Behavioral Realism in Urban Transportation Planning Models

by

M. Ben-Akiva*, J. Bowman, S. Ramming, and J. Walker

* corresponding author

Massachusetts Institute of Technology
Department of Civil and Environmental Engineering
Room 1-181, 77 Mass. Avenue, Cambridge, MA, 02139, USA
Tel: (617) 253-5324; Fax: (617) 253-0082; Email: mba@mit.edu

prepared for

Transportation Models in the Policy-Making Process:
A Symposium in Memory of Greig Harvey

Asilomar Conference Center, California

March 6, 1998
**Introduction**

The principal goal of travel demand modeling is to accurately predict the behavioral responses to changes in the relevant policy variables affected by applications such as congestion management, travel demand management, congestion pricing, and environmental sustainability. Greig Harvey in his 1985 paper “Research Directions in Travel Demand Analysis” identified several research themes aimed at achieving this goal:

- Technology Transfer
- Modeling Methods
- Data
- Behavioral Realism

Technology transfer refers to the act of making accessible to practitioners the tools and the knowledge that constitute modeling improvements. This is the area in which Greig Harvey made his greatest and unparalleled contribution. Modeling methods consist of the statistical techniques that underlie the demand analysis. In recent decades, there have been numerous advances in such techniques, including disaggregate analysis, advanced discrete choice methods, and methods for incorporating stated preference data. In addition, increasingly rich data sets are becoming available, including travel/activity surveys and panel data sets. With the statistical tools in place and the availability of improved data, the focus in travel demand modeling now is to use this increased power to improve the behavioral realism and thus the forecasting ability of models. This paper discusses the evolution of behavioral realism in Urban Transportation Models, focusing on the representation of travel and activity patterns. Our focus is on discrete choice model systems. Other researchers have been developing detailed rule-based simulation systems such as AMOS (RDC Inc. 1995), SMASH (Ettema et al. 1995), STARCHILD (Recker, McNally, and Root 1986a; 1986b), and TRANSIMS (Barrett et al. 1995).

**The Importance of Behavioral Realism**

Concerns about phenomena such as congestion, emissions and land use patterns lead governments to consider policies aimed at controlling them. These include, for example, employer based commute programs, single occupant vehicle regulation, road pricing, multimodal facilities and transit oriented land development. These policies achieve their objectives through their affect on individual behavior. Individuals adjust their behavior in complex ways, motivated by a desire to achieve their own objectives subject to their personal circumstances. There are numerous examples of Urban Transportation Planning models that fail to capture the behavioral realism necessary to accurately reflect the impacts of transportation policy.

For example, the value of time (VOT) is a key concept in transport planning in terms of the economic valuation of travel time savings and the relative importance of time versus cost in travel forecasting models. A standard method for deriving values of time is to use the trade-off ratio implied by the time and cost coefficients estimated in travel choice models, resulting in a fixed value of time for each segment of the population. Ben-Akiva et al. (1993) found that allowing for a randomly distributed value of time resulted in
a flatter response (that is, lower price elasticity) than the models that assumed a single fixed VOT, as shown in Figure 1. An assumption of a fixed value of time ignores the extremes of the behavior, for example the fraction of the population who are willing to pay much higher than the average rate to save time. This result suggests that it is vital to capture such heterogeneity for analysis of policy issues involving pricing.

![Figure 1. Effect of randomly distributed value of time on behavioral response to pricing policies.](image)

Another common assumption in Urban Transportation Models is that of perfect information; that is, assuming that travelers have full information about the existence and attributes of their alternatives. The need to evaluate Advanced Traveler Information Systems (ATIS) proposals highlight the inadequacy of this assumption. A survey of MIT faculty and staff indicated a high correlation between familiarity with the transportation network and the propensity to make modifications to the work trip (Table 1), which suggests that different levels of knowledge result in different choice sets and travel behavior. Figure 2 provides a simple example in which information affects choice sets. Originally, a traveler knows of two routes between his or her origin and destination: freeway and subway. After the implementation of an information strategy, such as kiosks or a web-based travel planner, a traveler may become aware of an express bus route which is competitive with the alternatives in the original choice set. Note that varying levels of knowledge not only impact route and mode choice, but cascade through all travel decisions including destination and residential choice.

