times approach 1 h, as in Toronto in 1971, the speed implied in the travel forecast is still rather high: 40 km/h.

These results suggest that the Ottawa-Carleton forecasts were somewhat overoptimistic. The budget concept provides a mechanism for deflating these forecasts to reflect the physical capacity of the roadways. If it is assumed that travel speeds remain at 32 km/h, the actual demand or number of trips may be estimated as follows:

$$\text{Number of trips} = (0.7 \times 10^6 \text{ cars} \times 0.8 \text{ h/car} \times 32 \text{ km/h})/(8.8 \text{ km/trip}) = 2\ 040\ 000 \qquad (2)$$

The degree of overestimation in the Ottawa forecast can therefore be estimated as approximately 40 percent.

CONCLUSIONS AND RECOMMENDATIONS

This paper provides further evidence in support of Zahavi's theory of the travel-time budget. The data are based on the travel characteristics of the Canadian cities of Calgary, Toronto, and Montreal. As a result of this evidence, it is suggested that this new concept should be studied further. Two applications discussed in this paper are the use of the budget concept to verify conventional traffic forecasts and a method for developing equilibrium travel forecasts.

Much more research is required to truly establish the validity of the travel-time budget. If successful, the budget concept can be very useful in improving our understanding of travel behavior and consequently our ability to forecast it. Particularly useful applications of the budget concept, which should be investigated in further research, are identified below.

1. Traffic assignment--During periods of peak congestion, it is likely that some travelers will transfer nonessential trips to other periods of the day or simply forgo them. Conventional assignment techniques do not recognize this transfer, and trip generation rates are unaffected by congestion levels. The travel-time budget may provide a mechanism for deflating travel demand to equilibrium. Through further research, it may be possible to establish a criterion that states that, as long as the travel-time budget is being exceeded, the generation of some nonessential (nonwork) trips should either be transferred from the peak period to off-peak periods or, if necessary, completely suppressed. One very important research need is to examine whether the travel-time budget remains valid under increased congestion, when speeds drop below 30 km/h. All analysis to date has only considered cities where speeds are higher than 30 km/h.

2. Modal split--The personal travel-time budget reveals some interesting data about the behavior of transit and automobile trip makers. Preliminary data suggest that transit is acceptable for work trips only if the average travel time for the entire system is held to about 1 h. If this limit is

exceeded, a shift to automobile travel should be expected. Similarly, if transit speeds are improved through the development of better transit systems, and work travel could be accomplished in less than 1 h, then the travel-time-budget concept indicates that the use of the transit mode for additional nonwork trips may increase. This concept, if researched more thoroughly, could improve our understanding of the modal-split model.

3. Mobility--Whenever transportation plans are evaluated, a key concern is the impact on the mobility of residents, particularly those who do not own a car. It has always been very difficult to define what is an adequate level of mobility. The travel-time budget may provide the basis for a suitable mobility criterion. This preliminary research suggests that mobility may be defined as the ability to make more than the basic two work trips within the travel-time budget of 1 h. Further research of this concept is required.

ACKNOWLEDGMENT

We wish to express our appreciation to Y. Zahavi for his many comments and his advice during the course of this study. Richard S. Clark and D. J. Reynolds of the federal government of Canada also provided valuable input. We would also like to thank the staff of the various municipal transportation departments throughout Canada, especially Mike Kushner of the city of Calgary, who were most cooperative in providing the base data.

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Analyzing Traveler Attitudes to Resolve Intended and Actual Use of a New Transit Service

MICHAEL R. COUTURE AND THOMAS DOOLEY

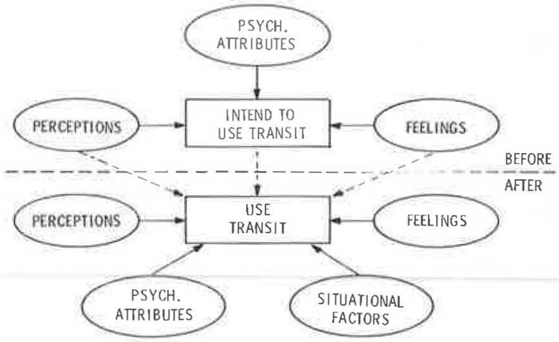
Traveler attitude data have been shown in the literature to be important in helping to predict the use of new transportation technologies or services. Reported prior intentions to use a new service often significantly overstate actual use once the service has been implemented. Differences obviously exist between the processes of intention formation and choice. An analysis is described that explores the differences between behavioral intentions and actual use of a new transit service by using extensive attitudinal data collected before and after implementation of a new transit system in Danville, Illinois. Several econometric models were developed, and the results are analyzed and compared. Choice constraints are treated explicitly in the analysis. Among the major findings are that level-of-service perceptions such as "convenience" and "enjoyment" and general feelings or biases regarding different transportation modes are important determinants in forming both intentions and choices. However, significant differences were found in terms of the relative importance of these attitudinal factors in the choice and intention processes, and these differences are highlighted.

During the past decade, a number of research efforts have been conducted on the use of attitudinal measures in travel demand models (1-4). Attitudinal measures that describe individuals' feelings, perceptions, and intentions with respect to the transportation system have been found to significantly improve the explanatory power of demand models, particularly disaggregate models of modal choice, because they take into account subjective or unobserved factors that are important in the travel decision process. Factors such as convenience, comfort, and safety have been shown in past research to be of considerable importance in modal-choice travel decisions (5,6) and should be included in choice models if possible.

In addition to these considerations, a major reason underlying the desire to use attitudinal information in the models, whether to supplement or replace the conventional use of observed information in the model specification, is to be able to better understand, and ultimately predict, the response to the introduction of new (i.e., untried) or greatly improved transportation services. It is felt that problems that involve demand for new modes or services are perhaps most amenable to solution through analysis of traveler attitudes rather than through extrapolation of observed measurements (1).

This study develops a set of behavioral models that incorporate attitudinal measures to aid in understanding the relation between the intended use of a new public transit system (reported prior to implementation) and actual use (reported after implementation). It is recognized in the literature

Figure 1. Modeling framework: hypothesized causal relations.



(7) that behavioral intentions (e.g., reported demand for a new mode) tend to significantly overstate actual behavior (e.g., actual use of the new mode). This stems partly from individuals' lack of experience using the new mode, from changing attitudes, and from omission of choice constraints (i.e., accessibility to the new mode). Thus, these factors were taken into consideration in the development of the models.

The data set used to estimate the models contained information on traveler attitudes and other relevant factors. The data were collected before and after implementation of a new transit system in Danville, Illinois, as part of an Urban Mass Transportation Administration Service and Methods Demonstration Program project.

MODELING FRAMEWORK

The foundation of the analysis was the formulation of a causal framework that represents the relations between prior and current attitudes and intended and actual transit use. The hypothesized causal framework is shown in Figure 1. In developing this framework, attitudes were divided into three components: perceptions and feelings regarding the new transit service (versus other transportation modes) and intentions to use the new service. In this particular study, perceptions were measured as individual responses to survey questions regarding the relative comfort, convenience, speed, enjoyability, and cost of transit versus other modes including car, taxi, and walking. Feelings were measured as a respondent's agreement or disagreement with certain statements that clearly represented protransit or antitransit and procar or anticar biases. Intentions were measured (prior to service initiation) as a respondent's expected frequency of use of the new service (once implemented). This tripartite characterization of attitudes--i.e., perceptions, feelings, and intentions--is a concept widely accepted by social psychologists. However, the linkages among these components are still the subject of debate (4).

In reference to Figure 1, three primary relations should be enumerated.

1. Intention to use transit was hypothesized as determined by prior perceptions and feelings regarding the new service and underlying psychological attributes of individual travelers (upper portion of Figure 1). Underlying psychological attributes, which were represented in this study by sociodemographic factors such as sex and age, were expected to explain fundamental differences in attitudes and thus behavioral intentions.
2. Actual use of transit (after implementation) was hypothesized as determined by "current" (i.e., after) modal perceptions and feelings, psychological attributes, and situational factors. Situational factors represented such modal-choice constraints as automobile availability, transit accessibility (e.g., distance to the nearest stop), and individual mobility restrictions (e.g., physical disability).
3. Actual use of transit was hypothesized as determined, at least partly, by prior modal perceptions, feelings, and intentions (dashed lines in Figure 1).

The latter relation--i.e., actual use as a function of prior attitudes--was expected to be a tenuous one, depending in part on the stability of traveler attitudes from before to after initiation of the service (i.e., once the service became available and was experienced). However, even accounting for attitude changes from before to after, a relation was still possible if the choice process after implementation was consistent with attitudes before implementation. That is, a potential cause-and-effect relation could have been the following: Prior attitudes determined current behavior (i.e., actual choices), and this behavior in turn caused changes in current attitudes. This notion of interdependence between attitudes and behavior has received considerable attention from transportation researchers in recent years (4,8,9) and was an important consideration in analyzing the results of the models developed here.

THE MODELS

Based on the causal framework and primary linkages described, three models were relevant in addressing the problem: (a) a model describing intended transit use as a function of information collected prior to implementation, (b) a model explaining actual transit use using data collected prior to implementation, and (c) a model explaining actual transit use using information obtained after implementation. These models are represented explicitly below as models 1, 2, and 3:

1. Model 1--Intended use = f (prior perceptions, feelings, psychological attributes),
2. Model 2--Actual use = f (prior perceptions, feelings, intentions, psychological attributes, situational factors), and
3. Model 3--Actual use = f (current perceptions, feelings, psychological attributes, situational factors).

For application purposes, a model such as model 2, in which prior information is used to explain behavior after implementation, is most desirable. However, the model as formulated here is more a learning tool than a forecasting tool, as is discussed later.

To represent the processes of intention formation (model 1) and actual choice (models 2 and 3), a binary logit model structure was chosen. The statistical properties of the logit model are well documented (10) and are not restated here. The particular form of the model used was as follows:

$$\mathrm{Prob}_i\,(\mathrm{transit}) = e^{U_i}/(1 + e^{U_i}) \quad (1)$$

where e^{Ui} is the exponential of the relative utility to individual i of transit versus other modes (i.e., personal automobile, taxi, and walking in this case).

For the model of intended use, the dependent variable was the probability of individual i intending to use transit versus other modes (i.e., versus not intending to use transit) for any purpose. For the models of actual use, the dependent variable was the probability of individual i using transit versus not using transit for any purpose. Thus, the models addressed generally the question of whether a person intended to use or actually did use the new transit service, regardless of the frequency of use or the purpose for using it.

The independent variables that composed the utility functions (Ui) of the models included measures of the perceptions of transit level of service relative to the level of service of the other modes available and measures of explicit feelings or biases toward or away from transit or automobile (the two primary competing modes). Measures of underlying psychological attributes, modal availability, and degree of intended transit use were also factored into the utility expressions of all or some of the models. The precise variable definitions are described in the next section of this paper.

The selection of a logit model structure was predicated on both practical and theoretical considerations. The successful application of logit models in analyzing discrete modal choice has been well documented in the literature, including applications using attitudinal data (2). In addition, a readily accessible estimation program that used a maximum likelihood technique was available. This program involved the use of the Time-Shared Reactive On-Line Laboratory (TROLL) econometric modeling system of the National Bureau of Economic Research, Inc.

DATA

The data used for estimating the models were obtained from a telephone survey administered one month before and eight months after the introduction of a bus transit system in Danville, Illinois, in 1977 (11). Danville is a city of approximately 42 000 people located 120 miles south of Chicago. The new transit service, which consisted of 11 routes, 6 operating at 60-min headways and 5 at 30-min headways, provided extensive coverage of the city. The base fare (using a prepaid ticket) was $0.40. After six months, the service was averaging 800 riders/day. The service characteristics (coverage, headways, and fare) of the actual service closely approximated the hypothetical service described in the preimplementation survey. The before-and-after survey questions covered those choices, perceptions, feelings, intentions, situational factors, and sociodemographics discussed above in relation to the modeling framework.

A sample of 567 individuals responded to both the preimplementation and postimplementation surveys. The sample size was reduced to 485 by eliminating those respondents who were physically unable to use transit and those who lived more than five blocks from a transit stop.

Key socioeconomic and situational characteristics of the sample included the following:

Characteristic	Percentage of Sample
Sex	
Female	80
Male	20
Age (years)	
<20	4
20-65	59
>65	37
Occupation	
Working or going to school	44
Retired or keeping house	56
Carless household	19
Living within one block of new transit service	71

Construction of Variables

The complete set of variables constructed for the model-estimation process is given in Table 1. The socioeconomic variables (age, sex, and employment status) were stratified into 0,1 variables by categorization (e.g., 0 if male, 1 if female). The situational factors constructed characterized the availability of the automobile mode and the relative accessibility of individuals to transit. The other modes--taxi and walk--were assumed to be available equally to all individuals.

Variables of level-of-service perception were defined in four ways by using ordinal-type specifications:

1. Assign a value of 1 if transit is ranked best (i.e., least expensive or most enjoyable, fast, comfortable, or convenient), else 0;
2. Assign a value of 1 if transit is ranked best (as above), a value of -1 if transit was ranked worst (i.e., most expensive, least comfortable, etc.), else 0;
3. Define as in method 1 but multiply by a weight depending on the reported relative importance placed on that perception (see the variable for relative importance of perceptions in Table 1), regardless of mode (e.g., convenience is most important, least important, etc.); and
4. Define as in method 2 above but weight as in method 3.

All of these methods were consistent with the model of transit choice relative to other modes (personal automobile, taxi, and walk). Method 2 included additional perceptual information, whereas methods 3 and 4 included additional information about individual values.

The feelings variables were defined as 1,0 variables: 1 if the respondent agreed and 0 if he or she disagreed or was neutral regarding a particular transportation modal issue. A variable for intended frequency of transit use (TRIPFREQ) was defined as the sum over all purposes (work, shop, and other) of the number of intended trips per week by transit given that transit was to be used for those purposes. This variable was used in model 2 to represent the degree of prior intent to use transit.

Preliminary Data Analysis

Extensive cross-tabulation and correlation analyses were conducted to determine initial variable sets for model estimation and to assess potential colinearity among the independent variables.

The cross-tabulation results showed that 81 percent of the women and 71 percent of the men in the sample intended to use transit and that only 35 percent of the women and 24 percent of the men actually used it. This translates into approximately three intenders for every actual user and confirms the earlier assertion regarding intentions overstating actual behavior. There were no significant differences among age or employment groups with respect to intended or actual use of transit. The results also showed that 37 percent of those who said they intended to use transit did use it whereas 84 percent of those who did not intend to use transit in fact did not. This is consistent

Table 1. Available model variables.

Category	Variable	
Sociodemographics	SEX	= 0 if male, 1 if female
	OLDAGE	= 1 if age >65, else 0
	WORKAGE	= 1 if age >20 and <65, else 0
	FULLT	= 1 if full-time worker, else 0
	MUSTMOVE	= 1 if either full-time worker or student or looking for work, else 0
	NOMOVE	= 1 if keeping house or retired, else 0
Situational factors	HHFULL	= number of full-time workers in household
	NLIC	= number of licensed drivers in household
	AA	= 1 if automobile available, else 0
	TBLOCKS	= 1 if ≤1 block away from nearest transit stop, else 0
Level-of-service perceptions[a]	COSTA,B	= 1 if transit least expensive, else 0
	COMFA,B	= 1 if transit most comfortable, else 0
	CONVA,B	= 1 if transit most convenient, else 0
	ENJA,B	= 1 if transit most enjoyable, else 0
	FASTA,B	= 1 if transit fastest, else 0
Relative importance of level-of-service perceptions[b]	COSTWTA,B	= 3 if cost is a very important attribute
		= 2 if cost is a somewhat important attribute
		= 1 if cost is not a very important attribute
		= 0 if cost is not at all important
	COMWTA,B	= (3,2,1,0) if comfort is a very important attribute, etc.
	CONVWTA,B	= (3,2,1,0) if convenience is a very important attribute, etc.
	ENJWTA,B	= (3,2,1,0) if enjoyability is a very important attribute, etc.
	FASTWTA,B	= (3,2,1,0) if speed is a very important attribute, etc.
Feelings		
Protransit	REDCARA,B	= 1 if agree that use of cars should be reduced by supplying effective public transit, else 0
	IMPTRANA,B	= 1 if agree that drastic action must be taken to improve transit service, else 0
	FIGHTA,B	= 1 if agree that lack of adequate public transportation causes squabbles in family, else 0
	CHILDA,B	= 1 if agree that children need good public transportation, else 0
Antitransit	PUBTRANA,B	= 1 if agree that riding transit makes people feel uncomfortable, else 0
	EMBARA,B	= 1 if agree that it would be embarrassing taking someone to social function on public transit, else 0
	DIRECTA,B	= 1 if agree that getting directions from a bus driver is awkward, else 0
	AFFORDA,B	= 1 if agree that only people who cannot afford other means use the bus, else 0
Procar	GIVEA,B	= 1 if cannot imagine giving up car regardless of transit service provided, else 0
	NICECARA,B	= 1 if agree that having a nice car is appealing beyond just transportation, else 0
	LIKECARA,B	= 1 if agree that driving is or would be enjoyable, else 0
	TRAPA,B	= 1 if agree that not having a car available is like being trapped, else 0
	SOCSUFA,B	= 1 if agree that social life suffers if there is no car available, else 0
Anticar	NUISA,B	= 1 if agree that cars are a nuisance, else 0
	CARUSEA,B	= 1 if agree that cars have outlived their usefulness, else 0
	FRUSTA,B	= 1 if agree that driving in city is frustrating, else 0
	DISCRGA,B	= 1 if agree that cities should make it difficult to drive or park car in city, else 0
	CONGSTA,B	= 1 if agree that traffic congestion in this city is major problem, else 0.
Intentions	TCHOICEB[c]	= two-column matrix: column 1 = 1 if intend to use transit, else 0; column 2 = 1 if do not intend to use transit, else 0
	TRIPFREQ	= sum of number of intended work, school, shopping, and other trips per week on transit
Behavior	TCHOICEA[c]	= two-column matrix: column 1 = 1 if use transit, else 0; column 2 = 1 if do not use transit, else 0

Note: Suffix A in variables refers to postimplementation data and B refers to preimplementation data.

[a] An alternative formulation of level-of-service perceptions assigned 1 if transit was least expensive or most comfortable, convenient, etc.; -1 if transit was most expensive, least comfortable, etc.; and 0 otherwise.

[b] Weighted level-of-service perception variables were created by multiplying the level-of-service variable (e.g., COSTA) by the weight (e.g., COSTWTA).

[c] Dependent variable; format consistent with the requirements of the logit estimation program.

with the consumer research literature, in which negative intentions have been found to be better indicators of nonuse than positive intentions are of use (11).

Further analyses indicated that 63 percent of those who had no car available used transit whereas only 25 percent of those who had a car used transit. Among those to whom a car was available, 29 percent of those who intended to use transit did and only 11 percent of those who did not intend to use transit did use it. A similar pattern (20 percent difference) existed among those who did not have an automobile available, which suggests that intention is in fact important in determining use.

ESTIMATION RESULTS

Several variable specifications were tested for each of the three hypothesized models. Care was exercised not to incorporate into the model sets of variables that were highly correlated in order to avoid multicolinearity.

