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Time-use data, analysis and modeling: toward the next generation of transportation planning methodologies

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This paper argues that transportation planning methodologies must be built on the central thesis of the activity-based approach to travel demand modeling, namely, that travel is a derived demand that reflects people's desire and need to participate in activities. The paper discusses why this foundation for transportation planning methodologies is necessary to address contemporary planning and policy analysis issues. The paper also argues that the introduction of time-use data, analysis and modeling is a key element in the development of the next generation of transportation planning methodologies. Following a brief review of time-use studies, the paper discusses a number of planning and policy analysis areas in which time-use data will be of particular value, including the evaluation of induced or suppressed travel demand. The concepts advanced in the paper are illustrated with two brief numerical examples. These examples show how model systems based on time-use data can be used to (i) estimate the number of induced trips that would result from a reduction in commute travel time, and (ii) evaluate the impacts of alternative transportation improvement projects.

Introduction

Travel behavior analysis and modeling for transportation planning and policy development is based largely on records of reported trips, modal attributes, and the demographic and socio-economic characteristics of households and individuals, combined with network and land use data. While analyses using these data have offered invaluable information for transportation planning, it is likely that in the near future, if not now, there will be needs for behavioral analysis based on more extensive and richer data. This is because (i) more fundamental approaches to travel behavior are needed to effectively address the issues of congestion, energy consumption, and air pollution, and (ii) methodologies need to be developed to assess the impact of transportation on the quality of life.

Underlying the first statement above is the central thesis of the activity-based approach to travel demand analysis, namely that travel demand is a derived demand. To fully understand and predict travel demand for planning purposes, especially in the context of policies that might restrict travel choices, it is necessary to understand what drives people to travel. Instead of looking at trips and networks, the analysis must examine why, with whom, where and when activities are engaged in, and how activity engagement is related to the spatial and institutional organization of an urban area.

In this article, it is argued that the idea that travel is a derived demand must truly permeate the methodologies for transportation planning. This calls for the development of a new generation of data collection procedures and analytical methodologies for transportation planning. It is further argued that the introduction of time-use data, analysis, and models into transportation planning analysis is a key component of the development of the next generation of transportation planning methodologies. To illustrate the concepts put forward in this paper, the results of two simple numerical examples are presented. In these examples, model systems that are based on time-use data are applied to estimate the amount

*Eric Pas died on 21st November 1997. He will be sadly missed.

of induced trips brought about by a 10-min reduction in commute travel time, and to evaluate the impacts of alternative transportation improvement projects.

Framework of current approaches to transportation planning analysis

Standard approaches in transportation planning analysis are reviewed from a broad perspective in this section. The discussion points out that the current approaches are based on limited sets of input data and measures of effectiveness, and that, like travel demand analysis, they are 'trip-based' and attempt to evaluate the merits of planning alternatives based only on measures associated with trips and trip-making. Consequently the impact of planning alternatives on the welfare of urban residents, or their quality of life, is not adequately captured.

Conventional inputs to transportation planning analysis typically comprise:

- records of reported trips;
- demographic and socio-economic attributes of households and individuals;
- highway and transit network data; and
- land use and other zonal attributes.

Principal measures of effectiveness, other than the cost, in transportation planning have been:

- level of service;
- capacity;
- pollutant emissions impacts; and
- safety.

The first measure is defined for highways based on traffic density and speed, and is an indicator of travel time and cost savings, relative to the status quo. The second represents the maximum number of vehicles or passengers which a network link can carry per unit time. Environmental and safety measures for highways are based on speed and volume estimates, while vehicle occupancy is one of the key determinants of pollutant emissions per passenger–mile for public transit.

The use of these measures of effectiveness implies that a transportation planning alternative that provides cleaner, faster and more transportation is a better alternative. These measures have constituted the value system that has driven transportation planning. To be able to determine which planning alternative will provide cleaner, faster and more transportation, information concerning trips has been regarded as the only data needed. This focus has led to the above conventional inputs to transportation planning analysis.

New contexts for transportation planning

This preoccupation with trips was presumably an effective strategy during the postwar period when motorization and suburbanization were progressing at rapid rates in the industrialized nations and the principal concern of urban transportation planning was to determine where highways should be built and how many lanes they should have. The emphasis of transportation planning, however, has shifted considerably from infrastructure expansion, first to Transportation Systems Management (TSM) and more recently to Travel Demand Management (TDM) and more inclusively to Transportation Control Measures (TCM). For example, in the United States, public concerns about environmental damage and uncontrolled urban growth are ever rising, and new transportation planning agendas have been set forth in part by the Clean Air Act Amendments (CAAA) of 1990 and the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991. In the United Kingdom, the policy has shifted away from road construction, which in turn has generated issues such as whether economic growth can be attained, or even whether current levels of economic activities can be sustained, without continued investment in transportation infrastructure.

The changes in the planning and policy environment call for significant shifts in transportation planning methodologies. In particular, planning tools are now required to have the capability to adequately assess the impacts of the broad range of policy options now considered by planning organizations. For planning tools to have this capability, requires

- a more fundamental understanding and modeling of travel demand, and
- development of methodologies to assess the impact of transportation planning options on the quality of life.