<table>
<thead>
<tr>
<th>Percentage of trips to MIT by primary mode and route</th>
<th>To what extent do you agree with the statement “I know my way around the city well, and can easily find another route?”</th>
</tr>
</thead>
<tbody>
<tr>
<td>100%</td>
<td>agree 29% neutral 8% disagree 7%</td>
</tr>
<tr>
<td>50 to 99%</td>
<td>agree 41% neutral 7% disagree 5%</td>
</tr>
<tr>
<td>less than 50%</td>
<td>agree 3% neutral 1% disagree &lt;1%</td>
</tr>
</tbody>
</table>

Note: Table reflects 1,090 of 1,381 employees (79%) responding to both questions

Table 1. Day to day variability and familiarity (MIT faculty and staff, 1997).
Another example of complex behavioral response to policies is shown in Figure 3. This figure represents the day activity and travel pattern of one person who drove alone to work at 7:30 a.m., returned home at 4:40 p.m., and stopped to shop on the way home. In response to an employer sponsored program which gave strong financial incentives to commute by transit, this person switched to transit. This required them to begin their commute earlier, at 7:00 a.m., in order to arrive at work on time. Because their preferred shopping destination wasn’t on the transit path, they decided to come straight home after work, then drive alone to do their shopping after arriving at home in the evening. This response was rooted in demand for activity, and involved a complex adjustment in their entire day’s pattern. In this case, a model that treats work and non-work trips independently would fail to predict the compensating peak period auto trip induced by the transit incentive program. Forecasting models will only be able to accurately capture this kind of response if they represent how people schedule their day activities.

A few statistics drawn from a survey of Boston area residents in 1991 reveal some of the complexity and variety in people’s activity and travel schedules. Looking first at the number of tours in the day activity pattern, Figure 4 shows that a substantial percentage of people stay home for the entire day, and 40% take 2 or more tours away from home during the day. The patterns vary dramatically across the population. For example, adults in households with small children are much more likely to take 2 or more tours. Among these, the patterns of males and females differ substantially. Males are less likely to stay home all day and females are more likely to take 3 or more tours.

Looking at the complexity of the work commute tour in Figure 5, we see that 25% of workers conduct activities away from the workplace sometime during of the workday, and another 39% make stops for other activities on the way to or from work. Here again, the patterns vary within the population. In households with small children, males are more likely than females to travel directly to and from work.
Figure 3. Responses to policies involve complex behavioral adjustments motivated by a desire to achieve activity objectives.

Figure 4. Number of tours in the day activity pattern (Boston, 1991).
These examples and statistics reveal the variety of patterns in which travel occurs, the heterogeneity of people, and therefore the necessity to enrich urban transportation planning models with greater behavioral realism.

**Evolution of the Modeling Framework**

Greig Harvey noted in the 1993 *NARC Manual of Regional transportation Modeling Practice for Air Quality Analysis*:

“For some time the travel behavior research community has recognized a need to rethink the basic paradigm of travel demand analysis in light of three decades of advances in the cognitive sciences, in economics, and in computational capabilities.”

This research direction has led to Urban Transportation Planning models that more realistically represent travel and activity patterns, and therefore provide greater insight into current policy debates. This section describes the evolution of these models, from those that represent the day schedule as isolated trips, to models that combine trips explicitly in tours, and finally to models that combine the tours in a day schedule. Figure 6 illustrates the representation of travel and activities in each phase of the model evolution for a simple day schedule consisting of two home based tours. The trip based model represents the schedule as independent one-way trips, with no explicit relation between trips. In the tour based model the trips are explicitly connected in tours, introducing spatial constraints and direction of movement. Finally, the day schedule model explicitly links the sequence and timing of activities across tours. The evolution of models also led to the inclusion of other dimensions of detail about the travel (e.g., time of day decisions).
and increased complexity of the explanatory variables in terms of personal and household characteristics and attributes of travel alternatives and activities. In the following sections, we provide an example of each of these modeling approaches. (See Ben-Akiva and Bowman 1997 for further details.)

**Trip based systems**

The so-called “four-step” model is a trip based system. In its simplest state, the four-step model consists of sequential, independent steps in which the trip purposes are dealt with separately and there are no linkages among trips as shown in Figure 7.
Over the years, numerous incremental improvements have been made to the four-step process, introducing more linkages between purposes and trip segments and iterating through the steps to obtain equilibrium in the system.