In the first phase of the modeling effort, specifications including sociodemographic characteristics, situational factors, and level-of-service perceptions were tested. Feelings variables were incorporated in a second phase to test for their additional contribution to the models' explanatory powers.

Phase 1 Models

Table 2 gives the estimation results of the final specifications developed for the three models in the first phase. All coefficient estimates have the correct signs, and nearly all are highly significant (i.e., they have large t-statistics). A positive coefficient in the model indicates a tendency (i.e., greater utility) for using transit versus the other modes of travel. The goodness-of-fit statistic p^2 (commonly called the McFadden coefficient) is moderately high, considering that the scale from worst to best ranges from $p^2 = 0$ to approximately $p^2 = 0.6$.

As Table 2 indicates, some variables were excluded from the model specification because of colinearity with other variables. Several of the perceptions and feelings variables were correlated,

Table 2. Phase 1 estimation results.

	Model 1		Model 2		Model 3	
Independent Variable	Coefficient Estimate	t-Statistic	Coefficient Estimate	t-Statistic	Coefficient Estimate	t-Statistic
Constant	0.51	1.31	-1.46	-3.37	-1.63	-3.92
Sociodemographics						
Sex	0.64	2.42	0.64	2.10	-[a]	
Situational factors						
Within one block of transit	NA		0.69	2.57	0.45	1.67
Automobile available	0.11	0.33	-1.56	-5.63	-0.81	-2.63
Level-of-service perceptions						
Transit least expensive	-[a]		-[a]		0.68	2.37
Transit most comfortable	-[a]		1.05	2.93	-[a]	
Transit most convenient	1.02	2.24	1.17	3.66	2.07	6.32
Transit most enjoyable	1.52	2.82	-[a]		1.09	3.73
Intention						
Number of intended transit trips per week	NA		0.13	5.22	NA	
Model goodness of fit						
ln likelihood	235.08		238.59		226.90	
ρ^2		0.30		0.29		0.33

[a]Indicates that variable not included in model specification because of multicolinearity or insignificance of coefficient estimate.

as one would expect, because of the large number and qualitative nature of these variables. In cases where colinearity was detected among variables, those variables that provided the greater explanatory power were left in the specification and the others were excluded.

The only sociodemographic variable found to be of significance in any of the models was sex in models 1 and 2. Apparently, women felt more positive about using transit service prior to and after the implementation of service than did men. These results correspond to those of the cross tabulations, in which a higher percentage of females indicated intended and actual use of transit than did men. The sex variable was excluded from model 3 because of colinearity with the variables for postimplementation perceptions of level of service. This was primarily caused by the characteristics of the sample, in which, after service implementation, women as a group had positive perceptions of transit versus other modes whereas males' perceptions of transit were generally negative with respect to other modes.

As hypothesized, situational factors (e.g., automobile availability and transit accessibility) were significant in explaining actual choice to use transit (models 2 and 3). By comparing the respective coefficients, it can be observed that having a car available was considerably more important (in a negative sense) in the choice to use transit than having superior access to transit (i.e., living within one block of a transit stop). In addition, as hypothesized, situational factors were not significant determinants of peoples' intentions to use transit. This hypothesis was tested by including the variable of automobile availability in model 1 and observing that the estimated coefficient was not significantly different from zero (note the small t-statistic in Table 2).

The variable that represented the number of intended weekly transit trips (or degree of prior transit intent) was found to be a significant positive explainer in model 2. This indicates that the more trips an individual planned on taking prior to the new service, the greater was the likelihood that he or she would actually use transit after initiation of service.

With respect to level-of-service perceptions, the simple 0,1 variables provided better model fits for all three models than did either the weighted variables or the 0,1,-1 variables. This suggests that the constructed perception variable weights were not consistent with the true choice or intention processes (i.e., the true variable weights). Furthermore, it suggests that there was an unevenness in the scale between the perception of transit as best or worst or neither best nor worst along the given level-of-service dimensions. The symmetric 1,0,-1 scale used did not capture this unevenness, and hence the 1,0 measures (i.e., transit best or not best) were better explainers.

The perception of relative convenience was an important factor in all three models, and relative modal enjoyment was important in forming both intentions (model 1) and actual choices (model 3). Relative comfort and cost were also important factors in forming choices in models 2 and 3, respectively. In reference to the earlier discussion of the interdependency between behavior and attitudes, several inferences can be drawn from these results. That relative modal cost and enjoyment were significant in model 3 but not in model 2 suggests that perceptions had changed from before to after to become consistent with the choice to use or not use transit. Another important result is that relative comfort was significant in model 2 but not in model 3, which tends to support the hypothesis that attitudes regarding relative comfort had changed but that behavior (i.e., the choice process) was consistent with the preimplementation perceptions of comfort. These results suggest that along some level-of-service dimensions (i.e., comfort) prior perceptions were better explainers of actual use, along other dimensions (i.e., cost and enjoyment) current perceptions were better explainers, and along still other dimensions (i.e., convenience) prior and current perceptions were both significant explainers of actual use.

Since all of the variables in the models, except the number of intended weekly transit trips in model 2, were 0,1 measures, comparison of variable weights within each model is straightforward. In model 1, it can be observed that perceptions of whether transit was most enjoyable or convenient were the most important determinants of intentions to use the system. In model 2, prior perceptions of relative convenience and comfort and automobile availability were the key factors in explaining actual use, along with the number of intended weekly transit trips (if

Table 3. Phase 2 estimation results.

Independent Variable	Model 1 Coefficient Estimate	Model 1 t-Statistic	Model 2 Coefficient Estimate	Model 2 t-Statistic	Model 3 Coefficient Estimate	Model 3 t-Statistic
Constant	-1.32	-2.47	-1.55	-3.36	-2.08	-4.13
Sociodemographics						
Sex	0.69	2.32	0.60	1.92	-[a]	
Situational factors						
Within one block of transit	NA		0.66	2.46	0.38	1.35
Automobile available	0.25	0.65	-1.42	-5.06	-0.74	-2.29
Level-of-service perceptions						
Transit least expensive	-[a]		-[a]		0.47	1.57
Transit most comfortable	-[a]		0.92	2.50	-[a]	
Transit most convenient	0.80	1.64	1.14	3.55	2.02	5.77
Transit most enjoyable	1.27	2.17	-[a]		0.98	3.22
Intention						
Number of intended transit trips per week	NA		0.12	4.79	NA	
Feelings						
Protransit						
Need to improve transit to reduce cars	0.74	2.79	-[a]		1.22	3.87
Children need good transit	0.80	2.82	-[a]		-[a]	
Antitransit						
Embarrassed to use transit	-0.56	-1.84	-0.59	-1.79	-[a]	
Some can only afford transit	-0.84	-2.95	-[a]		-[a]	
Procar						
Feel trapped without car	-[a]		-[a]		-0.72	-2.88
Anticar						
Cars are a nuisance	0.96	3.14	0.45	1.93	-[a]	
Cars are no longer useful in city	-[a]		-[a]		0.56	2.08
Driving in city is frustrating	0.67	2.18	-[a]		-[a]	
Traffic congestion is a problem	0.57	1.98				
Model goodness of fit						
ln likelihood	195.57		235.05		209.94	
p^2		0.42		0.30		0.38

[a]Variable not included in model specification because of multicolinearity or insignificance of coefficient estimate.

that number was significantly large, i.e., eight or more trips). Finally, in model 3, current perception of relative transit convenience dominated all other variables by about two to one in explaining actual transit use.

Phase 2 Models

The estimation results of the final specifications for the three models, in which "feelings" variables are incorporated, are given in Table 3. Nine of the 18 feelings variables available proved to be a significant factor in at least one of the models. All coefficients had the correct signs. Anticar sentiments dominated the list of important feelings variables. In the case of all three models, the feelings variables contributed significantly to the explanatory powers of the phase 1 models [at the 95 percent level or better according to the likelihood ratio test (12)]. Model 1 showed the most dramatic improvement in fit as p^2 increased from 0.30 to 0.42 with the addition of feelings variables.

Considering the potential for colinearity among the specified perceptions and feelings variables, it was surprising that in model 1 seven feelings variables could be incorporated that were statistically significant (at the 90 percent level or better). It is also apparent in model 1 in Table 3 that part of the explanatory power of the level-of-service perceptions (convenience and enjoyment) was subsumed by the feelings variables, particularly those biased toward transit or away from cars (note the smaller t-statistics for the coefficients for convenience and enjoyment compared with model 1 in Table 2).

In comparing models 2 and 3, changes in feelings from before to after implementation can be inferred (as was the case for level-of-service perceptions). Of the three feelings variables that were significant in model 3, none were significant in model 2, which indicates that those feelings changed from before to after and became consistent with the choice process. On the other hand, neither of the two significant feelings variables in model 2 was significant in model 3, which suggests that these preimplementation feelings were better explainers of the choice to use or not use transit than were the current feelings regarding those issues.

CONCLUSIONS

The results of this study reconfirm several well-established tenets of travel-behavior theory:

1. Intentions overstate actual behavior,
2. Negative intentions are better indicators of nonuse than positive intentions are of use,
3. Situational factors (e.g., automobile availability and transit accessibility) are important determinants of mode choice,
4. Attitudes are important in forming intentions and choices, and
5. Attitudes and behavior are interdependent.

In addition to confirming these established findings, this study has produced several important new insights:

1. Individual feelings regarding specific transportation issues, especially anticar sentiments, were shown to be powerful explanatory variables, particularly in forming behavioral intentions.
2. Although a measure of intended use versus nonuse of transit is not a useful explainer of ac-

tual use, intended frequency of use (indicating degree of intention to use) was found to be a significant determinant.

3. The perception of relative modal convenience was found to be a dominant factor in forming both intentions and actual choices to use transit, and its perception was more stable over time than were the perceptions of other level-of-service measures.

From a practical standpoint, perhaps the single most important development of the study was the simplicity with which the attitudinal variables were defined to produce effective explanatory models. All of the feelings and perceptions variables were constructed as 0,1 variables. Moreover, the 0,1 perceptions variables were found to have superior explanatory power over the more sophisticated variable definitions that were attempted by using relative weights or additional perceptual information. The implication is that the analysis method used here can produce useful results while being relatively easy to apply.

Although the models developed in this study are limited in their application as forecasting tools--primarily because of the categorical nature of the variables and the lack of variables based on objective data that can be transferred from one site to another--they can be used effectively as policy tools in planning and marketing new transportation services. For example, a planner who wished to market a new transit service could ascertain from a behavioral-intentions model that perhaps convenience, enjoyment, anticar sentiments, and being female were important factors in his or her marketing effort to build initial support for the service. Once the service was implemented, the marketing effort could focus more heavily on the convenience of the service, which was found to be the major determinant of actual use.

Clearly, these models need to be developed and tested further to substantiate their validity and usefulness. Similar data sets and models need to be collected and estimated for other sites and the results compared with those reported here. Similar models should also be developed by using objective data and be compared with the attitudinal-based models and evaluated with respect to model cost-effectiveness. Finally, work is needed in the area of attitude formation to gain a greater understanding of the factors that influence variations in attitudes (e.g., across time and individual travelers). Such knowledge would enable attitude changes to be controlled for in the models and make the models more useful for prediction purposes.

ACKNOWLEDGMENT

The research reported in this paper was sponsored by the Urban Mass Transportation Administration, U.S. Department of Transportation. We wish to thank Bruce Spear, Jesse Jacobson, and Lawrence Doxsey of the Transportation Systems Center for their helpful comments on an earlier version of the paper.

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Understanding the Effect of Transit Service Reliability on Work-Travel Behavior

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Research directed at understanding the impact of transit service reliability on work-travel behavior is described. The research focuses on the impact of service reliability on commuter decisions of modal choice and trip departure time. By working with the hypothesis that service reliability is an important attribute in explaining departure time and modal choice, measures of service reliability (tied in many cases to work-arrival-time considerations) are proposed that capture the impact of service reliability on work-travel decisions. The theory is subsequently tested empirically through the estimation of departure-time and modal-choice models by using data collected in the San Francisco Bay Area. Several interesting results emerged from the research effort. First, arrival-time

considerations have an impact on departure-time choice and on modal-choice decisions as well. Second, the arrival-time variables are not highly correlated with existing explanatory variables, which implies that existing travel demand models may not have biased coefficients but will still yield inconsistent forecasts where policy changes alter existing correlations between arrival-time conditions and independent variables in existing models. Finally, the departure-time and modal-choice decisions of commuters appear to be interrelated in a way that suggests that the problem should be structured as a nested rather than a joint choice. The implications of these results and research contributions are discussed, and directions for further research are proposed.

In recent years, increased attention has been focused on the importance of service reliability to the efficiency and attractiveness of transit operations. For the purpose of this research, service reliability is viewed as the variability of service attributes that influence the decisions of travelers and transportation operators. Since the service attribute most often associated with reliability is travel time (wait and in-vehicle time), service reliability can be considered as the travel-time uncertainty for a given trip caused by the variation in travel times experienced in day-to-day travel.

Although it is becoming apparent that service reliability is crucial in influencing both the demand for transit and the net cost of providing transit service (1), little research has been directed at understanding the effects of service reliability on traveler behavior and operator performance. The research described in this paper focuses on understanding the effect of service reliability on traveler behavior. Since commuters constitute the largest single group of travelers (and service reliability is hypothesized to have its most significant impact on this class of travelers), this study is restricted to work-travel behavior. Because work-trip frequency and destination are fixed in the short run, the analysis reduces to a study of the effect of service reliability on commuters' decisions of modal choice and trip departure time.

In developing an understanding of the impact of service reliability on work-travel behavior, a particular objective of this research is to estimate models that can explain the effects of service reliability on modal-choice and departure-time behavior. This would allow planners to conduct policy analyses of how service-reliability strategies affect modal-choice and departure-time decisions, predict peaking responses to service changes, and determine the trade-offs between policies directed at improving service reliability and those designed to improve other attributes of the system.

TRAVELERS' ATTITUDES ABOUT RELIABILITY

Several studies of the preferences of actual and potential transit users have been conducted by transportation planners in efforts to improve transit service, to evaluate demonstrations, and to formulate mathematical demand models. These studies point to the importance that travelers place on reliable transportation services. Reliability is typically associated with the attribute "arriving at the intended time" or "arriving when planned".

The survey results show arriving at the intended time to be among the most important service attributes for all travelers under a variety of travel conditions. For commuters its importance is paramount (2-4). For both work and nonwork trips, arriving at the intended time is considered more important than average time and cost (2), which are generally thought to be the dominant service attributes that affect demand. This result is also apparent in studying users of particular modes (5-8).

It should be recognized that, although the results of these surveys identify the importance of reliability-related attributes to the traveler, they do not provide data from which to assess the impacts of these attributes on traveler decision making. Thus, although it is a significant finding that travelers rank reliability-related attributes as extremely important, the survey results are limited in that they identify the need to establish a consistent set of reliability measures and analyze the impact of service reliability on travel behavior but are insufficient to provide an accurate assessment of this relation.

PREVIOUS RESEARCH

In the limited empirical work that has been directed at understanding the impact of service reliability on work-travel behavior, the departure-time decision has been modeled as conditional on modal choice, and the impact of service reliability has been examined separately for each decision level.

Early attempts to include objective measures of service reliability in modal-choice models ran into difficulty because of problems encountered in collecting accurate data (9). The inclusion of scaled reliability variables in modal-choice models has resulted in statistically significant coefficients for the reliability variables and has improved the predictive power of the models (3,10). However, the use of scaled variables poses serious questions about the validity of transferring the model for forecasting in other areas and also makes it difficult to evaluate policies of reliability improvement and to measure trade-offs of reliability investment versus investment in other transit improvement strategies. Since objective measures are likely to be monotonically related to scaled measures, past research provides motivation for developing relevant objective measures of service reliability and for measuring their impact on work-travel decisions.

Departure-time research has examined more closely the trade-off between travel times and work arrival times. Empirical work has been restricted primarily to automobile travelers, but important advances have been made in (a) the finding that travel-time uncertainty affects the probability of late arrival, (b) differentiation between traveler sensitivities to early and late arrival at work, and (c) recognition of the impact of work arrival flexibility and occupation on perceived trade-offs between travel time and schedule delay (11-12). (Schedule delay is defined here as the difference between actual arrival time and official work start time.)

Despite these accomplishments, there remain several obstacles that must be overcome. Although the significance of the trade-off between mean travel time and work arrival time has been demonstrated to some degree, the effect of travel-time uncertainty has not been completely considered, particularly in relation to traveler sensitivities to early and late arrivals that are caused by uncertainty in travel times. In addition, the potential interdependency of the decisions on modal choice and departure time has been virtually ignored. Finally, past research has been restricted primarily to a study of automobile travelers. The effect of service reliability on transit use and user departure-time decisions has not been examined.

This research effort was aimed at extending the study of service reliability and work-travel behavior by considering the interdependencies of the mode and departure-time decisions, explicitly accounting for travel-time uncertainty in these travel decisions, improving the definition of perceived loss associated with varying arrival times, and expanding the choice set to include a study of automobile, transit, and carpool commuters.

THEORY OF ROLE OF SERVICE RELIABILITY IN CHOICE OF MODE AND DEPARTURE TIME

For a given mode m and departure time d, each traveler will experience a particular travel-time distribution for his or her commute. Assuming that a commuter leaves home to travel to work at roughly the same time each day, this travel-time distribution translates directly to an arrival-time distribution at work. (The study of the commuting trip was restricted to a study of home-to-work travel only, partly because of a lack of available data on the return trip.) If we define T as the traveler's mean arrival time at work and T* as the traveler's official work start time, then a typical arrival-time distribution for a given mode and departure time might be similar to the distribution shown in Figure 1, where $F_m(t|d)$ is the probability of arriving at time t given departure time d and mode m. The figure suggests that individual commuters generally choose to arrive most of the time at or before their official work start time and usually do arrive sometime before the official start time.

Figure 1 is just an example of an individual's possible arrival-time distribution; different commuters will experience different arrival-time distributions. There would clearly be a different distribution for every combination of mode and departure time facing an individual, although it is possible that, whereas the parameters of a distribution may change, the distributional form may not vary.

In current models of travel behavior (which typically use the concept of utility theory and linearity in the parameters of the utility function in defining the impacts of service attributes), only a measure of mean travel time is included in the utility expression. Although it is apparent that there may be varying expected arrival times at work and a great deal of uncertainty about that arrival time, the specification used in current models of travel behavior does not explicitly account for either of these effects and their implications for the traveler. By not including measures that consider arrival-time implications, current models implicitly assume that travelers arrive at work when they want to and are "risk neutral" toward uncertainty in their arrival times. This implies that, for equivalent travel times, arriving at work extremely late or extremely early with equal probability is valued the same as arriving on time with certainty, which is clearly unrealistic for the majority of commuters. It also implies that travelers are indifferent as to alternatives that have the same mean arrival time but varying arrival-time distributions.

The question that arises is, Assuming that service reliability is an important input to the traveler decision-making process, how can we model this effect on commuter choice?

An appealing approach is to relate the arrival-time uncertainty to the commuter's perceived loss associated with different arrival times, since this would be a way to represent the importance of arriving at the intended time. To represent perceived loss, the notion of an arrival-time loss function is introduced.