The former stems from the limitations of the conventional four-step procedures whose most critical problems are that they are trip-based and they lack the time dimension. Discussions of the deficiencies and limitations of the conventional approaches and the advantages of alternative, activity-based approaches can be found in, for example, Kitamura *et al.* (1996a). The latter point represents the criticism that the conventional transportation planning tools, or more specifically, demand forecasting model systems, have not addressed the relationship between transportation and the everyday life of urban residents. In other words, these tools focused on trips and aimed at cleaner, faster and more transportation; their scopes, however, have never extended to quantify what changes in transportation mean to urban residents' welfare. Although this issue may appear trivial in the context of traditional, facility-oriented transportation planning, it is not the case in the current planning contexts. The following simulated dialogue illustrates this point.

Q. How do we determine which TCMs are best suited for our MPO region?
A. Why not get the best model available and do a scenario analysis?
Q. What shall we compare?

A. Work trip mode use.
Q. Because fewer commuters in single-occupant vehicles result in reduced congestion and improved air quality?
A. Exactly!
Q. But, would people be happier then? You see, the end goal of transportation planning is after all the welfare of our residents.
A. Of course, why not? Carpooling is fun. And you can read in the bus.
Q. But waiting for a bus is no fun when the weather is bad.
A. Well, that's already in the model. It's called the alternative–specific constant.
Q. How about the errand I have to run on the way to work?
A. Well, I'm not sure.... That's not in the model. So it must not be that important.... Well, let me see. Are we missing something?

TCMs, especially TDM strategies, more directly affect urban residents' way of life than do the traditional facility expansion options. The narrow perspective embodied in the practice of evaluating TCMs and TDMs by examining their impacts on trips alone is likely to fail in capturing the full implications of these strategies (Pas, 1993; Schofer, 1993).

Activity-based evaluation of TCMs

Partly as a result of CAAA, there is currently a strong emphasis on TCMs in the United States. Air pollution and traffic congestion problems that plague many urban areas of the United States are the driving force of this emphasis. For example, in the highly polluted Los Angeles metropolitan area, Regulation XV mandates that employers above a certain size appoint a transportation coordinator and reduce the number of vehicular commute trips to attain a target level of average vehicle occupancy. Air pollution is the problem; commute trip mode use is the target.

Such draconian measures have not extended to many metropolitan areas. This is probably fortunate because the effectiveness of such measures must be determined after rigorously examining their likely total impacts on urban residents' everyday life. Such TCMs impose trade-offs between air quality and convenience in everyday life. Then, their effects, either positive or negative, must be appraised while assessing their impacts on the daily life of urban residents, not just on their commute trips. For example, forcing solo-driving commuters to take other travel modes may impose serious constraints on their activity scheduling and travel throughout the day. Air quality may improve, but possibly at a great cost on individual commuters' part. The same is more or less the case with 'market-based' measures, especially for those population segments that are economically less capable.

In this context, it is worth repeating that travel demand is a derived demand. If urban residents' travel behavior collectively leads to a problem, then the solution should be sought in what derives travel. Travel *per se* is not the right target for measures that aim at resolving the air quality problem – or even the congestion problem. Attempting to solve these problems by TCMs is to search for a quick fix by treating a symptom, but without dealing with the real cause of the problems. A thorough understanding of the reasons underlying trip-making is required to be able to reduce travel as well as to be able to predict travel demand because one must reduce the reasons that motivate people to travel before one can effectively address the issues of traffic congestion and air quality. *Activity-based evaluation* of TCMs is called for.

Approaching transportation problems from a broader perspective

Since travel is an integral part of urban life, TCMs could affect every aspect of the daily lives of urban residents. Consequently the impact of a TCM cannot be assessed by just looking at its effects on trips; one must examine how the TCM affects urban residents' daily life, i.e. the whole set of activities and trips made over the course of a day, or, better, over a longer span of time. It must be recognized here that land use and life style, along with transportation supply, determine travel demand. Land use, or more precisely the spatial and temporal distribution of opportunities available for activities, is one key determinant of urban residents' activity and travel. Another key determinant is life style, namely what people do (which is equivalent to how they use their time) or what they aspire to do, along with what they possess and what they consume. Travel demand is a derived demand. What shapes travel demand is not just transportation supply, but also where opportunities lie and what people wish to do, when and with whom. And these three elements – land use, life style and transportation supply – are inter-connected, mutually affecting each other in an evolutionary process.

Given the above, it is clear that we need to address land use and life style to truly address negative consequences of urban transportation. This is a straightforward application of the activity-based approach to transportation policy. Environmental policy must first deal with these fundamental factors that determine trip-making. If reduction of trips is called for, then it must be achieved by reducing the needs and desire to travel, whether in terms of the number of trips or distance traveled. Addressing land use development and control is simply inevitable in this context. Likewise, aspects of urban residents' life styles – e.g. their activity patterns – must be explicitly incorporated into the analytical scope. Available data and models, however, do not support transportation policy analysis from this broader perspective. The central ingredient for such analyses is time-use data, along with microscopic land use data and possibly consumer expenditure data.

