# Synthesis of Traveler Choice Research: Improving Modeling Accuracy for Better Transportation Decisionmaking

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## FOREWORD

Travelers' choices are central to the performance of a transportation system, but little is known about what influences such choices or the impact they have on system performance. When selecting a transportation management strategy, a transportation management center operator must understand and anticipate how travelers will respond: Will they stay on the same routes or divert? Will they decide to walk, bike, or take a bus or train instead of driving? Will they leave earlier or later?

The operator must know the potential benefits of alternative overall strategies (e.g., variable pricing or information on dynamic message signs) as well as how to handle day-to-day operations by implementing strategies to provide effective responses to particular events. The operator must also account for non-network, predisposing factors that influence travelers' choices. Such factors, including land use, population density, and walkability, are generally out of the control of the network manager, and their influence may not be intuitively obvious.

The project "Analysis of Traffic Network and Non-Network Impacts Upon Traveler Choice" addresses the current state of the practice, advances understanding, and identifies gaps in knowledge regarding traveler choices. This synthesis report documents the project's first major activity: an assessment of current research and practices in traveler choice. It will be a resource for both traveler choice researchers and organizations considering transportation management strategies that influence traveler choice. This report also lays the foundation for the project's next step, the development of traveler choice models that can be incorporated into existing transportation analysis tools.

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Research and Development

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16. Abstract

Over the last 50 years, advances in the fields of travel behavior research and travel demand forecasting have been immense, driven by the increasing costs of infrastructure and spatial limitations in areas of high population density together with externalities in these areas. The field has changed from supply-oriented planning to incorporating and managing demand. As such, methods from a variety of disciplines have been borrowed and extended to explain human behavior and interaction. Many experts have called for better data collection and methods of analysis across a number of time horizons, that is, integrated supply and demand models that capture travel behavior over time and space. A new paradigm may be called for to address the present challenges of model integration; user preferences, heterogeneity, and endogeneity; habitual behavior; and human socializing. This report provides a synthesis of the state of knowledge in travel behavior research and identifies gaps in existing data, methods, and practices that must be filled to meet the analysis needs of an emerging class of supply- and demand-side interventions that seek to leverage the opportunities of real-time information.

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# SI* (MODERN METRIC) CONVERSION FACTORS

## APPROXIMATE CONVERSIONS TO SI UNITS

| Symbol | When You Know | Multiply By | To Find | Symbol |
|---|---|---|---|---|
| | | **LENGTH** | | |
| in | inches | 25.4 | millimeters | mm |
| ft | feet | 0.305 | meters | m |
| yd | yards | 0.914 | meters | m |
| mi | miles | 1.61 | kilometers | km |
| | | **AREA** | | |
| $in^2$ | square inches | 645.2 | square millimeters | $mm^2$ |
| $ft^2$ | square feet | 0.093 | square meters | $m^2$ |
| $yd^2$ | square yard | 0.836 | square meters | $m^2$ |
| ac | acres | 0.405 | hectares | ha |
| $mi^2$ | square miles | 2.59 | square kilometers | $km^2$ |
| | | **VOLUME** | | |
| fl oz | fluid ounces | 29.57 | milliliters | mL |
| gal | gallons | 3.785 | liters | L |
| $ft^3$ | cubic feet | 0.028 | cubic meters | $m^3$ |
| $yd^3$ | cubic yards | 0.765 | cubic meters | $m^3$ |
| | | NOTE: volumes greater than 1000 L shall be shown in $m^3$ | | |
| | | **MASS** | | |
| oz | ounces | 28.35 | grams | g |
| lb | pounds | 0.454 | kilograms | kg |
| T | short tons (2000 lb) | 0.907 | megagrams (or "metric ton") | Mg (or "t") |
| | | **TEMPERATURE (exact degrees)** | | |
| $^oF$ | Fahrenheit | 5 (F-32)/9 or (F-32)/1.8 | Celsius | $^oC$ |
| | | **ILLUMINATION** | | |
| fc | foot-candles | 10.76 | lux | lx |
| fl | foot-Lamberts | 3.426 | candela/$m^2$ | cd/$m^2$ |
| | | **FORCE and PRESSURE or STRESS** | | |
| lbf | poundforce | 4.45 | newtons | N |
| lbf/$in^2$ | poundforce per square inch | 6.89 | kilopascals | kPa |