Figure 2 shows a hypothetical arrival-time loss function l(t) (loss associated with arrival at time t, expressed in units of utility), which is based on the premise that commuters are most satisfied when they arrive at work close to their official work start time. As the commuter arrives increasingly later than the official work start time, the magnitude of the perceived loss increases, representing employment penalties that may be associated with tardiness (e.g., loss in pay, poor reputation, and negative impact on promotion). It is presumed that the penalties for being a few minutes late will be far less severe than those for arriving 15-30 min late.

Perceived loss is hypothesized to increase with early arrival as well, since the commuter could have used the extra time as leisure time at home, which is likely to be valued more than being at the office. It is important to note, however, that the magnitude of the slope of the loss function for lateness is expected to be larger than that for earliness, reflecting perceived penalties for late arrival at work that are greater than perceived penalties for not maximizing leisure time at home. It is assumed that overtime benefits, such as compensatory pay, are not available.

The loss function in Figure 2 represents just one possible functional form. While each individual has only one mean arrival-time loss function, there is reason to believe that the parameters (and form) of the loss function will vary according to each individual's occupation (i.e., clerical, management,

Figure 1. Typical commuter arrival-time distribution for a given mode and departure time.

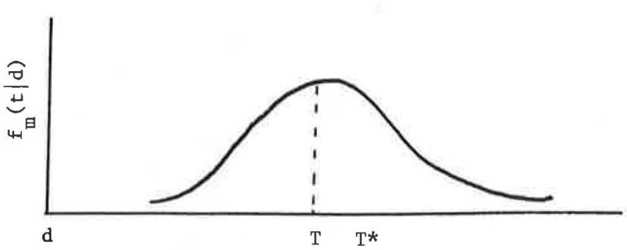
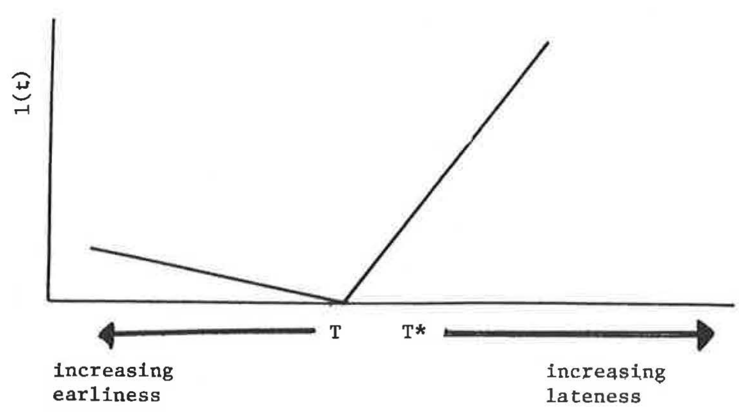


Figure 2. Arrival-time loss function.



etc.) and work flexibility. For example, a member of the clerical staff on hourly wages will have a much higher perceived loss for late arrival than a manager who works for a firm that operates a flexible-work-hours policy.

The effect of service reliability on the process of modal and departure-time choice can be defined as the expected loss for each choice alternative by using a commuter arrival-time loss function and by representing the uncertainty of arrival time by a probability density function of the arrival-time distribution. Assuming that the modal-choice decision has been resolved at the time at which a departure-time decision is made (although the choices may be interdependent), the choice of departure time can be structured conditional on modal choice being fixed. The impact of service reliability on departure time could then be defined as follows:

$$E(l|d,m) = \int_{d}^{\infty} f_m(t|d)l(t)dt \tag{1}$$

where $l(t)$ is the loss associated with arrival at time t. The expected arrival-time loss could be included in the utility specification for departure-time choice, which would result in a new departure-time utility specification.

Because of the assumed sequential structure of the problem of modal and departure-time choice, output from the departure-time model forms inputs to the modal-choice model. The information required at the modal-choice level is the optimal departure time for each mode, since travelers presumably make modal-choice decisions on the basis that they will choose to depart at the time that maximizes their departure-time utility for each mode being considered.

For the logit model form (which is used in this research), the optimal departure-utility inclusive terms to be input in the modal-choice model are derived from the departure-time model and can be expressed as follows (13):

$$D_m{}^* = \underset{d=1,I}{\operatorname{Max}} U_{d|m} = \log\left[\sum_{i=1}^{I} e^{U_{i|m}}\right] \tag{2}$$

where I is the number of alternative departure-time choices and $U_{i|m}$ is the utility for departure time i given mode m.

It should be noted that, although D* includes the effect of service reliability on work-travel time, there may be cases where commuters are sensitive to travel-time uncertainty even though the expected loss associated with arrival time is quite low. This situation might arise in the case of a traveler who likes to be in control of his or her own schedule. For this type of person, not knowing when the vehicle will arrive at the destination may be very upsetting, even though there is nothing pressing when the traveler reaches his or her destination (14,15). Furthermore, traveler exposure to infrequent but excessively long delays may also affect modal-choice decisions. These effects are represented as separate modal-reliability attributes.

The previous discussion has implications for the validity of existing models of work-travel behavior. An obvious deficiency of current models is that they do not explicitly account for service reliability (and other arrival-time considerations) and hence are clearly not sensitive to policies directed at improving service reliability. For example, if a federal agency is considering sponsoring a program to improve service reliability, there is no existing way of quantifying the expected benefits of such a program or the cost-effectiveness of supporting service-reliability strategies as opposed to fare programs or programs designed to improve mean vehicle speeds.

The omission of service-reliability variables, however, may affect more than just the availability of an analytic tool sensitive to service-reliability policy. When reliability-related variables are omitted, it is possible that the coefficient estimates of other independent variables in the utility expression may differ asymptotically from their true values because of their correlation with omitted reliability attributes (16). If this is the case, when the omitted model is used in forecasting, biases may be present that affect the accuracy of the forecast.

METHODOLOGY

Based on a review of previous research, and through the design and implementation of additional analyses, the final analysis methodology was formulated. A multistage methodology was defined in which examination of service information and loss-function analysis combined to form arrival-time variables that included reliability effects and that, in turn, were studied in the estimation of a departure-time model. Results from the departure-time model were then used in the estimation of the modal-choice model.

A sequential modeling structure was used in which departure-time choice was conditional on modal choice. Separate models were estimated for modal and departure-time choice. This structure was selected because of a belief that the decisions are interdependent in that the departure-time decision is made conditional on a modal-choice decision having been reached.

Departure time was modeled as a continuous choice by using a logit model formulation. Since alternative departure times may not be free of the independence of irrelevant alternatives (IIA) assumption implicit in logit, diagnostic tests of IIA violation were conducted. Multinomial logit was also used to estimate discrete alternatives of modal choice; one would expect there to be less correlation between error terms of the alternative modes than in the case of departure-time choice, although diagnostic tests of IIA violation were conducted on the modal-choice model as well.

The range of departure-time choice was such that expected arrival times varied from 42.5 min earlier than the official work start time to 17.5 min later than the official work start time, to conform with available departure-time data. Modal-choice alternatives were restricted to single-occupant automobile, transit, and carpool.

The Urban Travel Demand Forecasting Project (UTDFP) data set collected in the San Francisco Bay Area was selected for this research effort, primarily because it contains detailed level-of-service data (network-computed, which may introduce some bias) for each individual for various modes at different peak-period departure times, in addition to more traditional travel-behavior and socioeconomic data. The UTDFP sample of 991 observations was reduced for this study by omitting the following:

1. Park-and-ride users (of which there were few),
2. Observations where the respondent's official work hours begin outside the morning peak (because of an interest in studying the morning peak period only),
3. Nonworkers (because this is a study of work travel only) and part-time workers (because they would be facing off-peak return-trip conditions for which data did not exist),
4. Observations where the respondent has an ex-

pected work arrival time more than 40 min earlier or more than 15 min later than his or her official work start time (to eliminate commuters who have regular nonwork activities that result in their extreme arrival-time behavior), and

5. Observations for which data were incomplete.

This resulted in an estimation sample of 425 respondents.

A generalized loss function was estimated by using a small sample of respondents (17). Many of the travel-time data used in this research were derived from previous studies of automobile, transit, and carpool travel or were assumed because of the lack of available literature on the subject. In many cases, previous studies were based on data that did not adequately represent day-to-day service levels experienced by travelers. As a result, the data used in this research suffer from these problems, and a future research priority should be to collect better data on reliability.

Departure-Time Model

The departure-time period of study involved expected arrival times that ranged from 42.5 min earlier than the official work start time to an expected arrival 17.5 min later than the official work start time. Twelve departure-time alternatives were defined for the departure-time model. Each alternative represented a 5-min departure-time interval, and the data input for each alternative represented a discrete approximation of departure attributes for the continuous interval. Since the discrete observation for each interval consisted of information at the mean point of the interval, 12 discrete alternatives were defined as follows: 40E = departure such that the expected arrival is 37.5-42.5 min earlier than the official work start time, 35E = departure such that the expected arrival is 32.5-37.5 min earlier than the official work start time, etc., to 15L = departure such that the expected arrival is 12.5-17.5 min later than the official work start time. It was assumed that the frequency of transit service was sufficiently high during the peak period that transit users were faced with the full set of alternative choices. In cases where headways are long, the departure-time choices of transit users can become somewhat discontinuous.

A two-phase approach was used to select the most appropriate departure-time model. The initial phase consisted of selecting variables that, a priori, made intuitive sense as explanatory variables of departure time. These variables are defined below:

TIME = total travel time;
EARLOSS = early-arrival expected loss;
LATELOSS = late-arrival expected loss;
FLEXON = 1 if can be late to work (on-time alternative), 0 otherwise;
FLEXLATE = 1 if can be late to work (late alternatives), 0 otherwise;
ADUM = 1 if automobile drive alone is chosen mode, 0 otherwise;
BDUM = 1 if transit is chosen mode, 0 otherwise;
BRIDGE = 1 if transit user who crosses Bay Bridge to get to work, 0 otherwise;
INCOME = 1 if annual earnings \$5000 or less (1972 dollars), 0 otherwise;
AGE = 1 if over 50 years of age, 0 otherwise;
OCC1 = 1 if occupation is professional/technical or management/administration (extremely early alternatives), 0 otherwise;
OCC2 = 1 if occupation is professional/technical or management/administration (slightly early alternatives), 0 otherwise;
ONTIME = 1 if arrival between 2.5 min before and 2.5 min after official work start time, 0 otherwise;
EARLY1 = 1 if arrival earlier than 17.5 min before official work start time, 0 otherwise;
EARLY2 = 1 if arrival between 17.5 and 2.5 min early, 0 otherwise;
LATE1 = 1 if arrival between 2.5 and 7.5 min after official work start time, 0 otherwise; and
LATE2 = 1 if arrival between 7.5 and 12.5 min after official work start time, 0 otherwise.

The variables were generically specified and were introduced one at a time into the departure-time specification. For the addition of each new variable, a logit model was estimated, and the results were examined for statistical significance, proper signs, and the possibility of different independent variables explaining similar effects in the model (by comparing the magnitude and statistical significance of the suspected variables when both were included in the same specification). This process was repeated several times until all variables had been considered. During the initial phase, variables were only entered into alternatives where, a priori, one could justify their presence. A number of constants were also specified in the model to represent omitted effects. Because of the size of the departure-time choice set, departure-time alternatives were assigned group constants.

In the second phase, the variables in the final phase 1 model were individually tested in alternative specifications in an effort to refine the model specification. The "best" departure-time model was selected after the phase 2 analysis.

Tables 1 and 2 give the selected specification and estimation results for the departure-time model. All of the independent variables have the expected sign and are significant (t-statistic with an absolute value of ≥ 1) with the exception of some of the constants.

It was found that the arrival-time variables, EARLOSS and LATELOSS, have significant coefficients and appear to lend additional explanatory power to the departure-time model. Since the arrival-time variables consist of loss derived from arriving at work at a particular time and the uncertainty of arrival about that time, the estimation results imply that the implications of when the traveler will arrive at work and the uncertainty associated with it, as well as the perceived penalties for arriving about that particular time, are a departure-time consideration. However, in separate tests it was found that the effect of loss derived from arrival-time considerations consists primarily of loss derived from arriving at a particular time and much less so from the uncertainty of arrival about that time. This result is somewhat surprising but may perhaps be attributable to the quality of the data used in estimation (leading to lack of variation in the reliability data) or methodological problems rather than an indication that travel-time uncertainty is truly of marginal importance.

A further step in the departure-time research was to compare models estimated with and without the reliability-related variables, EARLOSS and LATELOSS. The estimation results for the model from which reliability-related variables were omitted appear in Table 3 and were compared with the results for the selected model (Table 2).

Table 1. Definition of alternatives for selected departure-time model.

Variable	40E	35E	30E	25E	20E	15E	10E	5E	On Time	5L	10L	15L
TIME	X	X	X	X	X	X	X	X	X	X	X	X
EARLOSS	X	X	X	X	X	X	X	X	X	X	X	X
LATELOSS	X	X	X	X	X	X	X	X	X	X	X	X
FLEXON									X			
FLEXLATE										X	X	X
ADUM									X			
BDUM	X	X	X	X	X							
BRIDGE	X	X	X	X	X	X	X	X				
INCOME						X	X	X	X			
AGE	X	X	X	X	X	X	X	X				
OCC1	X	X	X	X	X							
OCC2						X	X	X				
ONTIME									X			
EARLY1	X	X	X	X	X							
EARLY2						X	X	X				
LATE1										X		
LATE2											X	

Note: X denotes that the variable listed in the stub column of the table is entered into the utility for the alternative listed at the top of the table.

Table 2. Estimation results for selected departure-time model.

Variable	Coefficient Estimate	Asymptotic Standard Error	Asymptotic t-Statistic
TIME	-0.041	0.032	-1.279
EARLOSS	-3.168	2.296	-1.380
LATELOSS	-25.728	23.411	-1.099
FLEXON	1.084	0.227	4.780
FLEXLATE	3.162	0.756	4.184
ADUM	0.496	0.269	1.846
BDUM	-0.794	0.319	-2.487
BRIDGE	2.764	1.063	2.600
INCOME	2.042	1.032	1.979
AGE	1.104	0.308	3.583
OCC1	-0.492	0.277	-1.774
OCC2	-0.575	0.250	-2.304
ONTIME	-3.606	6.894	-0.523
EARLY1	-6.483	8.734	-0.742
EARLY2	-5.874	8.717	-0.674
LATE1	-5.211	4.018	-1.300
LATE2	-2.880	2.062	-1.397

Note: Log likelihood = -820.974, L(constants) = -875.846, L(0) = -1056.082, number of observations = 425, and number of cases = 5100.

Table 3. Results for model from which reliability-related variables were omitted.

Variable	Coefficient Estimate	Asymptotic Standard Error	Asymptotic t-Statistic
TIME	-0.039	0.031	-1.271
FLEXON	1.072	0.226	4.736
FLEXLATE	3.160	0.756	4.181
ADUM	0.648	0.224	2.900
BDUM	-0.724	0.314	-2.304
BRIDGE	2.774	1.062	2.612
INCOME	2.055	1.032	1.991
AGE	1.090	0.308	3.543
OCC1	-0.467	0.277	-1.690
OCC2	-0.564	0.249	-2.261
ONTIME	3.741	0.757	4.938
EARLY1	2.647	0.754	3.510
EARLY2	3.444	0.748	4.605
LATE1	-0.851	0.533	-1.597
LATE2	-0.683	0.500	-1.365

Note: Log likelihood = -822.719, L(0) = -1056.082, number of observations = 425, and number of cases = 5100.

The major difference between the two models is the values of the constants. There is very little change in the coefficient value of the other explanatory variables. What is particularly interesting is that the coefficient for mean travel time changes by only 5 percent. These results present a strong argument that the arrival-time variables in the departure-time model are not highly correlated with variables used in existing models and that most of the implications of on-time arrival and related uncertainty are omitted effects absorbed into constants in existing models. The implications of this finding are that explanatory variables in existing models may not have overly biased variable coefficients because of the omission of arrival-time variables, but existing models will still provide inconsistent forecasts for any policy changes that alter the existing correlation between arrival time and variables in existing models. (It is also interesting to note that a χ^2 test conducted on the hypothesis that the loss variables have coefficients equal to zero could not be rejected at the 0.05 level.)

Statistical tests were conducted to see whether the selected departure-time model differed significantly from a uniform probability departure-time model or from a departure-time model consisting of only constants in the specification. For both the uniform probability model and the model consisting of only the constants, the hypothesis that the model is the same as the selected departure-time model is easily rejected at the 0.05 level, which implies that the explanatory variables are adding statistical significance to the model.

A validation test was also conducted on subsamples of the sample used for model estimation to determine whether the selected model was properly specified. The sample was separated into single-occupant-automobile, transit, and carpool users, and chosen departure times were predicted for each modal group by using the departure-time models. The predictions were obtained by applying the model to each individual in the sample for the purposes of predicting individual probabilities of selecting particular departure times. These results were compared with actual chosen departure times reported in the UTDFP data set and did validate the reasonableness of a selected departure-time model.

Diagnostic tests based on conditional choice (18) were also conducted on the selected departure-time model to determine whether it violated the underlying logit assumption of IIA. The results indicated that use of the logit form to estimate the selected departure-time model cannot be rejected.

Table 4. Definition of alternatives for modal-choice model.

Variable	Automobile	Transit	Carpool
ACON	X		
BCON		X	
COST/WAGE	X	X	X
$\hat{D}$*	X	X	X
SEX	X		
FLEXARR		X	
DENSITY		X	X
CLOTRANS		X	
AUTDRA	X		
AUTDRC			X
AUTWKA	X		
AUTWKC			X
BAY		X	
HOMELOC2		X	
HOMELOC3			X
HEADWAY		X	

Note: X denotes that the variable listed in the stub column of the table is entered into the utility for the modal alternative listed at the top of the table.

Table 5. Estimation results for modal-choice model.

Variable	Coefficient Estimate	Asymptotic Standard Error	Asymptotic t-Statistic
ACON	-0.804	0.659	-1.220
BCON	2.875	0.656	4.378
COST/WAGE	-0.044	0.020	-2.230
D*	0.572	0.292	1.962
SEX	0.513	0.261	1.967
FLEXARR	0.480	0.332	1.448
DENSITY	0.003	0.001	3.071
CLOTRANS	0.874	0.432	2.021
AUTDRA	3.248	0.812	4.000
AUTDRC	1.267	0.680	1.863
AUTWKA	1.432	0.530	2.704
AUTWKC	1.375	0.523	2.629
BAY	1.014	0.532	1.905
HOMELOC2	0.981	0.407	2.411
HOMELOC3	0.386	0.263	1.468
HEADWAY	-0.104	0.037	-2.851

Note: Log likelihood = -299.429, L(constants) = -400.8, L(0) = -450.61, number of observations = 425, and number of cases = 1235.

Modal-Choice Model

A multinomial logit model of modal choice was estimated for the alternatives of single-occupant automobile, transit, and carpool. As in the case of the departure-time model, selection of the "best" modal-choice model specification was based on intuitive reasoning, the coefficients having the expected sign, the statistical significance of the coefficients (in terms of t-statistics), and the overall statistical fit of the model (in terms of log likelihood).