Time-use data and analysis

Time-use data generally provide information on what individuals do over the course of a day or several consecutive days. Both activities in the home as well as outside the home are usually included in a time-use data set, which most typically comprises either daily or weekly data. Some time-use data sets contain information on activity location and trips, while there is an example where the satisfaction level was reported by the respondent for each activity (Juster, 1990).

Studies of time-use date back to the early part of this century. The first time-use study with a specific focus on travel was undertaken 50 years ago. The largest undertaking was the multi-national comparative time budget project in the late 1960s in which nearly 28 000 time-use diaries were collected in 12 countries (Szalai, 1972). Consistent coding schemes have been developed to classify activities into detailed categories, facilitating comparative studies of these time-use data sets. There are now many large-scale survey results in North America and Europe that are based on mutually comparable survey instruments.[1] Longitudinal studies have been undertaken in the past 10 to 15 years (an extensive discussion of time-use studies and their relationship to travel demand modeling is presented by Pas and Harvey, 1991).

Several, fairly standardized methods exist for the collection of time-use data. Kalfs (1993) compares paper and pencil interviews (PAPI), computer assisted telephone interviews (CATI), and computer assisted self-interviews (CASI).[2] Methods for collecting time-use data may also be classified according to the method of sampling activities into:

- time point;
- interval; and
- episode.

Activities may be sampled at time points, which may be randomly generated or recur at fixed intervals (e.g. every 15 min). The activity being performed is recorded at each time point. This sampling method leads to unbiased estimates of the total time allocated to respective types of activities. It, however, will lead to underestimation of the frequency of activity episodes,[3] especially for those activities which tend to have short durations. In the interval-based sampling, the representative activity, or activities, are recorded for each time interval. The representative activity is typically defined as that activity to which most time is allocated in the interval. When a single representative activity is recorded, then this sampling method leads to the systematic bias that activities of shorter durations are under-represented, both in their frequencies and the amounts of time allocated.

The sampling by activity episode is probably most suited for travel behavior analysis. In this sampling method, information is recorded for each activity episode. The data obtained can reproduce both episode frequency and time allocation properly, provided that all episodes are recorded. Data are collected by this method most typically by asking the respondent to recall and describe (often in an open-ended manner) the activities performed on the day before the survey, activity by activity sequentially as they were performed across the day. Computer-aided telephone interview (CATI) techniques are often used. It is often argued that this survey procedure produces more accurate reporting of trips. For example, Robinson *et al.* (1992) maintain:

> In contrast [to the episode-based time-use data collection method], data on travel activities of the public taken from ordinary recall surveys are usually incomplete. Such surveys almost naturally introduce problems for respondents because they are asked to recall from memory rather selected and partial behaviors (van der Hoorn, 1979; Ampt *et al.*, 1985). In attempting to recall *only* travel, respondents are likely to have trouble recalling all their 'trips' as they search through their memories. Moreover, respondents learn that the more trips they report, the longer will be the interview experience. (emphasis in the original)

The focus of the analysis of time-use data has been on time allocations to target activities, and time-use behavior by target subgroups. Issues addressed have been mainly sociological or economical, such as the value of in-home unpaid work. Little attention has been devoted to the modeling of time-use, activity sequencing, and activity location choice. Despite this relative inattention to travel behavior by time-use researchers, time-use data facilitate thorough analysis of activity engagement as well as trip-making, in particular, the analysis of substitution between in-home activities and out-of-home activities.

For example, there will be occasions where one wonders whether to go out to a movie theater or stay home and watch TV. This in-home versus out-of-home activity choice has an obvious implication for trip-making; the former involves travel while the latter does not.[4] By approaching travel behavior from the perspective of activity analysis, it is possible to probe into 'why' people make trips, and, consequently, investigate how trip-making is induced or suppressed.

[1]Nippon Hoso Kyokai (NHK, Japanese Broadcasting Corporation) collects time-use data with five year intervals. Unfortunately, the raw data are not released to researchers and therefore these data are typically not included in comparative analyses of time use behavior.

[2]In addition to the methods discussed by Kalfs (1993), direct observation may be useful to collect a small sample of data when observation can be made without being intrusive (e.g. Kitamura and Supernak, 1997).

[3]A period in which the same activity is continuously engaged constitutes an episode.

[4]Some in-home activities do, however, involve travel. For example, watching a movie on a rented videotape generates two trips to the video store – one trip to rent the movie and a second one to return it. Similarly, cooking and eating a meal at home is an alternative to eating out. However, the ingredients need to be purchased, and this entails travel to the grocery store, although the visit to the grocery might or might not be specifically associated with the preparation of the meal in question.