## APPROXIMATE CONVERSIONS FROM SI UNITS

| Symbol | When You Know | Multiply By | To Find | Symbol |
|---|---|---|---|---|
| | | **LENGTH** | | |
| mm | millimeters | 0.039 | inches | in |
| m | meters | 3.28 | feet | ft |
| m | meters | 1.09 | yards | yd |
| km | kilometers | 0.621 | miles | mi |
| | | **AREA** | | |
| $mm^2$ | square millimeters | 0.0016 | square inches | $in^2$ |
| $m^2$ | square meters | 10.764 | square feet | $ft^2$ |
| $m^2$ | square meters | 1.195 | square yards | $yd^2$ |
| ha | hectares | 2.47 | acres | ac |
| $km^2$ | square kilometers | 0.386 | square miles | $mi^2$ |
| | | **VOLUME** | | |
| mL | milliliters | 0.034 | fluid ounces | fl oz |
| L | liters | 0.264 | gallons | gal |
| $m^3$ | cubic meters | 35.314 | cubic feet | $ft^3$ |
| $m^3$ | cubic meters | 1.307 | cubic yards | $yd^3$ |
| | | **MASS** | | |
| g | grams | 0.035 | ounces | oz |
| kg | kilograms | 2.202 | pounds | lb |
| Mg (or "t") | megagrams (or "metric ton") | 1.103 | short tons (2000 lb) | T |
| | | **TEMPERATURE (exact degrees)** | | |
| $^oC$ | Celsius | 1.8C+32 | Fahrenheit | $^oF$ |
| | | **ILLUMINATION** | | |
| lx | lux | 0.0929 | foot-candles | fc |
| cd/$m^2$ | candela/$m^2$ | 0.2919 | foot-Lamberts | fl |
| | | **FORCE and PRESSURE or STRESS** | | |
| N | newtons | 0.225 | poundforce | lbf |
| kPa | kilopascals | 0.145 | poundforce per square inch | lbf/$in^2$ |

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

## TABLE OF CONTENTS


**OBJECTIVES, MOTIVATION, AND STRUCTURE** .......... **1**

**SCOPE AND CONCEPTUAL FRAMEWORK** .......... **3**
- **BACKGROUND** .......... **3**
- **SCOPE DELINEATION** .......... **3**
- **CONCEPTUAL FRAMEWORK** .......... **4**

**TRAVEL BEHAVIOR STUDIES REVIEW** .......... **7**
- **DAY-TO-DAY AND WITHIN-DAY BEHAVIOR CHANGES** .......... **7**
  - Effect of Tolling and Other Costs on Mobility Decisions .......... 8
  - Walk Quality on Day-to-Day Travel Behavior and Patterns .......... 9
- **BEHAVIORAL PATTERN CHANGES** .......... **10**
  - Sociodemographics and Household Composition .......... 10
  - Effect of Travel Demand Management Measures and Parking Pricing on Mode Choice 11
  - Learning, Experience, and Inertia .......... 11
- **LIFESTYLE- AND MOBILITY-BASED BEHAVIOR CHANGES** .......... **12**
  - Effect of Transit-Oriented Development/Density on Behavior Patterns and Long-Term Choices .......... 12
  - Residential Self-Selection and Vehicle Ownership .......... 13
- **BEHAVIORAL MECHANISMS** .......... **14**
  - Household Interactions .......... 15
  - Social Networks .......... 17

**TRAVEL BEHAVIOR MODELS REVIEW** .......... **19**
- **ACTIVITY-BASED MODELS** .......... **19**
  - Utility-Based Econometric Models .......... 19
  - Rule-Based Computational Process Models .......... 21
  - Agent-Based Modeling Systems .......... 22
- **MODEL INTEGRATION** .......... **22**

**TRAVEL BEHAVIOR DATA REVIEW** .......... **25**
- **STANDARD SOURCES** .......... **25**
- **TRAVEL DIARIES** .......... **25**
- **STATED PREFERENCE AND REVEALED PREFERENCE** .......... **26**
- **EMERGING POTENTIAL IN DATA COLLECTION** .......... **27**
- **GROWING ROLE OF EXPERIMENTS AND GAMING METHODS** .......... **28**