The independent variables used in the selected modal-choice model are defined below:

ACON = 1 if automobile drive alone, 0 otherwise;
BCON = 1 if transit, 0 otherwise;
COST/WAGE = total cost/after-tax wage rate;
$\hat{D}$* = log of the denominator of the estimated departure-time model;
SEX = 1 if male, 0 if female;
FLEXARR = 1 if can be late to work, 0 otherwise;
DENSITY = employment density of work location;
CLOTRANS = 1 if choosing a house close to transportation was very important, 0 otherwise;
AUTDRA = automobiles per licensed driver (drive alone);
AUTDRC = automobiles per licensed driver (carpool);
AUTWKA = automobiles per worker (drive alone);
AUTWKC = automobiles per worker (carpool);
BAY = 1 if cross Bay Bridge to work, 0 otherwise;
HOMELOC2 = 1 if home location is central business district (CBD) (transit), 0 otherwise;
HOMELOC3 = 1 if home location is CBD (carpool), 0 otherwise; and
HEADWAY = peak transit headway.

The estimation results for the model are given in Tables 4 and 5. All of the estimated coefficients have the expected signs, and all are statistically significant.

Statistical tests were conducted to see whether the selected modal-choice model differed significantly from a uniform probability modal-choice model or from a choice model consisting of only the constants in the specification. For both the uniform probability model and the model consisting of only the constants, the hypothesis that the reduced model is the same as the selected modal-choice model is easily rejected at the 0.05 level.

The "value of time" is often derived from model results and used as a test of whether the model estimates are plausible. Value of time is computed by examining the coefficients for the variables of mean travel time and travel cost in the model specification. However, for the model structure adopted for this research, the mean-travel-time variable appears in the departure-time model whereas the travel-cost variable is divided by the wage rate and appears in the modal-choice model. Some simplifying assumptions are required to compute the value of time.

The observable utility for modal choice can be written as follows:

$$V_m = \ldots -0.044\ \mathrm{TCPTWR}_m + \ldots\ 0.597\ \hat{D}_m{}^* \tag{3}$$

Since $\hat{D}^*_m = \ln e^{V_{\Sigma d|m}}$, if we assume that all departure-time utilities have the same attributes, then

$$\begin{aligned}\hat{D}_m{}^* &= \ln 12 \exp(\bar{V}_{d|m})\\ &= \ln 12 + \bar{V}_{d|m}\\ &= \ln 12 + (-0.041\ \mathrm{TIME}_m + \ldots)\end{aligned} \tag{4}$$

Thus,

$$V_m = \ \ldots\ -0.044\ \mathrm{TCPTWR}_m + 0.597\,(\ln 12 - 0.041\ \mathrm{TIME}_m \ldots) \tag{5}$$

Now that all variables of interest are in the same expression, the value of time can be derived as

$$(dV_m/dt)/(dV_m/dc) = 0.597(-0.041)y/-0.044 \tag{6}$$

where y is the after-tax wage rate expressed in cents per minute. To convert y to dollars per hour, we multiply by 0.6, which results in

$$\text{Value of time} = 0.597\,(-0.041)\,(0.6)y/-0.044 = 0.334y \tag{7}$$

where y is the wage rate in dollars per hour. This result compares quite favorably with the accepted ballpark commuter value of time of 35-40 percent of the hourly wage rate and helps to support the validity of the estimated models.

Three conditional choice tests of IIA violation were conducted on the modal-choice model, and one alternative mode was eliminated from each test. The null hypothesis is that the IIA assumption holds;

the results showed that, for all tests, the hypothesis cannot be rejected at the 0.05 level.

Reliability-related attributes are represented in the modal-choice decision in the departure-time inclusive term variable ($\hat{D}^*$) and the peak transit headway variable (HEADWAY). $\hat{D}^*$ (which denotes the estimate of D^*) is the term computed from the estimated departure-time model that represents the utility of the optimal departure time for each mode. This enters into the modal-choice model because of the belief that, when a commuter makes a modal-choice decision, he or she takes account of the optimal departure-time circumstances for each mode. Recall that D^* is the log of the sum of the exponentiated utilities for the departure-time alternatives. Thus, D^* includes explanatory effects of work flexibility, occupational characteristics, income, age, Bay Bridge travel, travel time, and arrival-time expected loss as they relate to departure-time choice.

It is well known that transit travel-time variance can be related to the variance of the headway distribution and that headway variance can be related to mean headway. Therefore, it was felt that peak transit headway might be a good proxy for uncertainties independent of arrival-time considerations. Furthermore, it was felt that the frequency of excessively long delays might also be related to the peak transit headways. Thus, peak transit headway was included in the transit alternative to represent those previously omitted transit reliability problems that are not present in automobile-related modes. It was recognized, however, that the headway variable might also serve as a proxy for other omitted transit effects (i.e., discontinuities of transit service) related to transit headway.

Three rather interesting research results emerge from an examination of the modal-choice model. The first is that the model provides insight into the interdependence of commuters' departure-time and modal-choice decisions. For a nested logit model of departure time and modal choice, the coefficient for the inclusive term D^* provides information on the random component in the modal-choice specification, ε_m (19). If the coefficient for D^* is equal to one, Var $(\varepsilon_m) = 0$, and the only random component present in the model is ε_{dm}, the joint random component of the conditional departure-time decision. If this were the case, a joint departure-time and modal-choice structure would be appropriate.

The estimated coefficient is equal to 0.572, with a standard error of 0.292. Use of a t-test shows that one can be 85 percent confident that the estimated coefficient differs from one. However, the true standard error of the coefficient for D^* is likely to be higher than 0.292, since $\hat{D}^*$ itself is an estimate subject to error. Nevertheless, it would still seem likely that Var $(\varepsilon_m) \neq 0$. This result suggests that modal and departure-time decisions should be structured as a nested choice rather than as a joint choice.

The second result is inferred from the significance of the headway variable. Recall that this variable is a proxy for transit unreliability independent of arrival-time considerations and the frequency of excessive delays (as well as a proxy for other omitted transit effects). The significance of the headway coefficient suggests that these modal-reliability attributes may have a separate and significant effect on the modal-choice decision.

The third result is derived from examination of the estimated coefficient for the variable FLEXARR in the modal-choice model. This variable represents the individual's perceived arrival-time flexibility. The statistical significance of this variable in the modal-choice model suggests that arrival-time considerations affect modal-choice as well as departure-time decisions.

SUMMARY

This research has focused on understanding the impact of service reliability on work-travel behavior. Since work-trip frequency and destination are fixed, the research problem was narrowed to a study of the impact of service reliability on commuter decisions in regard to modal choice and trip departure time. The problem was further restricted by studying only home-to-work travel, in part because of the lack of available data on the afternoon (evening peak) return trip. By working with the hypothesis that service reliability is an important attribute in explaining departure time and modal choice, measures of service reliability were proposed that capture the impact of this attribute on work-travel decisions. The theory was subsequently tested empirically through the estimation of departure-time and modal-choice models.

A number of conclusions were drawn based on the departure-time model results and related analyses. It was found that reliability-related arrival-time variables have significant coefficients and appear to lend additional explanatory power to the departure-time model. Since the arrival-time variables consist of loss derived from arriving at work at a particular time and the uncertainty of arrival about that time, the estimation results imply that the implications of when the traveler will arrive at work and the uncertainty associated with it, as well as the perceived penalties for arriving about that particular time, are a departure-time consideration. It is also apparent that this effect arises primarily from traveler sensitivity to arriving at a particular time and much less so from the uncertainty of arrival about that time. This result is somewhat surprising but may perhaps be attributable to the quality of the UTDFP data and reliance on previous studies that used inadequate data (either of which might lead to the lack of variation in the reliability data) or other methodological problems rather than an indication that reliability is truly of marginal importance.

Another important finding was that reliability-related arrival-time variables in the departure-time model are not highly correlated with explanatory variables used in existing models and that most of the implications of on-time arrival and related uncertainty are omitted effects absorbed into constants in existing models. This implies that the independent variables in existing models may not have biased coefficients because of the omission of reliability-related arrival-time variables, but existing models will still provide biased forecasts for any policy changes that alter the existing correlation between arrival-time conditions and independent variables in existing models.

Three rather interesting research results emerged from an examination of the estimated modal-choice model:

1. Departure time and modal choice appear to be interrelated in a way that suggests structuring departure-time and modal-choice decisions as a nested choice rather than as a joint choice.
2. It appears that arrival-time considerations affect modal-choice decisions as well as departure-time decisions.
3. The significance of the estimated headway coefficient suggests that additional reliability considerations independent of arrival-time considerations may have a significant effect on modal-choice decisions. However, the explanatory effect of this

variable may also be attributable to other transit effects that were omitted.

Through the development of a sequential departure-time and modal-choice decision structure and the subsequent estimation of departure-time and modal-choice models, the interdependencies of these decisions can be represented in the planning process. This gives planners the capability of predicting both modal shift and peaking responses to service changes.

The estimated models should also enable planners to consider how strategies for improving service reliability affect travel decisions. Since reliability-sensitive variables were not previously included in travel demand models, until now there was no way to analyze the potential impacts of reliability-related policies. Furthermore, use of these models should lead to improved forecasts in general, since the explanatory effect of a previously omitted variable will be included in the model.

Another contribution has been the definition and use of objective measures of service reliability. Past research had demonstrated that the inclusion of scaled reliability variables was statistically significant, but questions were raised concerning the transferability of scaled measures and how they could be used to evaluate reliability improvement policies. The measures developed in this research are not only behaviorally appealing but should also alleviate the problems encountered in the use of scaled measures.

It is important, however, to note that the results and implications of this research should not be interpreted as conclusive but rather as indicative of directions transportation researchers should pursue more vigorously in future travel demand research. In particular, future research should be directed at improving the quality of data collection on reliability, developing simpler measures of reliability, studying how the problem is affected by discontinuities in transit service and return-trip reliability considerations, examining the impact of reliability on nonwork trips, and conducting additional model validation efforts.

ACKNOWLEDGMENT

The research reported in this paper was supported in part by the Office of Planning Methods and Support of the Urban Mass Transportation Administration (UMTA), U.S. Department of Transportation. I am grateful for contributions made by Moshe Ben-Akiva, Steven Lerman, Marvin Manheim, Howard Slavin, David Rubin, Don Ward, and Nigel Wilson as well as other staff members of UMTA and the Transportation Systems Center. The efforts of Jo Ann Grega in typing the original manuscript are also much appreciated.

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Laboratory-Simulation Versus Revealed-Preference Methods for Estimating Travel Demand Models

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The results are reported of an empirical comparison of two different approaches to deriving models of travel-choice behavior: models based on revealed choices and models based on responses to controlled scenarios. In particular, interest centers on the results of a longitudinal study in which both methods were used to derive models of modal choice for a random sample of persons living in two Iowa cities over a five-month period during 1979. Models were compared on the basis of (a) predictive ability and (b) consistency of the parameter estimates over time and space. Specifically, the laboratory-derived models were shown to be equal to conventional models in terms of predictive ability for revealed-behavior data. Moreover, the parameter estimates of the laboratory-derived models were for the most part temporally and spatially stable and were consistent with the parameter estimates of revealed-choice models. Finally, the laboratory models provided a more cogent interpretation of the modal-choice process than did the revealed-choice models.

Choice models based on the revealed or observed choices of individuals have historically received the most attention in the area of research and application in travel-choice modeling (1-3). Recently, attention has been given to the possibility of deriving models based on individuals' responses to hypothetical situations that simulate variation in travel-choice attributes (4-6). Both methods have advantages and disadvantages. Revealed-behavior, or econometric, choice models have high face validity in that they are calibrated to real data; models based on scenario responses have lower face validity in that choices are made in hypothetical, not real, situations. Revealed-behavior models suffer from a lack of controls in that variables may have limited ranges, attributes may be highly correlated (e.g., times and costs), and some choice alternatives may not yet exist; laboratory-simulation models can be designed to cover broad ranges of choice attributes, can reduce or eliminate attribute intercorrelations, and can include choice alternatives that do not now exist. Revealed-behavior models must rely on assumed functional forms that, at best, can be tested only weakly and must cope with biases introduced by unobserved attributes and/or other misspecification problems; laboratory-simulation models, of course, can control for these potential sources of bias by appropriate design techniques before data are collected.

Clearly, therefore, the approaches are complementary: Each is strong where the other is weak, and vice versa. The intent of this paper is not to argue the virtues of one against the other but to compare aggregate model forms derived from the two methods to see whether an even closer relation exists than has previously been assumed. In particular, we will derive parallel models from two sets of data obtained from the same individuals. We wish to compare the coefficients derived from the two approaches both separately and globally. We shall assume throughout that the revealed-behavior data constitute the "true" state of the world, but, of course, there is no guarantee that this is correct.

Revealed-behavior data require an observation of what was chosen (or how often it was chosen) and what was rejected (or how often it was not chosen), plus actual measurements of associated travel attributes and interpersonal factors. Models are calibrated directly to these data, and statistical tests determine their "adequacy". The true validity of these models, however, lies in their ability to reproduce other choices not drawn from the calibration sample or an associated "hold-out" sample. Results in transferability tests have been mixed (7-9), and few would argue that overwhelming success has been achieved.

In contrast, laboratory-simulation methods do not require revealed-behavior data for calibration. They do, however, require real data for initialization. That is, given a set of initial conditions described by a vector of attribute measures and interpersonal measures, the laboratory-simulation models "forecast" the choice behavior of the individual. The difference is that the simulation method calibrates its models to the laboratory response data and not to real choice data. The validity issue for these models, therefore, is their ability to recover parallel real choice data as well as to transfer successfully. The first of these tests is the most obvious and the one that is examined in this paper; later papers will explore the issue of transferability.

The strongest argument for the comparability of the two methods is that they are the same in philosophy and theory and that there are only minor analytic differences; they differ in the type of data obtained. In fact, the theoretical similarities have recently led some researchers to propose that the above problems need not be inherent in modeling social behavior (5,10); that is, econometric models have problems because of data, not because of theory. In particular, the problems discussed earlier could be largely overcome if it were possible to conduct controlled social experiments in which individuals could be observed making repeated choices in a variety of situations that exist now and that might exist in the future. Such data, therefore, would permit both the estimation of models at the individual level and forecasts of likely responses to system changes over time.

Given that it is practically infeasible to conduct such experiments in the "real world", a second alternative is to design simulation experiments in which individuals are confronted with a number of hypothetical choice scenarios in which they are required to respond in the way they would be most likely to if they were placed in that situation. Individual choices (or other responses) can be analyzed given sufficient observations for each individual.

Despite consistent evidence amassed over the past five years (5,10-12) that models built on responses to hypothetical scenarios are accurate predictors of real behavior in analogous situations, little attention has been directed to this work. This situation prevails despite the continuing failure of econometric models to predict very well to any data other than those from which they are calibrated (7-9). Of course, the noneconometric approach contradicts the established dogma of "revealed preferences" being the only legitimate data for econometric analysis, and therein lies the crux of the matter. The counterarguments typically run as follows (13):

Yes, in principle the limitations of revealed preference methods could be circumvented, but what guarantee is there that the way people behave in hypothetical situations bears any resemblance to the way they behave in the "real world".

As mentioned earlier, however, this argument does not fit the facts because so-called "laboratory" models have enjoyed surprising, if unheralded, success (5,10,11). Hence, there seems to be strong evidence that models derived from responses to hypothetical situations can predict actual behavior very well. Previous research examples include modal choice, store selection, and residential location (4,12).

This evidence, however, does not imply that laboratory-simulation methods are better than more conventional revealed-behavior methods. It does suggest, however, that they deserve equal attention and that they can no longer be dismissed as unacceptable on "religious" and not scientific grounds. Although few comparisons with revealed-behavior methods have been undertaken to date, there is some evidence to suggest that both methods may be comparable from a purely predictive standpoint (5,11).

This paper attempts to provide a comparison based on data derived from a two-city, longitudinal study of modal-choice behavior. The study design is described in the sections that follow. The background and results of the investigation are described in detail, and the implications of the results for current research in travel-choice modeling are discussed.

METHOD OF APPROACH

Overview

Comparison of econometric and laboratory-type simulation methods requires parallel data-collection efforts in which identical data are obtained. As part of a longitudinal study of traveler mode preferences and choices in two cities in the state of Iowa--Iowa City (a university town of about 50 000 population) and Cedar Rapids (a city of about 100 000 population)--parallel data necessary for the conduct of such a test were obtained. The data collection was done in survey form and consisted of two main sections of interest: (a) an experimental design or simulation section, in which respondents were asked to indicate mode choices for each of a number of hypothetical scenarios, and (b) a current-behavior section, in which respondents were asked to provide information about their current travel habits.

The Simulation

The simulation section comprised a set of 30 hypothetical bus-automobile scenarios that consisted of different combinations of levels of 10 mode attributes: (a) automobile parking cost, (b) automobile travel time, (c) gasoline cost, (d) bus fare, (e) bus travel time, (f) walking distance from home to the closest bus stop, (g) walking distance from the closest bus stop to the work destination, (h) frequency of bus service, (i) bus crowding, and (j) season of the year (survey 1) or gasoline availability (survey 2). Each of these 10 variables was assigned three levels reflective of past, current, and likely future conditions. The attributes and their levels and typical resulting scenarios are given in Table 1.

There are 3^{10} possible combinations of these attribute levels in a complete factorial enumeration. From this total, a set of 405 combinations was selected that have the property of permitting the derivation of orthogonal estimates of all main and two-way interaction terms in a regression-type model. Fifteen different sets of 27 combinations each were created to produce survey designs that were manageable in size for respondents to complete. Each of the 15 sets of 27 combinations has the property of being a main-effects plan--i.e., permitting estimates of all main effects, assuming negligible interactions.

Three common treatment combinations were added to each of the sets of 27 to ensure that all respondents faced some common items. These combinations were (a) all attributes favoring bus, (b) all attributes favoring automobile, and (c) all attributes at middle levels. Hence, all respondents were required to evaluate 30 hypothetical bus-automobile scenarios.

The hypothetical modal-choice section was further divided into (a) a category ratings or judgment task, in which respondents estimated on a 1-20 scale the percentage of the time that they would use the automobile to travel to work in each scenario (1 = 0-5 percent, ..., 20 = 95-100 percent, and (b) a choice task, in which respondents were asked to indicate which of 11 possible modes (bus, automobile

Table 1. Attributes, attribute levels, and sample scenarios.

	Automobile Situation			Bus Situation						
Scenario	Parking Costs (¢/h)	Travel Time (min)	Gasoline Cost ($/gal)	Fare (¢)	Travel Time (min)	Walking Distance from Home to Bus Stop (blocks)	Frequency of Service (min)	Walking Distance from Work to Bus Stop (blocks)	Crowding	Gasoline Situation
1	Free	5	0.85	50	27	10	60	10	Standing room only	No waiting, no limit
2	10	15	1.25	30	17	4	30	4	Share seat	No waiting, 7-gal limit
3	25	25	1.75	10	7	1	15	1	Seat by yourself	Thirty-min wait, 7-gal limit
4	25	15	1.75	10	27	1	15	10	Share seat	No waiting, no limit
5	Free	5	1.75	50	27	10	60	1	Seat by yourself	No waiting, no limit
6	10	15	1.75	10	7	1	60	4	Seat by yourself	No waiting, 7-gal limit
7	Free	25	1.75	30	17	4	30	1	Share seat	No waiting, 7-gal limit
8	25	5	1.75	50	17	10	15	10	Standing room only	No waiting, 7-gal limit
9	Free	25	0.85	50	27	1	15	4	Share seat	No waiting, 7-gal limit
10	25	25	1.75	30	7	4	15	10	Seat by yourself	Thirty-min wait, 7-gal limit
11	Free	25	1.25	10	7	10	60	10	Share seat	No waiting, 7-gal limit
12	10	25	1.25	10	17	10	15	1	Standing room only	No waiting, no limit
13	25	15	1.25	50	17	4	30	4	Share seat	No waiting, no limit
14	Free	5	1.25	30	17	1	60	10	Seat by yourself	No waiting, no limit
15	Free	15	0.85	30	17	10	30	4	Standing room only	Thirty-min wait, 7-gal limit

alone, etc.) they would be most likely to use to travel to work or (for university students) to school in each scenario. Respondents were assigned to each of these tasks on an equal probability basis by random number assignment.