In addition to their ability to support more rigorous analysis of travel behavior and policy development, the full impact of TCMs on everyday life can be captured by a model of time-use. Recent efforts on the analysis of activity durations (Mannering *et al.*, 1994; Bhat, 1996), time allocation (Golob, 1996; Lu and Pas, 1997), in-home and out-of-home activity split (Kitamura *et al.*, 1996b) and activity sequencing and scheduling (Ettema *et al.*, 1993; Kitamura *et al.*, 1995; Pendyala *et al.*, 1995) are building blocks of model systems to be developed to fully depict individuals' time-use and travel. Important near-term application areas of time-use data and analysis are discussed in the following sections.

Applications to transportation planning and policy analysis

There are several areas in transportation planning and policy analysis where time-use data and analysis will be of particular value. They include:

- improved travel data collection;
- evaluation of induced or suppressed travel;
- project evaluation;
- transportation and quality of life.

The first of these four has been discussed briefly in this paper. Further discussion of the value of time-use data in the collection of household travel data can be found in Pas (1997), Lawton and Pas (1996) and Stecher *et al.* (1996). Each of the remaining three issues will be addressed in the following subsections.

Induced/suppressed travel

Daily or weekly time-use data facilitate rigorous analysis of travel behavior since they contain records of all activities performed by the respondents over the survey period. For example, as noted earlier, a fundamental treatment of trip generation is possible by examining the substitution between in-home and out-of-home activities. This is of particular importance when induced or suppressed travel is concerned.

Consider how a reduction in commute travel time may induce trips (the term 'induce' is used here in a narrow sense; 'induced trips' here refers to those trips that were not made in the past, but are newly made due to improvements in the level of service). Conventional trip generation models are not sensitive to changes in the level of service and are not able to capture the effects of such travel time reductions. Behaviorally, the commuter would wonder how to take advantage of the time savings, and may decide to spend the time gained at home with the family, or may decide to make more frequent and/or longer visits to the gym. The latter choice involves induced trips, while either choice would improve the commuters welfare. As this example illustrates, whether new trips are induced depends on how the trip maker decides to use time; the time savings may be allocated to activities which do not induce trips (e.g. spending more time at home) or to those which induce trips. Clearly, then, the issue of induced trips is the issue of time-use, or, activity choice.

Likewise, increasing congestion may lead to suppressed travel demand; as travel consumes more time, less time is left for activities, and sooner or later some of the activities must be foregone, leading to fewer trips. Clearly, the key question to be addressed when dealing with induced or suppressed trips is how people use time; what do they do when they gain extra time, and what do they do when they run out of time? Zahavi (1977) advanced the conjecture of constant travel time budgets (and constant travel expenditures as a percentage of income) in the development of the UMOT model of travel. Under the assumption of constant travel time budgets, an individual will allocate a fixed amount of time to travel; thus, if travel speed improves, then the time saved will be used to travel more or further, while if congestion worsens, then people will make fewer trips, choose faster modes, and/or choose closer destinations. This controversial notion of constancy in travel time budgets is essentially the sole behavioral paradigm that has been applied to the issue of induced/suppressed demand.[5]

The paradigm of constant travel budgets, viewed from the perspective of time-use analysis, implies that time allocation is absolutely inelastic as far as travel is involved. This hypothesis about time-use behavior conflicts with the utilitarian hypothesis that a rational person would allocate the available time optimally to different types of activities while considering trade-offs; one might, for example, allocate more time to travel if that would enable a visit to a destination where time spent produces greater utility, thereby increasing one's total utility. Empirical evidence is unfortunately scant to conclude which of these competing hypotheses is more plausible. Recent results using time-use data, however, are starting to shed light on behavioral mechanisms underlying time-use behavior. Some examples will be presented later in this paper.

Since time-use data provide information about what people do throughout the course of the day, their use facilitates more fundamental analysis of travel demand. In addition to the issue of induced/suppressed demand, time-use data will support general travel demand analysis, in particular the analysis of:

- substitution between in-home and out-of-home activities;

[5]Another approach is the use of accessibility measures in trip generation models. Improvements in speed implies improved accessibility measures. The inclusion of accessibility measures will thus make trip generation models sensitive to traffic congestion. Early examples include Nakkash and Grecco (1972), whose results, however, were not conclusive. A model system for the San Francisco–San Jose Bay Area (Harvey and Deakin, 1993) contains a trip frequency model for social-recreational trips which incorporates as one of its explanatory variables the expected utility of a trip derived from a destination–mode choice model. This expected utility measure can be interpreted as an accessibility measure.

- departure time decision;
- activity and trip sequencing and timing; and
- impacts of policies or changes in the travel environment that affect daily activities, but not necessarily travel.

Time-use data will also aid in providing better travel inputs to conventional models, as noted previously.

Project evaluation using models of time-use behavior

The benefit of travel time reduction brought about by an investment into infrastructure or an improvement in system operation is often difficult to measure. Traditionally this has been done by multiplying a representative 'value of time' by the total amount of time saved (see, e.g., AASHTO, 1977). This, however, is a crude method and does not reflect the fact that the value of time differs from occasion to occasion, depending on: the nature of the activity at the destination, the time of day and other trip attributes, household and person attributes, and a number of other, often situational, factors. Establishing a value of time for each of the probably astronomical number of combinations of these contributing factors would be impractical, while using a representative value of time implicitly assumes that these contributing factors are identically distributed geographically and temporally, and will not change over time.