**CONCLUSIONS, RECOMMENDATIONS, AND FUTURE RESEARCH** .......... **31**

**REFERENCES** .......... **33**

**BIBLIOGRAPHY** .......... **45**

## LIST OF FIGURES

Figure 1. Chart. Conceptual Framework....5
Figure 2. Equation. Generalized Indifference Band Framework....20
Figure 3. Equation. Random Utility Formulation....21
Figure 4. Equation. Joint Versus Single Utility Threshold....21
Figure 5. Equation. Weighted Sum of Joint Versus Single Utility Threshold....21

## LIST OF TABLES

Table 1. Recent and Continuous National Travel Surveys....25

## LIST OF ACRONYMS

| | |
|---|---|
| ATDM | Active Transportation and Demand Management |
| ATIS | Advanced traveler information systems |
| GPS | Global Positioning System |
| HOV | High-occupancy vehicle |
| ICM | Integrated Corridor Management |
| IT | Information technology |
| MATSim | Multi-Agent Transport Simulation Toolkit |
| MTD | Managing Travel Demand |
| RP | Revealed preference |
| SOV | Single-occupancy vehicle |
| SP | Stated preference |
| TCRP | Transit Cooperative Research Program |
| TRANSIMS | Transportation Analysis and Simulation System |
| VMT | Vehicle miles traveled |

# OBJECTIVES, MOTIVATION, AND STRUCTURE

The goal of this report is to organize the existing knowledge, the state of the art, and the current state of practice for transport modeling into a framework to give an overview of travel behavior research with particular relevance to traveler choice dimensions impacted through programs such as Active Transportation and Demand Management (ATDM), Managing Travel Demand (MTD), and Integrated Corridor Management (ICM), including weather-related dynamic system management. Because these programs entail a significant real-time operational element, choice models should enable understanding of users' dynamic responses to information-rich environments and the interdependencies of users' decisions over time. Some impacts of interventions applied as part of ATDM, MTD, and ICM projects are short-term, such as adjustments to a less congested route or departure time. Others appear over the long term, such as gradually shifting users' behavior toward more environmentally friendly or reliable trajectories with feedback information. Also of interest are the effects of non-network factors on users' decisions and responses to operational interventions, especially in terms of peak demand reduction and carbon-conscious behaviors.

Operational interventions offer substantial opportunity to optimize transportation networks, and they represent significant investment by agencies and contractors. Understanding user response at the facility, corridor, and network levels over short-, medium-, and long-term horizons is crucial to designing appropriate interventions. Without comprehensive knowledge of systems and user response, policies such as tolling and ramp metering may not lead to expected improvements or could cause externalities elsewhere in the network. The effects are complex, and such complexity demands a comprehensive look at how traveler behavior is studied and modeled. Adding to the complexity, geographic and human heterogeneity mean shared results and insights may not lead to similar outcomes in different locations. A comprehensive and easily transferable framework could overcome these issues to determine the structural causes and mechanisms of travel behavior.

This report is structured into five sections. First, a conceptual organizing framework is established and discussed. The framework links operational interventions associated with dynamic demand and traffic management programs, including information dissemination, to corresponding traveler choice dimensions and to network and non-network factors affecting user response.

Second, a literature review is presented, mainly covering relevant knowledge along the established conceptual framework. The review is composed of a general knowledge section, a discussion of models to capture travel behavior, and an overview of available relevant data sources. The review addresses the question: "What do researchers know about traveler behavior?"

Third, travel behavior models are examined. Modelers must be careful, asking the appropriate questions and recognizing effects that are observed only through the modeling process. This section discusses the strengths and limitations of the variety of models available, pointing to areas of potential improvement. Improved model integration is needed to understand feedback loops and ensure model consistency.

Fourth, traveler behavior data sources are briefly reviewed. This section asks what data are needed based on existing and potential knowledge and modeling practices in travel behavior as well as how relevant and important behaviors can be measured.

Finally, a summary is provided, examining conclusions about the current knowledge and opportunities to develop and advance traveler choice models, particularly in connection with the motivating applications.

# SCOPE AND CONCEPTUAL FRAMEWORK

This chapter discusses the report's conceptual framework and defines categories to organize its key elements. The framework's core components are operational interventions, information dissemination, traveler choice dimensions, and network and non-network influencing factors.