Current-Behavior Data

The second section of the survey requested individuals to indicate which mode they had used to travel to work or school that day and how many times (out of 40 possible) in the past month they had used the bus, the car, and other modes. They were then requested to supply information on each of the 10 scenario variables for a typical work or school trip. All respondents supplied this information regardless of the task they completed in the first section.

Administration of Surveys

Virtually identical surveys were administered during April 1979, prior to the large rise in gasoline prices, and in August-September 1979, after the price rise. September surveys were slightly changed in two respects:

1. Gasoline prices were \$0.18, \$0.22, and \$0.26/L (\$0.70, \$0.85, and \$1.00/gal) in survey 1. Because the prevailing actual level was \$0.28/L (\$1.05/gal) by the time survey 2 was administered, they were changed to \$0.22, \$0.33, and \$0.46/L (\$0.85, \$1.25, and \$1.75/gal).
2. Season of the year was found to have little systematic effect in survey 1 and was replaced with a description of the current gasoline situation: (a) no waiting and no limit, (b) no waiting and a 26-L (7-gal) limit, and (c) a 30-min wait and a 26-L limit. (The survey forms themselves expressed all levels in U.S. customary units.) These levels were representative of the range prevailing in Iowa at the time. No other changes were made.

In both surveys, respondents were initially contacted by telephone before they were mailed copies of the survey. In survey 1, of 800 persons contacted in the two cities, 263 usable questionnaires were returned. In survey 2, 1493 persons were contacted, and 516 usable questionnaires were returned.

ANALYSIS

Overview

Analytic interest centers on a comparison between the laboratory-simulation results based on the scenario responses and the revealed-behavior results based on the reported modal-choice behavior of the respondents. This paper focuses entirely on aggregate results; other reports will deal in detail with disaggregate results. The dependent variables of concern are (a) the scenario ratings data, or respondents' estimates of the likelihood of using the automobile; (b) the scenario choice data concerning choice between automobile and bus; and (c) respondents' reports of recent past automobile and bus choices.

All of the aforementioned dependent variables may be regarded as continuous for the purposes of this study. In particular, the ratings data can be converted to "probability" estimates by associating each category with the corresponding midpoint of the relative frequency or percentage-of-time range; thus, 1 = 0-5 percent = 0.025, ..., 20 = 95-100 percent = 0.975. These data refer to the percentage of time that automobile would be chosen. A second, different scale estimate can be obtained by tabulating the relative frequency of responses in categories less than 10, the midpoint of the category scale. In effect, this scale estimates the relative frequency of a response "likely to take other than automobile." We interpret this to mean bus, although we realize that there are some other choices involved. Likewise, the choice data can be separately analyzed by tabulating the relative frequency of choices of any of the automobile-related modes and bus. Thus, there are four dependent variables that can be analyzed in the aggregate for the scenario data--two to represent bus choice and two to represent automobile choice.

Collectively, the four dependent variables observed as the choice outcome of the scenarios have a corresponding dependent variable in the reported choice data. Attention in this study centers on the relative frequency of work or school trips reported by the respondents and the respondents' own reports of the real-world levels of the scenario variables. In fact, these are theoretically parallel sets of data because both dependent variables are assumed to be conditional on the values that individuals believe the attributes to have. In this instance, the relation, if any, with physically measurable attribute levels is inappropriate as a comparison, although it will be of interest in future research. Moreover, this relation can be directly assessed by using the data at hand. Nonetheless, it is important to realize that the scenarios describe the levels that individuals believe attributes to have; respondents must believe the attribute levels to be true because we as investigators tell them they are true. Thus, the appropriate attribute comparisons are with reported or believed attribute levels. Other research will examine the relation between physically observable attribute levels and reported levels (14).

Model Forms

The model forms to be estimated are logit-transformed multiple linear regression equations. It is important to note that each model incorporates attributes of competing modes. Thus, we estimate

$$\ln [R_j/(1 - R_j)] = b_{0j} + \sum_k b_{kj} X_k + \epsilon_j \tag{1}$$

where

$\ln [R_j/(1 - R_j)]$ = logit of the scenario response transformed to the interval (0,1) for mode j;
b_{0j}, b_{kj} = regression coefficients for the 0th, 1st, ..., kth attributes, X_k; and
ϵ_j = a random disturbance, assumed to conform to the usual assumptions of classical, fixed-effects regression.

Equation 1 involves all linear and squared terms and all two-way interactions of the 10 attributes. The 450 observations divided into 15 subsets of 30 scenarios were specifically designed a priori to permit the independent estimation of all of these terms at the group level, assuming negligible higher-order effects. It is important to realize that it is always possible to know a priori exactly what effects can be estimated from given experimental designs; hence, one can design sets of scenarios to ensure that various terms of interest in the multiple linear regression or analysis-of-variance models can be estimated with known precision at known levels of power. This is, of course, fundamentally different from a typical econometrics analysis, which, practically speaking, can never know which terms are truly estimable, with what precision, or with what power. Thus, it must rely on potentially weak tests based on a priori assumptions about effects. Our approach permits the exact determination of what can and cannot be reliably estimated.

Thus, the number of terms to be estimated in the scenario models will probably seem overwhelming to analysts accustomed to econometric analyses. Yet all such terms are potentially estimable. Our approach, therefore, is to test all of the main and interaction effects noted above for each of the four dependent scenario variables. Our modeling criterion for acceptance of effects is that they are consistently significant; i.e., they are significant at least at the 0.10 level for both surveys for both dependent variables that correspond to a particular mode.

We first estimate models for the scenario data for each survey, for each city; then, based on these results, we estimate parallel models from the corresponding real-world bus and automobile choice data. Our criteria for testing the equality of the models derived in this manner are as follows:

1. Use the 0.05 and 0.01 levels for the standard errors of each coefficient estimated from the choice data reported by respondents (this is obviously better than using the standard errors of the scenario coefficients because the standard errors are all equal and very small by design; since no such precision can be achieved in the respondent-reported data, the appropriate criterion for the comparison should be based on the respondent-reported data estimates) and
2. Test whether the sum of squares for regression given by the model estimated from the reported choice data is significantly different from that for the model by using fixed regression weights derived from the simulation experiments [the test statistic is the F-value given by mean square (improvement in sum of squares) ÷ mean square (residual for reported choice data model); the degrees of freedom are equal to the difference in the number of parameters for improvement for the numerator and N, the number of coefficients estimated for residual].

Additional considerations that are important to note concern differences in the two sets of models caused by additional terms in the respondent-reported data that are not included in the scenario data. In particular, because the scenario data are aggregated over individuals, individual differences caused by factors such as income, automobile availability, and age are, in effect, averaged out. This is exactly true in the scenario results because each individual has a constant value for these factors within his or her 30 responses. Thus, there can be no correlation between scenario attributes and interpersonal factors, and we can legitimately ignore such factors in estimation. That is not to say that there are no effects attributable to these covariates but only that such effects cannot affect the estimation of aggregate coefficients in the controlled, experimental data.

However, in the case of the respondent-reported choice data, we cannot ignore the effects of interpersonal factors because they can have significant effects on the parameter estimates of the 10 attributes of interest. Thus, to minimize this source of potential bias, we include a number of interpersonal factors as terms in the respondent-reported choice models. This is accomplished in the following manner:

1. All main effects of attributes and interpersonal factors are tested in a multiple linear regression analysis. Nonsignificant interpersonal factors are dropped from further consideration.
2. All two-way interactions of the attributes and the remaining interpersonal factors are tested as follows. The main effects of attributes, significant attribute interactions uncovered in the controlled scenario data, and previously significant interpersonal factors are forced into a multiple linear regression equation, and the remaining two-way, attribute/interpersonal-factor interactions are tested by stepwise regression methods. The acceptance criterion is set at the 0.10 level.

The latter procedure will undoubtedly be objectionable to some, but it is strictly a matter of convenience. We are not interested in these estimates per se; rather, we wish to try and minimize as many sources of bias on the attribute parameters as possible. That is not to say that such effects are not important but only that interest in this analysis centers entirely on the 10 attributes, aggregated across respondents. Future analyses will examine interpersonal effects in the scenario data at the individual-respondent level. They are not of interest, however, in this paper.

RESULTS

Overview

There are a number of results of interest that involve a large number of parameters. In order to reduce the tabular material, standard errors and statistical tests are not reported for the scenario data. This is because the scenario conditions are controlled, which also fixes the standard errors. Virtually all t-values are significant in these data because of the power of the tests (450 df) and the precision of the estimates (complete details are available from the authors on request). The respondent-reported data, however, are tabulated with standard errors because of the test comparisons.

Simulation Results

Detailed Analyses

Table 2 gives the most detailed aggregate results available by survey (1 or 2), by city (Iowa City or Cedar Rapids), and by response measures for the scenario data. The response measures can be defined as follows:

RATE = 1-20 category ratings scale transformed to (0,1) interval,
R<10 = relative frequency of category ratings less than 10 on the 1-20 scale,
CHAUTO = relative frequency of choices of automobile in each scenario, and
CHBUS = relative frequency of choices of bus in each scenario.

The results given in Table 2 suggest the following.

RATE

The only significant ratings difference in the Iowa City data is in the crowding attribute. Survey 1 reveals a larger impact for crowding (-0.166) than survey 2 (-0.092). The timing of the surveys was such that crowding was considerably greater during survey 1. For Cedar Rapids, there are differences in the two walking-distance variables and crowding,

Table 2. Detailed model results for scenario data.

Variable	RATE		R < 10		CHAUTO		CHBUS	
	Survey 2	Survey 1	Survey 2	Survey 1	Survey 2	Survey 1	Survey 2	Survey 1
Iowa City								
Parking cost	-0.020 27	-0.023 70	0.031 05	0.037 36	-0.052 16	-0.075 73	0.027 97	0.034 57
Automobile travel time	-0.028 61	-0.018 70	0.039 66	0.041 223	-0.030 78	-0.011 41	0.055 23	0.047 06
Gasoline cost	-0.004 16	-0.003 15	0.006 69	-0.002 96	-0.009 57	-0.007 03	0.003 92	-0.007 67
Bus fare	0.005 86	0.006 64	-0.011 88	-0.011 00	0.003 35	0.005 98	-0.017 59	-0.019 33
Bus travel time	0.020 27	0.017 94	-0.029 39	-0.036 07	0.024 00	0.028 07	-0.033 08	-0.029 02
Walk from home	0.093 53	0.074 74	-0.143 22	-0.139 72	0.079 67	0.081 77	-0.205 12	-0.179 66
Bus frequency	0.008 51	0.007 93	-0.012 72	-0.009 63	0.001 83	0.009 45	-0.012 81	-0.025 62
Walk from work	0.088 28	0.065 95	-0.148 22	-0.103 07	0.006 50	0.095 33	-0.191 75	-0.183 68
Bus crowding	-0.092 12	-0.166 36	0.136 13	0.295 94	-0.053 66	-0.001 44	0.191 72	0.308 70
Season		-0.051 97		0.023 41		0.403 79		0.149 51
Gasoline situation	-0.172 56		0.220 80		-0.312 07		0.243 45	
Quadratic								
Parking cost	0.000 68	0.001 16	-0.000 05	-0.001 58	0.001 62	0.002 31	-0.000 84	0.000 24
Automobile travel time	0.000 48	0.000 05	0.001 00	0.001 22	-0.000 74	-0.000 36	0.000 68	0.000 94
Gasoline cost	0.000 07	0.000 10	-0.000 06	-0.000 01	0.000 06	-0.000 20	-0.000 03	0.000 61
Walk from home	0.001 77	0.003 77	-0.005 84	-0.001 27	-0.003 29	0.000 03	-0.005 03	0.000 18
Walk from work	0.006 59	0.005 88	-0.014 33	-0.002 93	-0.000 89	-0.002 65	-0.012 45	-0.004 74
Bus crowding	0.055 95	0.045 19	0.083 80	-0.016 35	-0.047 20	0.061 29	0.019 17	-0.072 62
Season		0.034 02		0.118 92		0.183 59		0.025 16
Gasoline situation	-0.101 02		0.131 96		-0.047 47		0.021 98	
Intercept	0.711 15	0.690 26	-1.391 31	-1.345 156	-1.512 474	-1.392 93	-1.503 388	-2.022 951
R^2	0.63	0.42	0.50	0.36	0.49	0.32	0.69	0.58
Cedar Rapids								
Parking cost	-0.014 84	-0.018 15	0.018 73	0.024 12	-0.043 93	-0.066 16	0.017 41	0.019 85
Automobile travel time	-0.021 228	-0.019 27	0.024 57	0.026 28	-0.024 33	-0.013 07	0.045 89	0.058 84
Gasoline cost	-0.005 118	-0.007 75	0.004 86	0.010 32	-0.013 47	-0.025 52	0.009 56	0.022 70
Bus fare	0.005 92	0.003 10	-0.010 69	-0.002 92	0.005 13	0.014 21	-0.008 05	-0.017 54
Bus travel time	0.018 91	0.018 29	-0.028 07	-0.031 91	0.013 61	0.031 83	-0.030 32	0.039 75
Walk from home	0.084 38	0.133 13	-0.137 06	-0.181 28	0.056 76	0.086 31	-0.182 46	0.162 43
Bus frequency	0.008 58	0.010 61	-0.013 71	-0.010 96	0.008 95	0.011 46	-0.023 15	-0.019 64
Walk from work	0.008 76	0.122 67	-0.135 79	-0.149 77	0.040 82	0.125 89	-0.158 09	-0.211 07
Bus crowding	-0.109 37	-0.143 76	0.198 86	0.177 29	-0.091 00	-0.122 97	0.090 75	0.394 01
Season		0.149 90		-0.134 74		-0.007 72		0.087 98
Gasoline situation	-0.159 40		0.191 75		-0.409 65		0.234 39	
Quadratic								
Parking cost	0.000 24	-0.000 27	-0.000 11	0.001 09	0.001 15	0.002 97	-0.000 45	-0.001 43
Automobile travel time	0.000 58	0.000 40	-0.001 39	-0.000 52	0.000 33	-0.003 39	-0.000 10	0.001 27
Gasoline cost	0.000 02	-0.000 06	-0.000 02	0.000 43	0.000 08	0.000 14	-0.000 07	0.000 51
Walk from home	0.005	0.004 12	-0.003 46	0.000 93	0.003 94	0.000 27	-0.007 61	-0.023 91
Walk from work	0.005 65	0.013 62	-0.009 70	-0.007 84	0.002 63	0.003 92	-0.008 59	-0.001 30
Bus crowding	0.027 83	0.123 79	0.028 38	-0.317 35	-0.176 91	0.131 92	-0.157 43	-0.211 58
Season		0.039 13		0.013 02		-0.002 43		0.063 21
Gasoline situation	-0.076 02		0.095 33		-0.154 32		0.114 32	
Intercept	0.723 168 8	0.997 03	-1.435 13	-1.705 44	-1.006 39	-0.947 684	-1.540 473	-1.930 946
R^2	0.74	0.54	0.56	0.40	0.58	0.33	0.70	0.53

all indicating the same thing--namely, less impact in survey 2. Again, the timing of the first survey was at the end of the winter peak season, whereas the second survey was near summer's end. There is a suggestion, therefore, that the weights change in response to seasonal differences.

There is an apparent difference in the intercepts between the two cities and the two surveys. The scenario attributes were all centered about their respective means; thus, the intercept can be directly interpreted as the likelihood of using the automobile given that all scenario variables are at their average level. The apparent difference is in the Cedar Rapids data between surveys 1 and 2. It appears that the likelihood of using the automobile dropped from survey 1 to survey 2. This drop coincides with the dramatic increase in gasoline prices. No such drop is evident in the Iowa City data, but levels of bus ridership were already quite high in that city.

It would be difficult to conclude that there are major coefficient differences between Iowa City and Cedar Rapids on the ratings-scale data.

CHAUTO

The automobile choice data reveal a pattern similar to that of the ratings data. Differences between cities and surveys are apparent in walking distances and crowding and in the intercepts. The interpretation of these differences would be similar to the interpretation for the ratings data.

R<10

The R<10 results largely parallel those of the previous response measures but with opposite signs. There are small differences in the walking-distance, crowding, and intercept terms between cities and larger differences between surveys within cities.

CHBUS

The CHBUS results are similar to the results for the preceding response measures. There are minor differences between cities and larger differences within cities between surveys with respect to the walking and crowding attributes and the intercept.

Aggregation Across Cities

The detailed scenario results lead us to conclude that the major differences between cities are in (a) the intercept term (on the average, Iowa City respondents are more likely to choose the bus than Cedar Rapids residents) and (b) gasoline availability and season (Iowa City residents are less sensitive to availability and respond differently to season). Differences between surveys are evident in the walking-distance and crowding attributes: The effect of these variables decreased from survey 1 to survey 2. There were also intercept differences, which indicates that, all things being equal, respondents became more positive toward bus and more negative toward the automobile between surveys 1 and 2.

The data were aggregated over cities because city differences were minor in comparison with survey differences. These aggregated results are given in Table 3, where the results of the different response measures are listed and the averages are over the bus (CHBUS and R<10) and automobile (CHAUTO and RATE) models, respectively. The season and gasoline-situation attributes are not comparable, except within a survey.

Table 3 reveals that within surveys there are major differences in the intercepts, which is to be expected because, for each response measure, the origin of each scale can be different, even if the units are comparable. Major differences in survey 1 within the two automobile responses (RATE and CHAUTO) are in the intercept, parking costs, and season. The ratings data yield a lower estimate for the effect of parking costs than the choice data; the seasonal effects are also totally different. The major differences in the bus responses (R<10 and CHBUS) are in the intercepts, walking-distance effects, and season; the choice data indicate larger effects for these attributes than do the ratings data.

In survey 2, there are major differences in the automobile response measures in the intercepts, parking cost, walking distance, crowding, and gasoline situation. The automobile choice data generally display a lower likelihood of choosing automobile, more sensitivity to automobile parking costs, less sensitivity to walking distance, less sensitivity to crowding, and considerably more sensitivity to the gasoline situation than do the ratings data.

The bus choice data show differences in intercepts, revealing lower average probabilities and more sensitivity to automobile travel times and walking distances. Hence, the bus responses are much more homogeneous than the automobile data. Nonetheless, it should be noted that, for the most part, only the intercepts exhibit dramatic differences, particularly when one considers that the attribute of gasoline situation and availability was constant in the real world during both surveys and that only crowding and gasoline costs actually changed between the two surveys. Of course, it is possible that perceptions of the onerousness of walking distances change from winter to summer in Iowa.