Logically speaking, the benefit of travel time reduction should be evaluated while looking at the opportunity cost of time; how the time saved can be productively used and how valuable that time allocation may be to the person concerned. Consider, for example, the case where the total daily travel time of an urban resident is reduced by 30 min due to a capacity increase. How should the value of this travel time reduction be measured? Although one could use the resident's wage rate, or some function thereof, as the value of time, this approach has limitations including that wage rates are undefined for those who are not employed, e.g. homemakers, students, retirees, or millionaire investors. Instead, we propose that we examine how the resident will use that extra 30 min and assess the benefit accrued based on the values – or utilities – of the activities to which the 30 min are allocated.

Developing a model to predict how individuals allocate their time is not a difficult task. Given such a model, how that 30 min would be used can be forecast and a benefit measure developed. Not only is this approach consistent with the notion of the opportunity cost of time, but it also offers performance indicators to evaluate transportation improvement projects which are intuitively understandable by citizens who ultimately provide financial support for transportation projects. Namely, it shows citizens how travel time savings coming from an improvement project can be used by themselves and by fellow residents – for more rest at home, more recreational activities outside home, or more travel. The second application example presented below illustrates the use of these ideas in project evaluation.

Transportation and quality of life

Another important benefit of time-use analysis concerns the evaluation of quality of life. In a study conducted for the Dutch Ministry of Transport (Kitamura *et al.*, 1992), time-use patterns were compared between Dutch and Californian residents. The study was motivated by the hypothesis that the Dutch, who are more dependent on public transit, would have a lower quality of life due to the limited accessibility to opportunities resulting from the limited mobility provided by public transit. Although the study examined only average time expenditures, its findings are nonetheless thought provoking.

The analysis indicated that Californians on average spend more time for paid work and travel than do the Dutch. The Dutch, on the other hand, spend more time on such discretionary activities as recreation, social visits, sports and hobbies. It so turned out that the only 'fun' activities that Californians spend more time on is watching TV! If these aggregate statistics portray accurately the everyday life in the two locales, then the results are entirely contrary to what one might anticipate. What emerges from the analysis is a picture of overworked Californians; they work longer hours and spend more hours behind the wheel to commute, and by the time they return home they are so exhausted that the only discretionary activity that they have energy left to engage in is watching TV.

What emerges from this analysis is the hypothesis that motorization and automobile-driven land use development may not necessarily contribute to the residents' quality of life. In the sprawling low density urban areas of California, opportunities are far apart, requiring the residents to traverse greater distances to engage in activities. Resulting vehicle–miles of travel collectively lead to traffic congestion, increasing travel time and worsening the situation. The Dutch, it seems, are able to find opportunities within their reach despite their heavier reliance on slower travel modes. There appears to be a density–speed relationship which in this case favors the Dutch living environment.

By looking at time-use, it becomes possible for the planner to assess how urban development and transportation systems contribute to the quality of lives the residents live. The richness of the analysis can be enhanced when, as some surveys have done, measures of satisfaction are introduced into time-use data (Juster, 1990). Tying time-use data to consumption data, and thus encompassing a wide spectrum of consumer behavior, would also be a valuable extension. Measures of attitudes and perception can also be introduced into the scope to form a robust welfare analysis. Through such efforts, transportation planning analysis will be able to address how transportation affects the quality of life and thus either increases or reduces the welfare of urban residents.

Two examples in which time-use models are applied in

transportation planning analyses are presented below. These examples may be viewed as prototypical transportation planning analyses from a time-use perspective.

Application example I: estimation of induced trips by a structural equations model system

Fujii *et al.* (1997a) developed a structural equations model system that explains commuters' time-use and travel after work hours. The data used were collected in 1994 in the Osaka–Kobe metropolitan area as part of an evaluation study of the impact of the new Wangan (Bayshore) Line of the Hanshin Expressway system. The survey took on a self-administered mail-out, mail-back format and targeted household members of at least 16 years old in the study area. The questionnaires were distributed to 4714 households along the Wangan Line and several competing routes. Usable responses were obtained from 594 households (response rate of 12.6%) for 1257 individuals.

The survey instruments included a one-day activity diary. The diary contained blanks to fill in, for each activity: the activity type, beginning time, ending time, facility type, type of accompanying person(s), spatial fixity, and temporal fixity. For each trip, information was collected on: travel mode, departure time, arrival time and number of accompanying persons. Also included were questions in which the respondent was asked to indicate the level of preference for several types of activities. In addition, the respondent was asked to rate how satisfactory the day as a whole was.

The endogenous variables of the model system are:

- number of trips after work and before returning home for the first time (N_{trips});
- total out-of-home activity duration (excluding travel) after work and before returning home for the first time (D_{out});
- increase in travel time due to trips made to engage in out-of-home activities after work and before returning home for the first time (D_{nctrips});
- number of home-based trip chains after returning home for the first time till retiring for the day (N_{chains}); and
- total time spent at home after returning home for the first time till retiring for the day (D_{home}).