The first tests of an integrated trip based model system were conducted at MIT during the early 1970’s (Ben-Akiva et al. 1976). The first implementation that followed was for the MTC in San Francisco (Ruiter and Ben-Akiva 1978). The demand model portion of the MTC system has three major components, as shown in Figure 8(a). The first component represents long term decisions related to auto ownership and home based work trips. The other two components represent the short term activity and travel decisions of other home based trips and non-home based trips. Each model component is conditioned by choices at the higher level, and the short term decision models influence the auto ownership and home based work trips via measures of accessibility. Figure 8(b) details the home based work component of the model system. The system explicitly models work travel decisions for two workers in the household. Arrows in the figure show how the models are integrated, with solid arrows indicating conditionality and dashed arrows indicating expected utility. For example, the auto ownership model is conditioned by the choice of workplace. That is, the model assumes the workplace is known when it models the auto ownership decision. The auto ownership decision itself conditions the mode choice model. The model also accounts for the impact that ease of travel for shopping and work has on the auto ownership decision by including variables of expected utility generated by the shopping destination/mode choice and work mode choice models.

In the late ’70s, Greig Harvey simplified and operationalized a version of the MTC model for sketch planning analyses, in which he retained much of the behavioral aspects. Over the years, he continued to expand the model, adding location, time-of-travel, and improved supply models. The resulting model system is known as STEP, an accessible and powerful travel demand modeling system that was applied to studies in San Francisco, San Diego, Los Angeles, Sacramento, Chicago, and Seattle (Harvey and Deakin 1996).
**Tour based systems**

In the tour based model the trips are explicitly connected in chains that start and end at the same home or work base, introducing spatial constraints and direction of movement. These systems improve upon the trip based method of sequential modeling of home based and non-home based trips in order to capture scheduling changes which can occur in response to changing conditions. Tour based systems were first implemented in the Netherlands (Daly et al. 1983; Gunn et al. 1987; Hague Consulting Group 1992), and are being used extensively there and elsewhere in Europe, with recent systems being developed in Stockholm, Sweden (Algers et al. 1995) and Salerno, Italy (Cascetta et al. 1993). Greig Harvey was working on a tour based version of STEP at the time of his death.

Figure 9 depicts the basic structure of the Stockholm model system and shows how the tours for various purposes are explicitly modeled. Work tour decisions condition all other activity and travel decisions. The model system makes heavy use of expected utility measures, strengthening the connections across dimensions of the activity and travel scheduling decision.

![Figure 9. The Stockholm tour based model system.](image)

The work tour decision, Figure 10, is modeled as a nested logit model. It includes the household’s decision of who will work today, how the household’s autos will be allocated among the workers, and the mode of travel for workers who do not use a household auto.

The model of household shopping tours, Figure 11, conditioned by the work decision, determines how many shopping activities the household will undertake, who will do them, the type of tour on which they will be done, and the mode and destination of the tour. The Stockholm nested logit shopping tour model assigns each shopping activity to one or more household members. If a shopping activity is assigned to a worker, the tour type model determines whether the activity occurs on a home based tour, a work based tour, or chained in the work tour.
The key features of this model are the explicit representation of tours, trip chaining within tours, and the explicit modeling of household decisions.

**Day Schedule systems**

Ben-Akiva et al (1996) proposed a day schedule system that explicitly links the sequence and timing of activities across tours. This model system explicitly represents the choice of a day activity pattern, which overarches and ties together tour decisions and incorporates the time of day decision (Figure 12). The day activity pattern is characterized as a multidimensional choice of primary activity, primary tour type, and the number and purpose of secondary tours. The model distinguishes between the primary tour of the day and secondary tours. For each tour, it models destinations, times of day and modes.
A prototype model system was estimated using the 1991 Boston survey. It consists of nested logit models with tour decisions conditioned by the choice of day activity pattern (Figure 13). The models are also linked through the expected utility mechanism described earlier for the trip and tour based systems. In the prototype, the day activity pattern model is a choice among 55 patterns including (1) whether to stay home all day or to participate in activities involving travel, and (2) conditional on travel, the choice of a particular pattern. The Boston travel survey did not include records of at-home activities. If such data were available, it could be incorporated at this level of the model.

Figure 12. (a) The day schedule system consists of a day activity pattern which overarches and ties together the tour decisions. (b) The day activity pattern and (c) the tour decisions are multidimensional choices.

Figure 13: Day schedule system prototype.
The key feature of this system, the integrated day schedule, is also the source of one of its two main weaknesses. Tying tours together in the day activity pattern results in a very large choice set which is computationally burdensome. Constraints, utilities and probabilities must be computed for literally billions of alternatives. Ironically, the prototype nevertheless suffers from an incomplete representation of the day schedule; the time of day is aggregated into only 4 time periods, secondary stops on tours are omitted, the time of day linkages are incomplete and household linkages are not explicitly modeled.