Examination of the average coefficients suggests that there may be less difference between surveys than previous, more disaggregate results have suggested. In particular, there does appear to be a consistent change in the intercept that reflects a definite change upward for bus and downward for automobile. Otherwise, only the crowding attribute appears to be very different, and only for bus, showing a lower effect in survey 2, when there is in fact less crowding. This result and the previous, more disaggregate results suggest that some of the coefficients may depend on the present situation of the respondent as well as on the levels of the experimental variables.

COMPARISON WITH ECONOMETRIC-TYPE RESULTS ON CHOICE DATA REPORTED BY RESPONDENTS

Disaggregate Results for Both Cities and Surveys

Table 4 gives the results for models fit to each choice variable, by city and survey, including only the nine scenario attributes (season and gasoline availability are constant in these data), the one quadratic term that consistently appeared in the scenario results, and three interactions that also consistently appeared: (a) gasoline cost and bus travel time, (b) walking distance to the bus stop from home and from the bus stop to work, and (c) walking distance from home to the bus stop and crowding.

The results reveal little in the way of consistency except in the case of bus travel time, which is significant in three of four tests in Iowa City, and the two walking-distance variables in Cedar Rapids. Of course, the intercepts are significant as well, revealing more positive bus probabilities and lower automobile probabilities in Iowa City, which is to be expected because of the high levels of transit patronage in Iowa City. The disturbing aspect of these results is that one would probably conclude that few of the attributes have any significant effects, but, as we shall see, the coefficients are fairly close to those estimated from the scenario data, almost all of which are highly significant. Of course, this could result from bias introduced by not including interpersonal factors in the model. To pursue this possibility, data for both cities were combined, and interpersonal factors were investigated.

Table 3. Model results for scenario data averaged over cities.

	Survey 1				Survey 2			
Variable	R < 10	RATE	CHAUTO	CHBUS	R < 10	RATE	CHAUTO	CHBUS
Intercept	-1.148 06	0.677 94	-0.939 03	-1.658 585	-1.251 12	0.711 998	-1.126 796 4	-1.419 782
Parking cost	0.028 70	-0.016 91	-0.057 65	0.030 38	0.021 28	-0.021 64	-0.044 31	0.025 90
Automobile travel time	0.028 55	-0.023 38	-0.014 95	0.054 54	0.029 968	-0.015 34	-0.024 17	0.046 51
Gasoline cost	0.005 52	-0.004 72	-0.012 68	0.006 95	0.005 94	-0.005 10	-0.011 24	0.005 78
Bus fare	-0.007 70	0.005 78	0.007 73	-0.015 75	-0.009 49	0.004 82	0.004 85	-0.011 59
Bus travel time	-0.025 35	0.018 90	0.028 97	-0.037 84	-0.026 27	0.015 17	0.015 99	-0.028 02
Walk from home	-0.128 85	0.082 80	0.082 92	-0.169 81	-0.124 09	0.087 44	0.062 40	-0.178 53
Bus frequency	-0.009 06	0.008 52	0.009 80	-0.022 28	-0.012 16	0.008 90	0.006 03	-0.016 46
Walk from work	-0.105 54	0.082 02	0.095 73	-0.181 71	-0.125 86	0.080 22	0.042 40	-0.151 80
Bus crowding	0.197 42	-0.099 61	-0.084 22	0.273 00	0.140 67	-0.145 63	-0.068 16	0.122 05
Season	-0.015 09	-0.158 85	0.160 57	0.085 74				
Gasoline situation					0.239 83	0.023 98	-0.338 92	0.268 67
R^2	0.55	0.79	0.62	0.71	0.67	0.66	0.72	0.79

Table 4. Model results for real-world data.

	Iowa City				Cedar Rapids			
	CHBUS		CHAUTO		CHBUS		CHAUTO	
Variable	Survey 1	Survey 2	Survey 1	Survey 2	Survey 1	Survey 2	Survey 1	Survey 2
Parking cost	0.024 87	0.065 42[a]	-0.054 72	-0.056 15[b]	0.008 70	0.081 37[a]	-0.065 55	-0.106 98[a]
Automobile travel time	0.005 11	0.030 14	0.045 86	-0.088 62[a]	-0.003 93	-0.006 22	-0.022 02	-0.010 56
Gasoline cost	0.012 34	-0.045 78	-0.056 00	-0.040 94	0.014 81	0.026 37	-0.031 773	-0.008 68
Bus fare	-0.000 06	0.033 54	-0.053 84	-0.016 60	0.004 29	-0.002 53	-0.008 46	-0.055 79[c]
Bus travel time	-0.000 40[a]	0.001 86	0.057 76[a]	0.053 67[a]	-0.006 69	-0.002 21	0.028 57[c]	0.010 29
Walk from home	-0.306 13	-0.173 52	0.258 59	0.125 90	-0.112 70[b]	-0.166 31[a]	0.131 05	0.182 69[b]
Bus frequency	-0.004 84[b]	-0.007 80	0.046 13[b]	0.009 81	0.008 21[c]	-0.004 74	-0.011 14	0.026 51[c]
Walk from work	-0.416 15	-0.450 97[a]	0.156 94	0.288 91	-0.150 59[c]	-0.136 31[a]	0.318 71[b]	0.350 64[a]
Bus crowding	-0.069 31	0.452 83[b]	-0.006 40	-0.740 35[c]	-0.051 84	0.016 19	-0.875 70[b]	-0.474 85
Quadratic (walk from work)	0.089 68	-0.074 87	0.047 02	0.089 20	-0.148 46[a]	-0.040 14	0.052 40	-0.025 68
Gasoline cost x bus travel time	-0.002 03	0.003 76	0.005 21	-0.004 87	-0.000 228	-0.001 27	0.001 96	0.004 74[c]
Walk from home x walk from work	0.139 095	-0.031 00	-0.161 74	-0.009 19	0.058 46[b]	0.037 35	0.138 09	-0.001 15
Walk from work x crowding	-0.109 92	-0.337 73	-0.492 32	-0.333 46	-0.103 15	-0.203 49[c]	-0.474 52	0.047 65
Intercept	-3.058 46[a]	-2.471 96[a]	-1.134 87[a]	-1.412 162[a]	-4.006 18	-3.773 63	1.534 817	0.930 82
R^2	0.13	0.20	0.28	0.18	0.20	0.21	0.16	0.14

[a]Significance level = 0.01. [b]Significance level = 0.10. [c]Significance level = 0.05.

Table 5. Model results for real-world data averaged over cities.

	CHBUS				CHAUTO			
	Survey 1		Survey 2		Survey 1		Survey 2	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Parking cost	0.022 56[a]	0.016 0	0.068 254	0.014 09	-0.066 29[b]	0.028 17	-0.096 71[b]	0.022 82
Automobile travel time	-0.004 41	0.008 55	0.011 357	0.011 225	-0.000 475	0.015 08	-0.036 03[c]	0.018 18
Gasoline cost	0.008 19	0.019 04	0.007 24	0.023 91	-0.031 64	0.033 59	-0.027 66	0.038 73
Bus fare	-0.007 77	0.019 33	-0.004 83	0.013 74	0.001 29	0.034 10	-0.023 96	0.022 26
Bus travel time	-0.002 986	0.006 02	-0.003 27	0.005 13	0.032 01[c]	0.010 62	0.021 07[c]	0.008 30
Walk from home	-0.183 58[b]	0.068 45	-0.190 355[b]	0.052 597	0.195 51[a]	0.120 73	0.193 03[c]	0.085 20
Bus frequency	0.008 12	0.005 35	-0.005 22	0.003 31	-0.000 43	0.009 43	0.012 98[c]	0.005 36
Walk from work	-0.160 82	0.067 88	-0.227 30[b]	0.050 44	0.173 76	0.119 72	0.333 77[b]	0.081 70
Bus crowding	-0.123 81	0.176 72	0.175 19	0.141 92	-0.151 73	0.311 68	-0.491 74[c]	0.229 88
Quadratic (walk from work)	-0.007 26	0.056 61	-0.059 17	0.042 22	0.063 76	0.099 84	0.085 18	0.068 38
Gasoline cost x bus travel time	-0.000 48	0.001 02	-0.000 215	0.001 07	0.001 137	0.001 79	0.002 31	0.001 74
Walk from home x walk from work	0.095 00	0.041 01	0.033 40	0.030 36	0.011 727	0.072 34	0.027 709	0.049 17
Walk from home x crowding	-0.057 98	0.137 58	-0.210 84	0.094 83	-0.389 91[a]	0.242 66	-0.055 81	0.153 60
Vehicle availability	-0.835 34[b]	0.321 43	-1.217 78[b]	0.257 26	3.453 12[b]	0.566 91	2.291 88[b]	0.416 70
Residence	0.371 36	0.393 01	0.004 69	0.246 5	-0.605 86	0.693 17	0.495 97	0.399 23
Number of family members	0.049 90	0.101 09	0.061 80	0.096 10	-0.203 19	0.178 29	-0.183 18	0.155 7
Number of children								
Under age 6	-0.060 86	0.202 76	-0.147 60	0.181 69	0.497 13	0.357 61	0.540 31[a]	0.294 29
Aged 6-14	-0.108 95	0.170 00	-0.021 41	0.146 49	0.463 92	0.299 68	0.310 03	0.237 28
Number of workers	0.158 03	0.079 25	-0.088 46	0.097 20	0.101 55	0.139 78	-0.169 63	0.157 45
Number of students	-0.005 85	0.104 33	0.003 36	0.132 32	-0.071 11	0.184 00	-0.231 53	0.214 32
Sex	0.137 74	0.195 77	-0.231 47	0.166 94	-0.669 30[a]	0.345 28	-0.099 62	0.270 40
Age	0.005 50	0.007 92	-0.003 65	0.006 97	0.009 26	0.013 97	0.050 74[b]	0.011 29
Bus rating	0.125 38	0.094 84	0.167 25[c]	0.072 04	-0.132 82	0.167 28	-0.064 10	0.116 68
Education	0.141 42	0.091 77	0.205 08[c]	0.098 83	-0.239 40	0.161 85	-0.118 94	0.160 08
Income	-0.158 52[b]	0.049 85	-0.013 79	0.040 05	0.173 67[c]	0.087 9	0.076 60	0.064 87
Intercept	-3.630 918	0.119 92	-3.130 278 2	0.092 030 1	0.175 473 5	0.211 512	-0.140 783	0.149 067

[a]Significance level = 0.01. [b]Significance level = 0.10. [c]Significance level = 0.05.

These results, given in Table 5, are better but still disturbing. Parking costs emerge as significant in both surveys for both modes. Bus travel time is highly significant in automobile mode choice but very marginal in bus mode choice; walking distance from home to the bus stop is consistently significant; frequency of bus service is probably significant, although survey 1 results have the wrong sign for bus mode choice; and walking distance from the bus to work is also consistently significant. Similarly, the intercepts have the same change in favor of bus as previously observed. Among interpersonal factors, vehicle availability is consistently highly significant with the appropriate sign; of the remaining factors, only income displays any consistent trend and, if we are to believe the data, the results suggest that its effect declines from survey 1 to survey 2. If true, this suggests that the increase in gasoline price manifests itself, inter alia, in a shift in bus probabilities across all income groups and has more impact on upper-income than on lower-income earners. It might be speculated that lower-income groups already had fairly high (relative) probabilities of bus use and that the effect of the price increase was to force some individuals in the higher-income groups to give the bus serious consideration.

The respondent-reported choice-data results are still disturbing despite the emergence of a few more consistently significant terms. This is because one would hope that effects found to be significant in the scenario data would also emerge as significant in the reported choice data. A comparison of Table 5 with Table 3, however, reveals some interesting similarities and differences. In general, in survey 1, for the automobile choice model in which interpersonal factors are included, all of the scenario coefficients are within the 95 percent confidence level of the respondent-reported estimates! For survey 2, there are only two coefficients outside the 95 percent confidence band: parking cost and walking distance to work from the bus. These coefficients are only slightly outside the 99 percent limits--again, an encouraging result for the scenario data.

In the case of bus choice data for survey 1, only the coefficients for automobile travel time and frequency of bus service are outside the 95 percent confidence limits of the reported choice data. Both of these attributes, however, have the wrong sign in the reported choice data. In survey 2, several coefficients lie outside the 95 percent confidence interval: parking cost, automobile travel time, bus travel time, and frequency of bus service. Automobile travel time is within the 99 percent confidence band; the others are generally just outside the 0.99 interval.

On the basis of the results thus far, we cannot reject the hypothesis that the models based on the average scenario coefficients are the same as the models based on the respondent-reported choice data. Because the hypothetical choice tasks in the surveys most closely parallel the respondent-reported choice data, we also examine these results for comparability.

For automobile choice data from survey 2, only walking distance from the bus to work lies outside both the 95 and 99 percent bands; in addition, parking cost lies slightly outside the 95 percent level. The intercept term is dramatically different, however. In survey 1, no coefficients lie outside the 95 percent confidence band except the intercept term, which is again very different.

For bus choice data from survey 2, three attributes lie outside the 95 percent bounds: parking cost, automobile travel time, and frequency of bus service. Of course, the intercept is very different. For bus choice data from survey 1, two attributes--automobile travel time and frequency of service--lie outside both the 95 and 99 percent limits; crowding is within the 99 percent bounds.

Once again, we find the evidence insufficient to reject the hypothesis that the models are the same. It should be noted that all previous results included missing data in the respondent-reported data by replacing the missing values with their respective means. As a final investigation, we examine the effects of removing those respondents who could not estimate walking distances--a likely source of error throughout the data because these individuals are likely to be ignorant of other variables as well. We also combine data from both cities for both surveys in order to gain degrees of freedom. The models using respondent-reported choice data were estimated by forcing all attributes and interpersonal factors as main effects and stepping any other significant attribute-by-interpersonal-factor interactions into the model. The stepwise criterion was set at 0.10.

Let us consider the average coefficient results for the bus choice data first: Parking cost, bus travel time, and the two walking-distance attributes are beyond the 99 percent confidence limits, whereas remaining attributes are within the limits. If we use the average coefficients of the bus choice data from surveys 1 and 2, we find that the same four attributes lie outside the range. In the case of the automobile choice data, the averages all lie within the 99 percent confidence limits. Averaging the CHBUS coefficients yields the same result. It appears that the automobile choice model is very well estimated but the bus choice model is less so. One can speculate that this is because the bus data, except for the choice task in the surveys, are less well defined; for example, the ratings data are for automobile choice, not bus. We must assume the residual to be bus, although there are other modes in the data.

The second test examined the relative predictive abilities of simulation and real-world models. The simulation models were related to actual behavior through a regression equation that included (a) the simulation-derived utility argument, averaged over surveys and cities, and (b) the same socioeconomic covariates used in the final real-world model. The simulation-behavior model, therefore, had an additional slope parameter associated with the entire simulation-derived utility model.

Results, as expected, suggested similar predictive abilities. In particular, the R^2s (adjusted for degrees of freedom) for the laboratory and real-world bus models were 0.15 and 0.19, respectively. Likewise, the adjusted R^2s for the laboratory and real-world automobile models were 0.30 and 0.31, respectively. The F-test, described earlier, indicated that the simulation and revealed-behavior automobile choice models were not significantly different from each other (F-value of 1.56 with 9 and 529 df). Conversely, the bus choice models were found to be significantly different (F-value of 4.04 with 9 and 597 df).

It might be added that the above predictive levels, although low, are not out of line with those usually reported when predicting individual behavior from aggregate demand models (15,16). Increased predictive ability could have been achieved, however, through complete disaggregation, which is possible only with the scenario data.

DISCUSSION OF RESULTS

This paper reports the results of a comparison of two methods for modeling travel-choice behavior: laboratory-simulation and revealed-behavior modeling. The results provide additional evidence that laboratory-simulation models are a potentially valuable tool for understanding and predicting individual reactions to travel alternatives. In particular, the findings showed that laboratory-derived models performed about as well as models based on revealed behavior in terms of predictive ability and that much stronger inferences can be drawn from such models about the likely effects (precision of estimates) of changes in transportation system variables on mode choice.

The predictive ability and parameter temporal and spatial stability of laboratory and revealed-behavior models were compared. The results suggest that the laboratory-derived models are strongest in terms of the diagnosis of important explanatory variables. This strength, of course, is inherent in the approach: Not only does the analyst obtain multiple observations for a single individual, but these observations are also purposefully designed a priori so as to maximize orthogonality among variables and to ensure precision of their estimates. In contrast, models based on revealed behavior cannot achieve such conditions except by a most unlikely accident. Furthermore, with traditional econometric methods, the analyst usually has merely one observation per individual, which further limits the ability to generalize. Thus, much larger samples are required to achieve the inferential power of the laboratory methods. Such limitations, of course, are especially troublesome in trying to draw inferences regarding interpersonal differences. The laboratory methods achieve greater power from smaller samples because it is possible to observe distributions of coefficients over samples of individuals. Clearly, these coefficients can be related to interpersonal measures so as to ensure a much stronger test for individual differences (7,17).

The results of this study suggest a potential danger in basing models on revealed-behavior data: The effects of two major policy variables--bus fare and gasoline price--were found to be not significantly different from zero in both the automobile and bus models. Hence, a policymaker confronted with these results might conclude that any changes in either bus fares or gasoline prices, or both, would be likely to have little effect on travel-choice behavior. Yet, in reality, this suggestion would be grossly misleading. The laboratory models produced coefficients that were virtually the same as those estimated by the revealed-behavior models; moreover, the laboratory results clearly revealed that the effects of fare and gasoline price were highly significant. In the revealed-behavior data, there was an insufficient range of variation in the observations on fare and price values to permit reliable inferences to be drawn. Thus, the results of the revealed-behavior models would completely mislead a policymaker regarding the underlying determinants of modal-choice behavior. It is therefore conceivable that such models might also lead to the formation of incorrect transportation policy decisions. Such problems could be avoided, of course, if laboratory-simulation methods were made an integral part of the analyst's bag of tools.

In terms of the spatial and temporal transferability of models, both methods appeared to be similarly robust. Indeed, the fact that both types of models were reasonably stable in relation to time was an important result. This implies that travel demand models are not necessarily purely descriptive. For example, the results suggest that reasonable forecasts of choice behavior after the major 1979 gasoline price rise could have been made based on the pre-price-rise models.

Despite this optimism, however, there were major changes between surveys: (a) a more favorable disposition toward bus (as inferred by changes in the intercepts) and (b) a uniform decrease in the effect of "bus crowding".

The more favorable disposition toward the bus between surveys is to be expected. Specifically, this might be traced to the fact that there was a gasoline price increase of some 7¢/L (25¢/gal) between survey 1 and survey 2 in the real world. One would expect this change to be associated with an increase in the mean probability of taking the bus. The decrease in the effect of crowding observed between surveys in the bus choice models is probably attributable to seasonal changes in actual bus conditions. Crowding peaked in the winter months, when survey 1 was conducted, and reached a low point during summer, when survey 2 was conducted. This implies that individuals' reactions to system attributes may depend on their context at the time. This suggestion would manifest itself in different coefficients during different seasons. This result should hold for both econometric and laboratory simulation methods. If true, it suggests that greater attention needs to be paid to contextual differences as they affect choices. This would require much more attention to joint longitudinal/cross-sectional studies, especially those involving multiple study sites.