The exogenous variables used in the analysis include: commute duration, regular work starting time, regular work ending time, flexible work hours, number of overtime hours, age, work trip mode, number of restaurants in work zone, preference indicator for out-of-home activities, and preference indicator for in-home activities. Appendix A describes the model system in more detail.

The resulting model system was used to perform a sensitivity analysis, whose results are summarized in Table 1. Evaluated in the analysis are the impacts of a 10-min reduction in commute time on time-use and travel. The model system indicates that the average total out-of-home activity duration will increase by 1.88 min to 27.44 min, while the total time spent in home increases by 7.11 min. The average total travel time increases by 0.36 min, while the number of home-based trip chains after returning home from work increases about 30%. Over 70% of the time saved is applied to additional in-home activities, and about 19% to out-of-home activities, while only a negligible amount of time saved is devoted to travel. Thus, the results reported here suggest that travel time savings of the magnitude analyzed here induce a relatively small amount of trips.

Table 1 Effects of 10-min commute time reduction on time-use and travel

	Base case	10-Min reduction	Difference
Total out-of-home activity duration (D_{out})	25.56	27.44	+1.88
Increase in travel time (D_{nctrips})	6.78	7.14	+0.36
Frequency of home-based trip chains (N_{chains})	0.03	0.04	+0.01
Total time spent at home (D_{home})	216.1	223.2	+7.11

Application example II: project evaluation using time-use utility

In the second application example, the utility of daily activity is quantified and the impact of travel time reduction on utility is evaluated (Fujii *et al.*, 1997b). The utility of an activity is assumed to be a function of the time allocated to it and increases as the allocated time increases. It is also assumed that the utility function varies according to the attributes of the individual. Furthermore, in order to account for differences across individuals that are not associated with objectively measured person attributes, the coefficients of the utility function are specified as linear functions of subjective preference ratings provided by the respondent for respective types of activity. The model formulation is given in Appendix B.

The resulting model system is applied to determine how travel time reduction affects the overall utility, hereafter 'time-use utility', which is defined as the sum of the utilities of all activities performed during the study period. Alternative travel time improvement strategies are evaluated on the basis of this utility measure.

Consider the network shown in Figure 1, which encompasses the home base, work location and an activity center. Consider the following two improvement strategies.

Strategy 1: reduce the travel time between work and the activity center by 15 min.

Strategy 2: reduce the travel time between work and home by 7.5 min, one way.

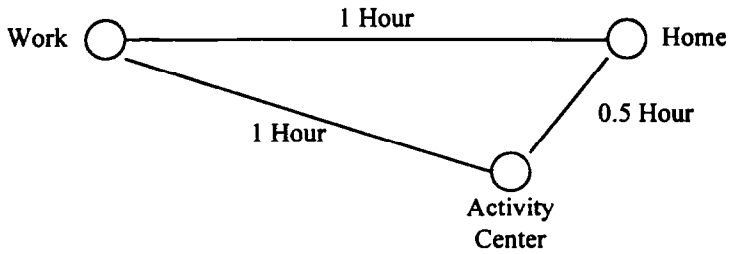

Figure 1 Hypothetical networks used in the example.

Table 2 Effects of alternative travel time reduction strategies on activity engagement and time-use utility

	Base Case		Strategy 1		Strategy 2	
	No stop	Stop	No stop	Stop	No stop	Stop
Discretionary out-of-home time (h)	0.000	0.902	0.000	0.975	0.000	0.902
Travel time (h)	1.000	1.50	1.000	1.250	0.875	1.500
In-home time (h)	5.000	3.597	5.000	3.775	5.125	3.597
Time returned home	19:00	20:24	19:00	20:14	18:53	20:24
Probability of choice	0.538	0.462	0.497	0.503	0.562	0.438
Representative time-use utility	0.290	0.138	0.290	0.303	0.389	0.138

For the daily travel pattern of home→work→home, Strategy 1 leads to no travel time saving, while Strategy 2 reduces the total daily travel time by 15 min. For the pattern of home→work→activity center→home, Strategy 1 produces a travel time saving of 15 min, while Strategy 2 offers a saving of 7.5 min.

The impacts of these alternative strategies are estimated from the model, while focusing on the activity and travel of a commuter after work, with the assumptions that work ends at 6:00 PM, utility producing in-home activities end at midnight (0:00 AM), and the commuter will make the choice between making a stop at the activity center or returning home directly from work without making a stop. The results are summarized in Table 2.

The table presents the amount of time allocated to out-of-home discretionary activities, travel time, and in-home activity time, for the base case and the two alternative strategies. It also shows the probability that an out-of-home discretionary activity will be pursued on the way home, and the expected utility associated with the activity pattern.