The day activity model approach was selected for implementation in Portland, Oregon, and was estimated using a 1994 household travel and activity survey. The structure of the Portland version is shown in Figure 14 (Bowman et al. 1998). A major advantage of the Portland survey is that it included information on at-home activities, which were included in the model.

![Day Activity Pattern Diagram](image)

**Figure 14. The Portland implementation of the day activity schedule model.**

The Portland day activity model has been found to be more sensitive to policy variables than the traditional trip based four step model used previously. The model is now being used for two policy evaluation projects: one on air quality and another on pricing initiatives.

**Future Directions**

Improvement to transportation planning models must be a continual process involving honest assessment of the profession's skills and shortcomings. Harvey (1985) asserts that most of the fundamental statistical tools have been developed, and that thought must be given to prioritizing the aspects of traveler behavior needed to evaluate future policy and investment options. The three areas of behavioral realism we identify as most promising — developing mobility decision models in an activity framework, incorporating lifestyle factors as motivations of travel choice, and advanced modeling methods to reflect the uniqueness of decision makers — are each described below.

**Extending the Activity Approach to Mobility Decisions**

The activity approach has been developed and implemented to allow practitioners to model travelers’ day activity schedule, tour formation and trip decisions. However, many policies are geared toward affecting
longer run mobility decisions such as residence choice, workplace location and auto ownership. These models must also be brought into the activity framework as shown in Figure 15. For example, the expected maximum utility from household members’ day activity schedules forms a natural measure of accessibility, which influences residential location decisions. Residents’ ability to chain trips into tours is highly constrained by the transportation technology available, and dissatisfaction with tour formation may lead to additional vehicle acquisition. Similarly, workers may exhibit preferences for certain job site locations because of their ability to make midday personal business tours. Developing activity based models of mobility decisions should be a research priority, as it completes the activity paradigm.

![Figure 15. Mobility, Activity, and Travel Framework.](image)

**Incorporating Lifestyle Factors.**

Current research in day activity schedule models has suggested that much of the impetus behind day activity schedule choice is still unexplained by traditional variables such as home and work location, vehicle availability, and objective time and cost components of travel. Many activity choices appear to be influenced by lifestyle decisions such as work orientation and role in the household. Considerable thought needs to be given to the representation of lifestyle variables in future research, and additional data collection may be necessary to assess these differences among travelers.

**Incorporating Advanced Behavioral Modeling**

Many techniques of advanced behavioral modeling have been used in specialized, limited scale applications to address particular behavioral concerns. Random coefficients and latent class choice models are two techniques that have been used to address heterogeneity of preferences and to avoid any bias caused by assuming all travelers have the same utility parameters. Latent variable techniques have been developed to include unobservable psychometric constructs such as attitudes and perceptions as explanatory variables in choice models. Latent choice set models reflect the true number of alternatives travelers consider, which may be smaller than the number of alternatives generated by the analyst, because travelers have limited time for information acquisition or processing. Future work should attempt to combine these treatments and to develop more compact mathematical models, while exploiting existing computational resources to reflect the greatest possible scope of behavioral realism in practice.
Conclusion

The fundamental problem facing the travel demand modeler is the trade-off between behavioral realism and complexity. The challenge is to adequately represent a decision process which has inordinate outcomes and dimensions, such that valid results are achieved. For example, Table 2 shows the size of the combinatorial problem for a day activity model and provides an estimate of the number of alternatives faced by an individual (discretizing timing and location), resulting in the neighborhood of $10^{17}$ alternatives available to the individual.

<table>
<thead>
<tr>
<th>Number of activities per day</th>
<th>10</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sequence</td>
<td>10!</td>
<td></td>
</tr>
<tr>
<td>Timing</td>
<td>10 per activity</td>
<td>100</td>
</tr>
<tr>
<td>Location</td>
<td>1000 per activity</td>
<td>10,000</td>
</tr>
<tr>
<td>Mode</td>
<td>5 per activity</td>
<td>50</td>
</tr>
<tr>
<td>Route</td>
<td>10 per activity</td>
<td>100</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>$10^{17}$</td>
</tr>
</tbody>
</table>

Table 2. An estimate of the number of day activity schedule alternatives facing an individual.

Like the decision maker, the modeler must simplify. Clearly, the analyst needs to simplify in a way that matches traveler behavior, but also in a way that yields useful forecasts within reasonable resource budgets.
References