The final point of comparison between models based on revealed behavior and those based on laboratory simulation was overall predictive ability. In this regard, the methods were comparable. It is important to note, however, that considerably improved predictive ability could be achieved by using the totally disaggregate, individual equations--that is, by using separate modal-choice models for each individual in the sample. Such total disaggregation, of course, would be impossible with the revealed-behavior approach. Given revealed-behavior data, the most an analyst can do is to include socioeconomic variables in the model in the hope that some (of the many) individual differences can be inferred.

CONCLUSIONS

Transportation planners increasingly have to develop policies regarding transportation system scenarios that often have no recent precedent in the real world. The need for accurate forecasting models to include unprecedented conditions is obviously important. But, despite some 20 years of active research, our modeling technology still fails to adequately meet this need. Although econometric models have become increasingly complex, they still cannot deal adequately with new technology or futures very different from the historic past.

Laboratory-simulation methods have been proposed to help overcome some of the limitations of current econometric models. In particular, laboratory simulation would appear to offer an efficient means by which an analyst could explicitly model behavior under a wide range of present and future transportation scenarios and do so at a completely disaggregate level.

We regard it as unfortunate that, despite five years of highly successful validity tests, simulation methods remain generally unaccepted and are forced to take a back seat to more traditional econometric methods. Although paradigms are slow to change (18), it is hard to understand the resistance to methods that have a good record in numerous validity tests over an extended period of time. Simulation models are at least as accurate as revealed-behavior models, offer greater flexibility in both data collection and analysis, and allow stronger model tests.

This paper has reported the results of a study in which laboratory-derived models of modal choice were shown to yield parameters and predictions comparable to those derived by using more conventional revealed-preference methods. The generality of these results can only be assessed through replication, but it is hoped that the results and the discussion will serve to attract more attention to laboratory-simulation methods as a complementary (and alternative) approach to existing methods of travel-choice analysis.

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Evaluation by Individuals of Their Travel Time to Work

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Modelers of transportation-related decisions have often drawn the distinction between "objective" measures of attributes used to describe the transportation system and individuals' perception and evaluation of these attributes. Only a few studies have been made, however, of the relation between these objective and subjective assessments. Individuals' satisfaction with the length of the work trip is examined, primarily with the aim of establishing the nature of the relation and its stability across different groups of travelers. The study is based on data collected in a home interview survey of residential location choice conducted in outer suburban Melbourne during 1978 and 1979. A number of broader issues are addressed, including implications for modeling and policy.

The ease with which people can participate in activities is influenced by the transportation system. A good transportation system may entice people to partake in certain activities, whereas a poor system may discourage such involvement. However, to ascertain what is a good or bad transportation system, it is necessary to investigate both objective and subjective measures of effectiveness. It may be that one individual views the separation between two activities in a much different light than another. Handicapped people, for example, are likely to view a trip to the corner shop as much more onerous than a neighbor who can walk without difficulty.

Transportation planners have often developed models of transportation choice or measures of accessibility that have assumed that individuals view the transportation system in the same manner. Car drivers are assumed to have the same satisfaction with a travel time of 10 min as those traveling by public transportation. Males and females are similarly assumed to have similar satisfactions with travel time. Yet these people experience quite different conditions and constraints. Moreover, most such models are calibrated by using data on existing travel patterns. This approach suffers from a major flaw--that all people clearly do not have the same sets of choices. Alternative choices must be built into the analytic procedure for evaluating spatial patterns before we can state firmly the nature of the relation (i.e., the shape of the curve) between satisfaction and journey length.

This paper explores individuals' perceived satisfaction with the length of the work trip. The primary aim is to establish the nature of the relation and its stability across different groups of travelers.

ATTRIBUTE EVALUATION

Evaluating attribute levels entails a number of steps (see Figure 1) (1):

1. Individuals must first have some estimate of the magnitude of the attribute in question (in this case, the length of the work trip). The relation between the actual length of journeys and travelers'

estimates is influenced by such factors as the traveler's level of familiarity with the trip, the purpose of the trip, time constraints (e.g., flexibility of arrival times), and conditions of travel. More often than not the relation is assumed to be monotonic.

2. Individuals must decide whether the particular attribute level is acceptable or not; that is, the perception of the attribute (trip length) must be transformed into a measure of satisfaction.

This two-stage process may not be the simple, one-dimensional transformation shown in Figure 1. Rather, it may take place in several dimensions, since the attribute may be evaluated on the basis of a number of characteristics. In the case of closeness to work, the individual may consider characteristics such as comfort, convenience, and ability to read the paper during the trip. There may also be a problem with being too close to work in that one is reminded of it during one's leisure time. The particular characteristics and the weighting given to each of them are closely tied to individual preferences.

This paper concentrates on the second part of the transformation shown in Figure 1. It is worth noting, however, that the findings may have wider applicability. Several studies indicate that the relation between perceived and objective measures of travel time--the first part of the relation--is in fact monotonic (1,2).

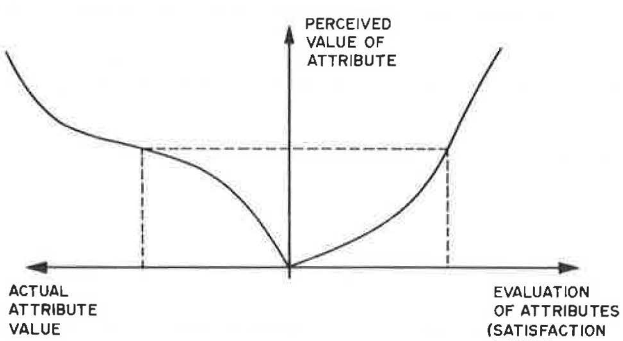
SURVEY METHOD

The information for this study was drawn from a survey of residential location choice conducted in three outer suburban areas of Melbourne, Australia, during 1978 and 1979. The three survey areas--East Burwood, Wantirna, and Belgrave (see Figure 2)--are in various stages of urban development. New residents in each area were asked, inter alia, to rate their level of satisfaction with closeness to their present workplace (see Figure 3), and then to evaluate a number of possible travel times to work (see Figure 4).

The first set of information relates to observed travel patterns; such data are usually termed "market" data. The information obtained in the second approach is more accurately described as "experimental" data (in that the respondents are presented with alternative hypothetical travel times).

In later questions, the respondents were asked to record further details of their present work journeys, including the time spent traveling and the mode used. In addition, respondents were asked to indicate the importance they attached to closeness

Figure 1. Transformation of individuals' attitude ratings from actual attribute level to satisfaction with attribute.



to work when deciding where to live (see Figure 5).

The survey took the form of household interviews, and information was collected for all major decision makers in the household. The usable sample of employed persons in this study was 1049.

Full details of the survey are given elsewhere (3,4).

SATISFACTION WITH THE JOURNEY TO WORK: COMPARISON OF OBSERVED AND EXPERIMENTAL DATA

The form of the relation between satisfaction and perceived length of work journeys is examined here by using both sets of data. The observed data were analyzed by using regression analysis, and the straight-line (AB) fit ($r^2 = 0.42$) is plotted in Figure 6. The experimental data were analyzed by calculating mean satisfaction ratings for the range of travel times presented; the resulting curve (OCD) is shown in Figure 6. Several nonlinear functions were fitted to the market data but without significant improvements in the level of explanation.

It can be seen that the straight line AB, which was fitted to the observed data, is a reasonable approximation to the curve OCD produced by the experimental data. However, theoretical interpretation of the relation between satisfaction and length of work journeys differs quite markedly, depending on which approach is adopted.

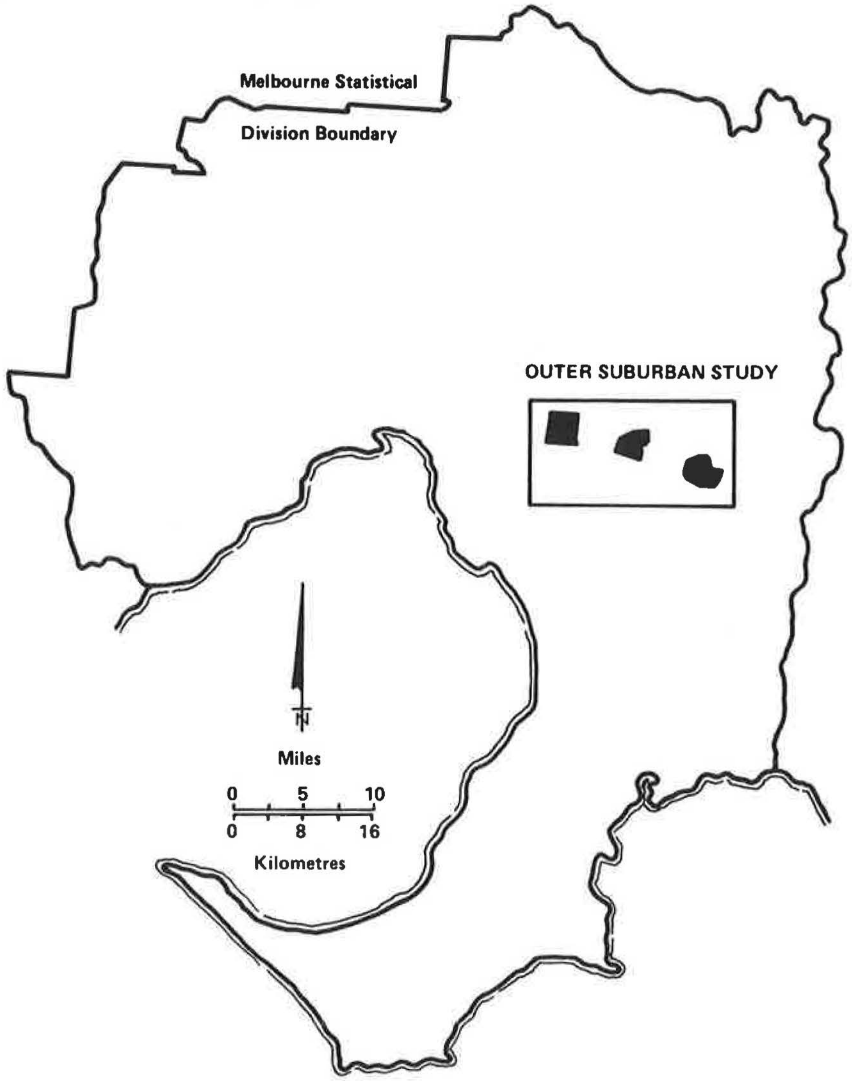
The relation AB is the classical distance decay function; this implies that satisfaction decreases directly with increasing travel time. By contrast, the curve OCD implies the existence of both "proximity" and "accessibility" thresholds; that is, people like to be close to work but not too close. Intuitively, this appears to be a reasonable finding. Close proximity to work may produce a stressful situation for households, through the noise, pollution, and congestion often associated with employment concentrations. Some amount of time spent traveling may also be necessary to achieve mental separation of work and home activities. On the other hand, poor accessibility may produce a stressful situation because of the large amount of time and energy spent traveling and the increased length of time spent away from home.

Empirical evidence from other studies also lends support to a curve of the form OCD. A series of studies undertaken at the University of Pennsylvania found that, for most services, people compromise between accessibility on the one hand and proximity considerations (e.g., noise, pollution, and congestion) on the other (5). By means of questionnaires, ordinal data were collected for a wide variety of public and private services for four distance categories: (a) on one's own block; (b) on a neighboring block; (c) within the rest of the neighborhood; and (d) within the neighboring community. Most curves were found to be of the form OC, although it has been suggested that extending the distance categories would probably produce an overall curve OCD with a distance from O to the peak C that varies for different services (6).

Redding (7) has also postulated a nonlinear relation between accessibility and locational valuation. This relation, as reproduced by Moore (8), is shown in Figure 7. Support for these ideas was provided in a study of four amenities (shopping center, elementary school, playground, and hospital) serving residents in Skokie, Illinois. It was found that most individuals had nearness as well as inaccessibility thresholds. The "inner" thresholds for these services were mostly from 0.25 to 0.5 block from the given amenity.

On both empirical and theoretical grounds, therefore, a nonlinear relation appears to be highly

Figure 2. Location of Melbourne outer suburban study areas.



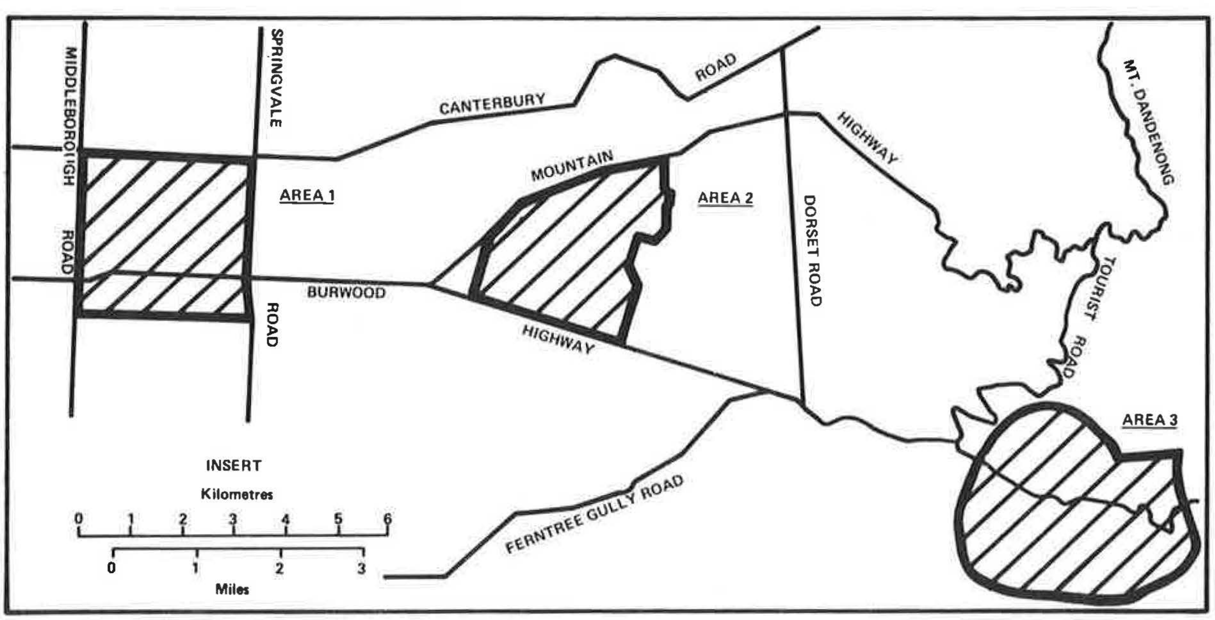


Figure 3. Question and measurement scale used to obtain satisfaction ratings for closeness to present workplace.

Q. *In this study we are interested in knowing how well you THINK particular suburbs would satisfy your needs. The areas we are studying are shown on the attached map. We now have a series of questions which aim at finding your impression of these areas. Could you please mark a cross (x) on the scale to indicate how you rate such locality for each of the following factors. If you have no view of what the area offers in respect to a particular factor, leave the appropriate scale blank.*

e.g. EAST BURWOOD

EXTREMELY BAD EXTREMELY GOOD

1 50 100

Closeness to present workplace

Figure 4. Question and measurement scales used to obtain satisfaction ratings for hypothetical alternative work journeys.

Q. *People travel different distances to work. For each of the travel times below could you please mark how satisfied you would be with this separation between home and work?*

EXTREMELY BAD EXTREMELY GOOD

TRAVEL TIME TO WORK (MINUTES) 1 50 100

0

10

20

30

40

50

60

70

80

90

Figure 5. Question and measurement scales used to obtain importance ratings for closeness to present workplace.

Q. *We are now interested in knowing how important these factors were in your choice to live in this area. Could you please mark a cross on the scale to indicate how important you feel each factor was in this decision. If any of these factors were not considered please leave them blank.*

NOT IMPORTANT VERY IMPORTANT

1 50 100

Closeness to present workplace

Figure 6. Comparison of observed and experimental relations for evaluation of travel time.

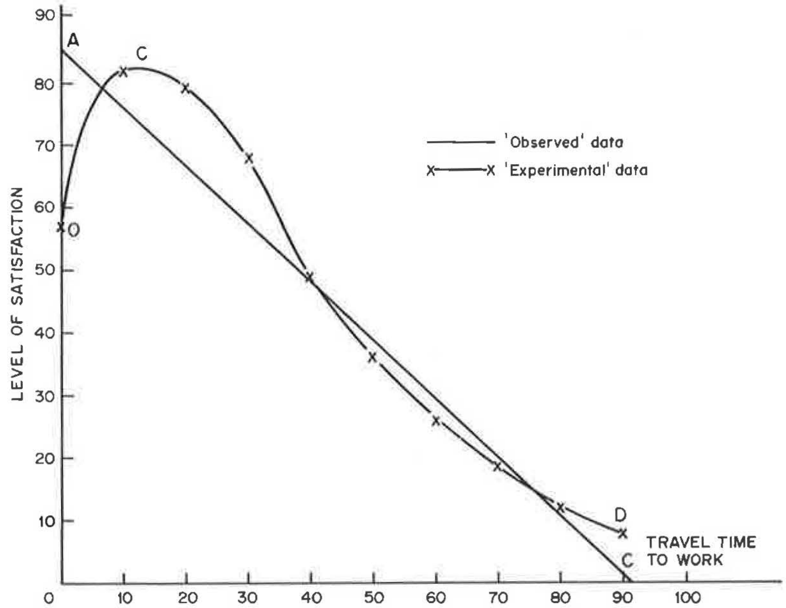
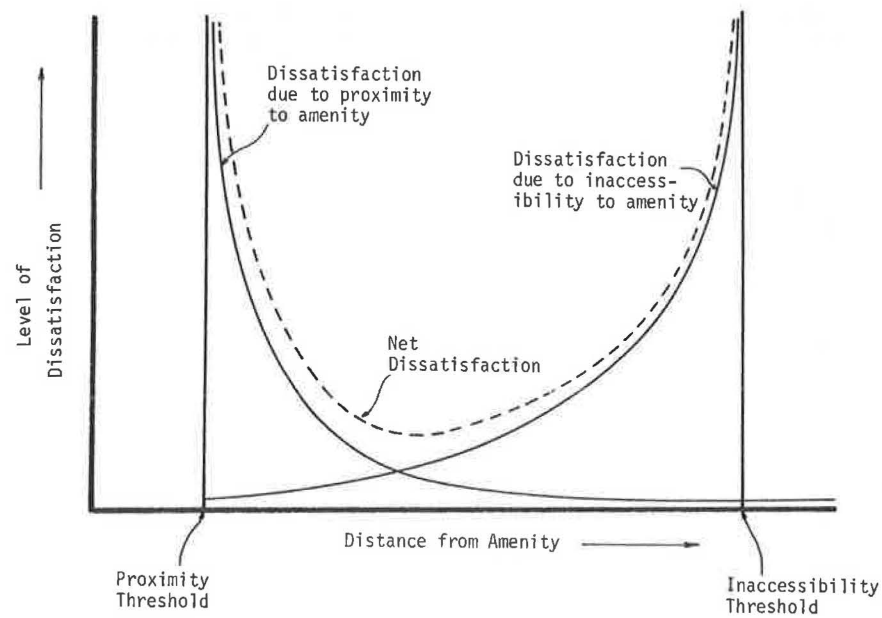


Figure 7. Relation between dissatisfaction and accessibility to amenity.



plausible. Of course, it might be argued that at this level of aggregation the observed data provide a reasonable empirical approximation. However, the choice of approach becomes more critical when the stability of this relation is examined across different population groups.