It can be seen from the table that, in the case a stop is made on the way home, the 15-min travel time reduction between work and activity center under Strategy 1 leads to an increase in out-of-home activity time by 0.073 h (4.3 min), which is about 30% of the travel time saved. The remaining 10.7 min is assigned to in-home activities. The time-use utility associated with this travel pattern increases from 0.138 to 0.303.[6] The probability that a stop will be made increases from 0.462 to 0.503 under Strategy 1. Likewise, it can be seen that the utility of the pattern without a stop increases from 0.290 to 0.389 under Strategy 2.

The conventional unconditional expected utility associated with each strategy (denoted as '$E[U]$') and the expected utility with the assumption that the commuter chooses that pattern which produces a larger utility value ('$\ln \Sigma e^{V}$'), are shown in Table 3 for the three cases. It can be seen that, regardless of the utility measure used, Strategy 1, which involves the improvement of travel time between work and the activity center, produces a larger expected utility than does Strategy 2.

Although only two simple alternative activity–travel patterns are considered on an extremely simple network, this example has shown that the time-use utility can be estimated and applied to evaluate transportation planning options while considering changes in utilities associated with activity–travel patterns. Importantly, the analytical framework proposed here automatically incorporates changes in behavior resulting from the implementation of a transportation planning option.

Table 3 Expected time-use utilities associated with the improvement strategies*

	$E[U]$	$\ln \Sigma e^{V}$
Base case	0.220	0.910
Strategy 1 (improvement between work and activity center)	0.297	0.990
Strategy 2 (improvement between work and home)	0.279	0.964

* Because the utility measures that can be identified from the discrete choice analysis used here are relative measures, $E[V]$ and $\ln \Sigma e^{V}$ are not comparable to each other.

[6]Being derived from a discrete choice model, these utility values have no absolute reference point. As a result, only differences in utility values are meaningful, but not their absolute values. The analysis here is based on the assumption of the logit model of discrete choice, that the perceived utility of an alternative, say j, can be expressed as $U_j = V_j + \varepsilon_j$, where V_j is the 'representative utility' and ε_j is an error term with an extreme-value distribution.

Toward the next generation of transportation planning methodologies

It is over four decades since the first home interview surveys of person trips were conducted. Very little has changed since then in terms of the data and analyses used in transportation planning, despite the drastic changes in the objectives of urban transportation planning, people's attitudes and values, politically acceptable solutions and economically feasible alternatives. Transportation planning, however, continues to be inspired by the desire for greater capacity and better level-of-service and the perceived need to 'meet the demand'. Little attention has been directed to the quality of life materialized by transportation service. Nor have any performance measures been introduced into the transportation planning process that attempt to quantify the impact of transportation on the quality of life. It is believed that time-use analysis presents itself as a key element as progress is made toward the next phase of urban transportation planning analysis.

Of course, effort needs to be expended on many fronts of time-use analysis, including data collection, behavioral theory, analytical methods, and development of tools for transportation planning and policy analysis. Furthermore, research is needed into the quantification of quality of life. It is hoped that the discussion and examples contained in this paper will constitute a small first step in the development of transportation planning methodologies that enhance the quality of urban life for urban residents in both developed and developing countries.

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Appendix A: Structural equations model system of time-use and travel

The model system used in Example I is described here. The system comprises measurement equations and structural equations defined as follows.

Measurement equations

$$N_{\text{trips}} = \begin{cases} 0 & \text{if } z_1^* < \theta_{11} \\ 1 & \text{if } \theta_{11} \le z_1^* < \theta_{12} \\ 2 & \text{if } \theta_{12} \le z_1^* < \theta_{13} \\ 3 & \text{if } \theta_{13} \le z_1^* < \theta_{14} \\ \ge 4 & \text{if } \theta_{14} \le z_1^* \end{cases}$$

$$D_{\text{out}} = \begin{cases} 0 & \text{if } z_2^* < 0 \\ z_2^* & \text{if } z_2^* \ge 0 \end{cases}$$

$$D_{\text{nctrips}} = \begin{cases} 0 & \text{if } z_3^* < 0 \\ z_3^* & \text{if } z_3^* \ge 0 \end{cases}$$

$$N_{\text{chains}} = \begin{cases} 0 & \text{if } z_4^* < \theta_{41} \\ 1 & \text{if } \theta_{41} \le z_4^* < \theta_{42} \\ \ge 2 & \text{if } \theta_{42} < z_4^* \end{cases}$$

$$D_{\text{home}} = z_5^*$$

where z_1^* through z_5^* are latent variables that correspond to N_{trips}, D_{out}, D_{nctrips}, N_{chains} and D_{home}, respectively; θ_{ij} is the jth threshold for the ith endogenous variable.

The home duration variable, D_{home}, is non-negative. There are no censored observations for this variable in the data set, however. No censoring is therefore assumed in the measurement equation.

Structural equations

$$z^* = Bz^* + \Gamma x + \varsigma$$

where

$$z^* = (z_1^*, z_2^*, z_3^*, z_4^*, z_5^*)'$$

x is the vector of exogenous variables representing personal attributes, preferences, and work conditions and other factors; B, Γ are matrices of coefficients; ς is a vector of error terms.

The coefficient estimates are shown in Tables 4 and 5.