STABILITY ACROSS MARKET SEGMENTS

Perceived satisfaction with both existing work journeys and hypothetical travel times was examined further by segmenting the sample into a number of groups. The groups were based on a number of variables commonly used in transportation studies (age, sex, travel mode, and occupation), plus two others that relate to the perceived importance of closeness to work and respondents' present travel times.

In comparing the observed and experimental approaches, however, there are a number of problems. The observed data pertain to only one travel time for each individual--i.e., their present travel time--whereas the experimental data yield satisfaction ratings for a range of travel-time values for each individual. It follows, therefore, that present travel time is a meaningful basis for testing the stability of travel-time evaluation only in the case of experimental data.

Comparison of the two approaches is also complicated by differences in the methods of analysis. Between-group differences in observed behavior were tested by using regression analysis and standard statistical tests (see Table 1). However, a somewhat simpler method was used for the experimental data, given the nonlinear form of the relation. The test developed here essentially compares the degree of overlap between the distributions of mean satisfaction (i.e., the OCD curves) calculated for the various subgroups. The method is capable of handling only two subgroups at a time. No overall test of significance is available, but the method is

Table 1. Perceived satisfaction with closeness to current workplace among population subgroups: regression analysis of observed data.

Category	r^2	N	Intercept	Standard Error	Slope	Standard Error
Total	0.42	1019	85.6	1.35	-0.93	0.0342
Sex						
Male	0.39	671	84.9	1.72	-0.91	0.0437
Female	0.48	347	86.6	2.15	-0.97	0.0546
Mode						
Car	0.42	845	89.0	1.50	-1.09	0.0438
Public transportation	0.34	149	82.7	5.40	-0.76	0.1880
Age (years)						
24	0.56	226	89.7	2.41[a]	-1.01	0.0597
25-29	0.37	343	82.8	2.50[a]	-0.87	0.0611
30-39	0.45	290	87.9	2.49[a]	-0.98	0.0644
40	0.27	154	80.6	4.02	-0.83	0.1238
Perceived importance[b]						
Unimportant	0.20	173	60.3	4.75[a]	-0.61	0.0945
Relatively important	0.30	256	71.0	2.89[a]	-0.68	0.0642
Important	0.37	327	87.1	2.13[a]	-0.85	0.0614
Very important	0.38	219	94.3	4.74[a]	-0.92	0.1163
Occupation						
White collar						
Upper level	0.45	342	86.3	2.1	-0.98	0.0603
Lower level	0.38	348	87.2	2.7	-0.94	0.0705
Blue collar	0.39	299	91.4	6.27	-0.94	0.1647

[a]Denotes significant differences with at least one other subgroup at the 5 percent confidence level.
[b]Derived on the basis of natural breaks in the frequency distribution of responses. The corresponding importance ratings are 1-18, 19-51, 52-84, 85-100.

Table 2. Differences in travel-time evaluation among population subgroups: sums of squares of differences in mean satisfaction ratings.

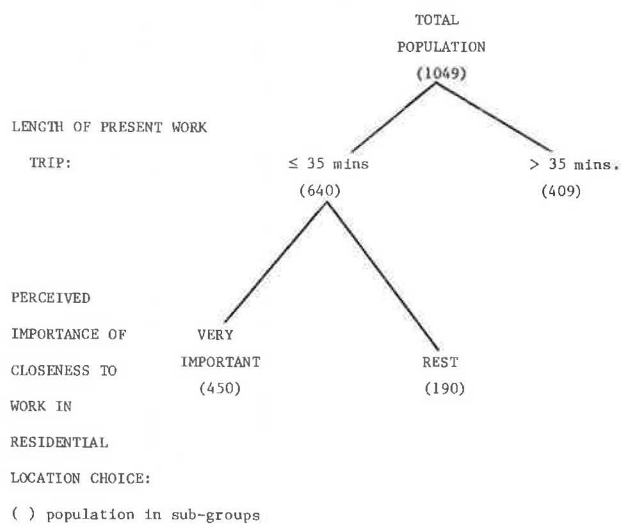
Category	Subgroup Comparison	Step 1 Grouping	Step 2 Grouping[a]
Sex	Male with female	131	128
Mode	Car with public transportation	466	200
Age (years)	≤24 with 25-29	31	52
	≤24 with 30-39	47	65
	≤24 with ≥40	119	82
	25-29 with 30-39	33	50
	25-29 with ≥40	54	70
	30-39 with ≥40	82	127
Importance	Very important with rest[b]	492	296
Occupation	Upper-level white collar with lower-level white collar	48	104
	Upper-level white collar with blue collar	34	36
	Lower-level white collar with blue collar	31	33
Perceived travel time to work (min)	0-15 with 16-35	265	265
	0-15 with 36-55	836	
	0-15 with ≥56	1597	
	16-35 with 36-55	381	
	16-35 with ≥56	986	
	36-55 with ≥56	216	
	0-35 with ≥36	723	

[a]Those whose current travel time is >35 min.
[b]Subgroups unimportant, relatively important, and important have been combined into a group called "rest".

capable of detecting localized differences between the subgroups.

Specifically, a simple t-test was used to determine whether the subgroups differed significantly (at the 5 percent level) in the mean satisfaction ratings assigned to each travel time. A measure of the total difference between the respective distributions was subsequently obtained by summing the squares of the differences in their average ratings. This measure is analogous to the between-group variance in analysis of variance. The grouping that produced the largest sum of squares of differences in the means was deemed to have the largest variance in evaluation and formed the basis for subsequent steps in the analysis. This process of dividing the sample into two groups and then investigating the lower-order groupings is similar in nature to the clustering program referred to as the

Figure 8. Breakdown of population subgroups with significant differences in travel-time evaluations (experimental data).



Automatic-Interaction Detector (9). Segmentation of the experimental data continued until there was no significant difference between the average evaluation ratings for any of the travel-time values (this step is analogous to the within-group variance produced in analysis of variance). Table 2 and Figure 8 summarize the results of this analysis.

COMPARISON OF RESULTS

First, in the results of the regression analysis (Table 1) there appear to be very few differences between the subgroups in their observed behavior. The variation in the slopes of the lines is not significant (at the 5 percent confidence level) for any of the groupings. The intercepts do, however, show some variation, which indicates some differences in their evaluation of low travel times. For example, those who feel closeness to work is relatively unimportant rate low travel times somewhat lower than the other groups.

Figure 9. Evaluation of hypothetical travel times by those currently traveling less than and those traveling more than 35 min to work.

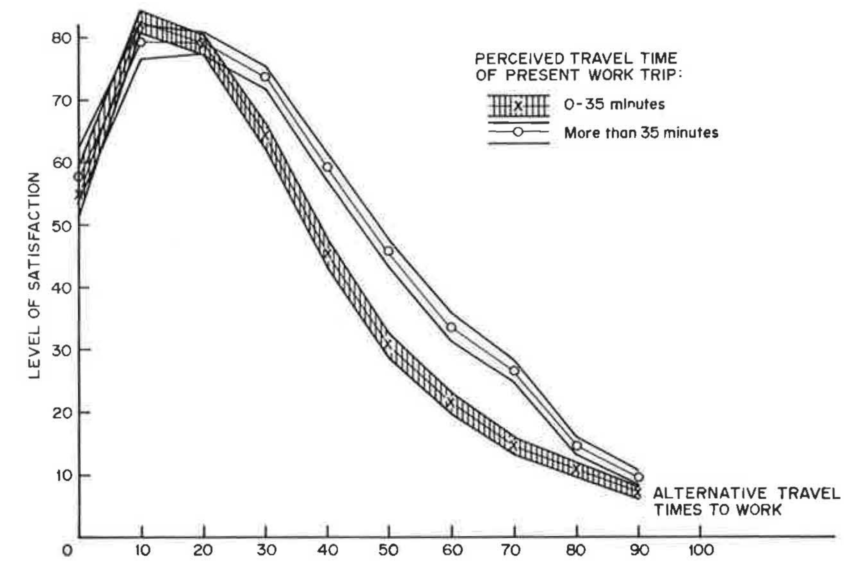
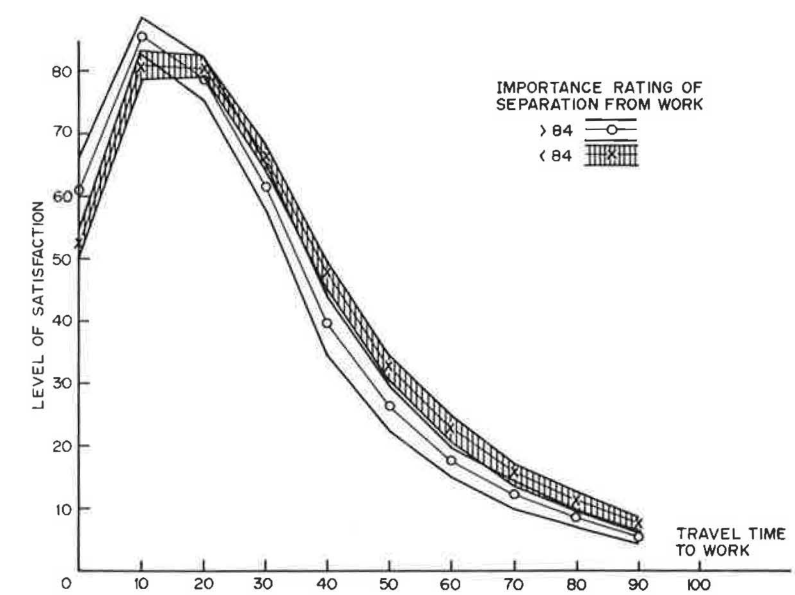


Figure 10. Evaluation of hypothetical travel times by perceived importance of closeness to work for subpopulation traveling less than 35 min to work.



Analysis of the experimental data, however, indicates that existing patterns of behavior impart a significant bias to travel-time evaluation (Table 2). By far the greatest difference in the preference distributions occurs when the population is grouped according to the perceived length of their work trips. Mode of travel and subjective ratings of importance also appear to be significant discriminators. But, as will be seen later, these show systematic relations with existing travel times.

Figure 9 compares the preference distributions for those who spend between 0 and 35 min and those who spend more than 35 min traveling to work. Generally, those who travel the shorter distance are less satisfied with travel times of more than 30 min than those who currently spend the longer time traveling.

Taking this as the second stage in the grouping, there are no significant differences in any of the possible groupings of the people who travel more than 35 min to work. Those who travel less than 35 min can, however, be grouped into (a) those who feel closeness to work is very important in the decision to live where they do and (b) the remainder of the population. Figure 10 shows that those who feel closeness to work is very important are less satisfied with longer travel times than the remainder of the subpopulation.

It is of interest to note, however, that grouping individuals who travel less than 35 min to work by importance produces only a slightly larger difference in the two distributions than would have resulted had the grouping used those who travel 0-15 min and those who travel 16-35 min (Table 2). Moreover, similar results using observed data and travel distance have been documented elsewhere (10).

The tendency of subpopulations to rate their existing travel time higher than the rest of the population may result from several factors:

1. The individual may adapt to a particular travel time once it has become part of his or her regular routine.
2. The individual may go through a process of rationalization in which, in order to accept certain decisions, he or she must be convinced that the

required travel distance is satisfactory.

3. The possible influence of other mediating factors should not be ruled out. For instance, a large proportion of those who use public transportation spend more than 35 min traveling to work (see Table 3). Moreover, users of public transportation tend to be less dissatisfied with these longer travel times (see Figure 11). This may partly reflect a greater opportunity to use the time spent traveling more productively (e.g., reading the paper and talking to friends).

4. The individual may in fact prefer the said travel time.

There is no clear evidence as to the degree of influence each of the above considerations has on the differences shown in Figures 8-10.

The findings of the experimental approach clearly highlight a major problem in using observed data. The observed-behavior approach implicitly assumes attribute evaluation to be independent of existing choices and conditions; that is, people are assumed to rate their existing travel time in the same way as would other individuals who travel different distances to work.

The second difficulty with the observed-behavior approach lies in the distribution of travel times at which people live from work. Figure 12 shows that the majority of the total sample live between 10 and 30 min of work, few people live within 5 min of work, and only a small number live more than 65 min from work. The small proportion of ratings in these areas means that they will only have a small influence on the regression line, which, in turn, is less representative of these travel times.

Table 3. Relation between mode use and perceived travel time to work.

Perceived Travel Time from Home to Work (min)	Mode of Travel: Car, Number	Car, Travel-Time Distribution (%)	Public Transportation, Number	Public Transportation, Travel-Time Distribution (%)
0-15	251	27.4	6	3.7
16-35	377	41.1	19	11.7
36-55	204	22.2	48	29.6
>55	85	9.3	89	54.9
Total	917	100.0	162	100.0

Figure 11. Comparison of observed and experimental relations for car and public transportation users.

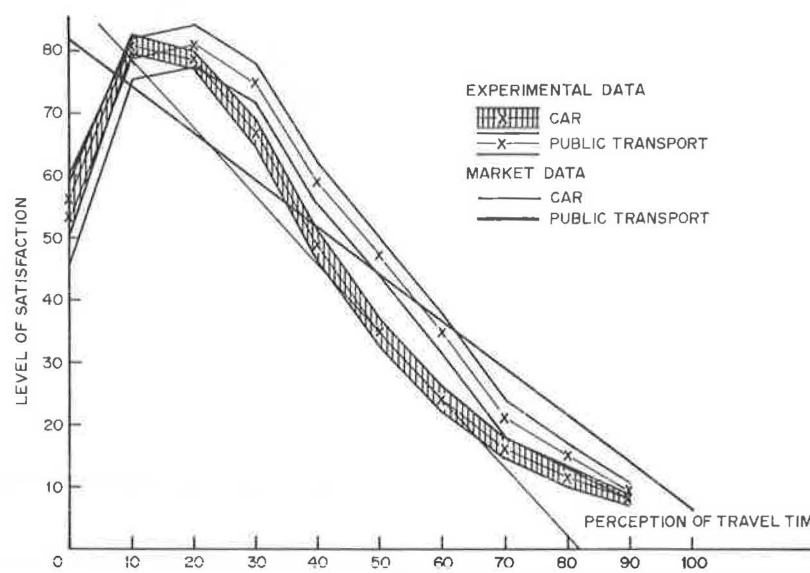
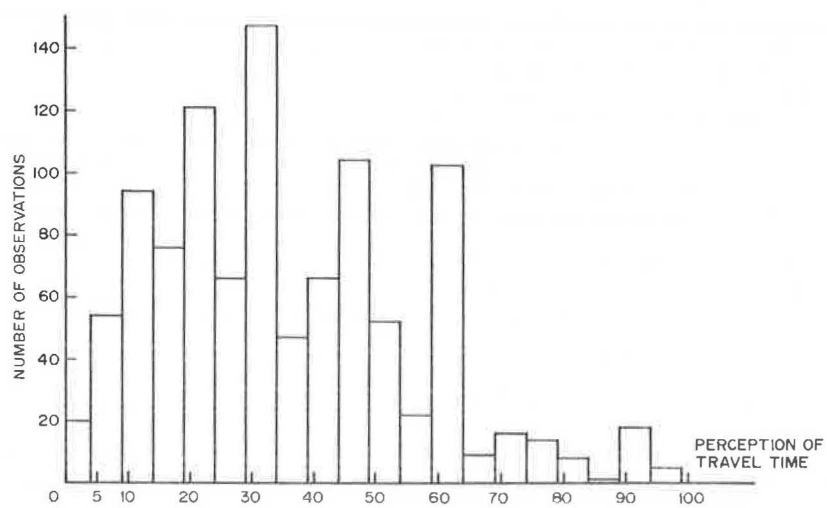


Figure 12. Frequency distribution of travel times reported by respondents to present journey to work.



Even with these apparent differences, however, a comparison of the relations obtained from the observed and experimental approaches shows marked similarities. Figure 11 is fairly representative of the level of correspondence between the results. Both approaches suggest that car users are less satisfied with longer travel times than are those who travel by public transportation. But, as has been emphasized earlier (Table 3), users of public transportation generally have longer travel times. Consequently, the regression coefficients are likely to produce less reliable estimates at the lower end of the travel-time range.

The general spread of data points in the observed-data approach and its inability to relate people's perceptions to their existing conditions cast doubts on its validity. The experimental approach appears to overcome some of the problems outlined, although it too has its limitations. One key unresolved issue is whether people are able to respond accurately to hypothetical attribute levels. It is also unclear whether the processes of travel-time estimation and evaluation are indeed independent as conceptualized in Figure 1. Even assuming this to be the case, it may be unrealistic to expect individuals to evaluate a given attribute in isolation from other considerations. The latter is more an argument for extending the experimental approach to a multifactorial design than a fundamental criticism of the method itself. Work along these lines has been carried out in other contexts under the guise of functional analysis (11,12).

IMPLICATIONS

The relations and procedures investigated in this paper have implications for both modelers and those who collect the data.

In regard to data-collection procedures, this paper provides some evidence for questioning the suitability of basing comprehensive data sets solely on observed patterns of behavior. The very nature of the urban system means that not all possible variations in choice and attribute levels will be available. Models based on observed data may be appropriate for predicting changes within a similar environment or range of experience, but as soon as one steps outside that environment the observed data and the models thus derived become less reliable. Experimental data such as those presented here would seem to provide a sounder basis for building models, by providing for greater control over attribute levels.

The general form of the relation between perceived satisfaction and travel time also has implications for modeling and for the development of accessibility measures. Most commonly, the impedance to travel is assumed to be (a) constant across groups of people and (b) a monotonically decreasing function of travel time. However, the evidence presented in this paper indicates that a monotonic relation does not hold for all people; there is a general tendency for individuals to be less satisfied with living close to work than with living 10-20 min from work. The exact form of the relation must await more refined analyses.

CONCLUSIONS

Two approaches for investigating the relation between individuals' evaluations of travel time and their perceptions of travel time were investigated. The observed-data approach used only information on existing travel patterns, whereas the experimental approach collected information on a number of hypothetical travel times. Although the observed-data approach provided relations similar to those provided by the experimental approach, it did so with an unrepresentative set of data points. Less reliance could, therefore, be placed on these results.

The experimental approach showed that the respondents tended to prefer a 10- to 20-min separation between home and work. Lower and higher travel times were found to provide a lower level of satisfaction. Although this general distribution held for all groups of individuals studied, there were variations between some subpopulations. These variations were most marked between those groupings of people who actually spent different amounts of time in traveling.

In closing, this paper questions the assumption made in many models and accessibility measures that individuals' satisfaction with temporal separation from the workplace decreases with distance. More realistic measures could result if the distributions discussed in this paper were incorporated.

ACKNOWLEDGMENT

We gratefully acknowledge assistance with the computer analysis given by Steven Goschnick and Gerard Garlick.

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