Appendix B: Outline of the time-use utility functions

The attributes given in Table 6 are considered as factors that define the utility of a daily activity–travel pattern.

The utility of pattern d for individual i, U_{id}, is formulated as

$$U_{id} = \sum_{j=1}^{J} \left\{ f_j(x_{ijd}) \left(b_{j0} + \sum_{m=1}^{M} b_{jm} \hat{\omega}_{im} \right) \right\} + \varepsilon_{id}$$

where U_{id} is the utility of activity pattern d for individual i; x_{ijd} is the jth attribute of activity pattern d for individual i; $\omega_{\hat{im}}$ is an indicator of the preference individual i has for activity type m; ε_{id} is a random error term; and b_{j0}, b_{jm} are constant coefficients.

The preference indicator is formulated as

$$\boldsymbol{\omega}_i = \mathbf{a}\mathbf{z}_i + \boldsymbol{\xi}_i$$

where $\mathbf{a}$ is a matrix of coefficients, $\mathbf{z}_i$ is a vector of the attributes of individual i, ξ_i is a vector of random error terms, and

$$\boldsymbol{\omega}_i = (\omega_{i1}, \ldots, \omega_{im}, \ldots, \omega_{iM}),$$

$$\mathbf{z}_i = (z_{i1}, \ldots, z_{ik}, \ldots, z_{iK}),$$

$$\boldsymbol{\xi}_i = (\xi_{i1}, \ldots, \xi_{im}, \ldots, \xi_{iM}),$$

Table 4 Coefficient estimates

		N_{trips} Coeff.	t	D_{out} Coeff.	t	$D_{nctrips}$ Coeff.	t	N_{chains} Coeff.	t	D_{home} Coeff.	t
Γ	Commute duration			−0.11	−3.8	−0.065	−2.2	−0.38	−18.0	−0.25	−11.1
	Work start time	0.023	2.0	0.078	3.3					0.10	4.5
	Work end time	−0.49	−8.1	−0.37	−10.0	−0.29	−7.4	−0.69	−6.7	−0.89	−40.0
	Flextime	0.21	9.9	0.12	3.3	0.074	2.2				
	Overtime hours							−0.089	−6.9		
	Age	−0.11	−4.4								
	Auto used to commute			0.0044	1.5			0.071	4.3	−0.055	−2.3
	No. of restaurants			0.062	2.3						
	B_{out}					0.071	2.1	0.40	6.6		
	B_{home}							−0.17	−3.2	0.072	3.1
B	N_{trips}							−0.62	−6.2		
	D_{out}									−0.37	−6.7
	$D_{nctrips}$									−0.059	−1.6
	N_{out}										
	D_{home}										
R^2		0.27		0.15		0.092		0.68		0.70	

Table 5 Covariance and correlation matrix

	ζ_1	ζ_2	ζ_3	ζ_4	ζ_5
N_{trip} (ζ_1)	0.718	0.644	0.528		
D_{out} (ζ_2)	0.818	0.863	0.530		
$D_{nctrips}$ (ζ_3)	0.653	0.598	0.910		
N_{out} (ζ_4)				0.325	−0.283
D_{home} (ζ_5)				−0.908	0.299

The upper-right triangle (including the diagonal elements) shows covariances, while the lower-left triangle contains correlation coefficients.

Table 6

Activity durations	Work duration
	Out-of-home non-work activity duration
	Total travel time
	Total in-home activity duration (excluding sleep)
Activity timing	Departure time for commute?
	Time returning home?
Monetary factor	Overtime payment

$$\mathbf{a} = \begin{bmatrix} \alpha_{11} & \dots & \alpha_{1k} & \dots & \alpha_{1K} \\ \alpha_{m1} & \dots & \alpha_{mk} & \dots & \alpha_{mK} \\ \alpha_{M1} & \dots & \alpha_{M1} & \dots & \alpha_{MK} \end{bmatrix}.$$

The coefficients in matrix **a** are estimated using subjective preference ratings, with the measurement equation

$$Y_{im} = q \text{ iff } \tau_{mq} \leq \omega_{im} < \tau_{m,q+1},\ q = 1, 2, \dots, Q$$

where τ_{mq} is a threshold, $\tau_{m1} = -\infty$, and $\tau_{m,Q+1} = \infty$. Let $\hat{a}_m$ be an estimate of the jth row of coefficient matrix **a**. Then, $\hat{\omega}_{im} = \hat{a}_m \mathbf{z}_i$ offers predicted preference ratings. Elements of the left-hand side, $\hat{\omega}_{im}$ are used in the equation for U_{id}.

Using the above formulation of U_{id}, unknown model coefficients are estimated using a stated-preference data set which contained the respondents' preferences of hypothetical alternative activity–travel patterns. The data set was obtained from the same panel survey from which the data used in the first example were obtained. Assuming that the ε_{id} are identically and independently distributed with an exponential extreme-value (Gumbel) distribution, the logit model of discrete choice was applied in the model estimation. For function, f_j, logarithmic functions, exponential functions and linear functions are used.

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