## BACKGROUND

For some time, transportation planning focused on meeting mobility needs by providing adequate infrastructure. This supply-oriented planning neglected demand-oriented models in that the main purpose was to predict aggregate long-term demand for the strategic planning of the transport infrastructure, not necessarily taking full account of the impact of such plans on travel demand. The increasing costs of infrastructure and the spatial limitations in areas of high population density together with the externalities in these areas have changed supply-oriented planning to incorporate and manage demand. Based on this shift toward demand-oriented management, operational interventions have emerged, including congestion pricing, which changes the service characteristics to influence travel behavior, and dissemination of real-time information on the level of service. The interest in analyzing transport policies in terms of their impact has led to the use of disaggregate demand models, which seek to understand short-term effects of policies such as congestion pricing, telecommuting, and ride-sharing programs. The limitation of traditional trip-based travel models to capture the complex ways travelers respond to such policies has led to the development of behavior-oriented, activity-based models as well as the introduction of traveler response to current cost and service information.

Traditional trip-based static assignment models cannot cope with time-varying properties of traffic flow, which is essential in managing travel demand with timely and dynamic optimized interventions. The limitations of static assignment models and increasing computational capacities have improved the supply side toward dynamic traffic assignment models, which are time-dependent and able to model the buildup and dissipation of traffic congestion. Dynamic traffic assignment models are therefore able to accommodate the effects of intelligent transportation systems and system management interventions such as ramp meters, traffic lights, and congestion pricing.

Although progress has been made on the demand side and the supply side, each area has progressed rather independently of the other. Since travel behavior studies are related to many different fields, most models do not capture all direct and indirect influences on travel behavior or all feedback effects from behavior decisions on travel volumes and service (which would capture the interaction between the demand and supply models).

## SCOPE DELINEATION

Traveler behavior research is a broad field. The synthesis presented in this report is not intended to be comprehensive of the whole field and all possible traveler choice dimensions, but rather, to focus on operational planning and management interventions influencing traveler behavior. The bounds at the operational management level have a more narrow scope than, for example, at a strategic level involving resource acquisition and network design. Nevertheless, long-term traveler decisions such as mode shifts, auto ownership, and location changes are of interest as activity assessments are becoming more realistic to model. On the intervention side, the focus is mainly on

ATDM, a strategy to operate technologies in a proactive way to address potential problems before they occur. ATDM covers MTD and ICM, including Dynamic Mobility Applications. This synthesis also covers active traffic management on the supply side, since supply and demand management overlap in certain areas, such as information supply. Because most supply management interventions change the network's level of service, the focus is on network factors influencing traveler behavior. However, demand management interventions change non-network factors as well. The bounds of focus for non-network factors influencing traveler behavior are broad and not clearly defined. Non-network factors range from weather, which is natural and easy to observe, to walkability, which can be designed for and is less straightforward to measure. Non-network factors are important, as they interact with network factors in decisionmaking and define the environment and attractiveness of choice alternatives. Traveler and vehicle characteristics also influence traveler choices.

Taken together, these confounding forces and influences become difficult to separate. The comprehensive framework presented in this report attempts to conceptualize these person-network interactions over short-, medium-, and long-term time horizons. The framework seeks to capture the anticipated and actual effects of operational interventions on the supply and demand sides.

## CONCEPTUAL FRAMEWORK

Transport planning aims to describe, understand, and model the choices made by households and individuals during the execution of their daily lives, including the more or less frequent journeys outside their daily activity space.(1,2) Behavioral demand models feed supply and network models to assign traffic to the infrastructure. These models are in turn used to evaluate and optimize changes to the transport system undertaken by the owners of its various components, including reductions or expansions of road capacity through interventions, where demand management and supply management are involved, as well as policy changes. Travelers make decisions based on the characteristics of the system and their own perceptions. For example, as new information becomes available, travelers adjust their perception and adapt their travel behavior. Factors of the system and en route decisions must be considered. Travelers also decide where they want to live, where their workplace is, and whether to own a car or buy monthly transit or toll passes. Travelers must decide how often and where their everyday and less frequent journeys take them, which mode of transport to use (if multimodal trip alternatives are available), when to start trips, and what route to take. In decisionmaking, bounded rationality plays a substantial role: people make rational decisions based on a limited amount of knowledge and assessment capacity, not necessarily fully informed or fully rational choices.

Operational interventions, supply and demand management, traveler choice dimensions, and factors affecting user response (either endogenous or exogenous) interact with each other, as summarized in the conceptual framework in figure 1.

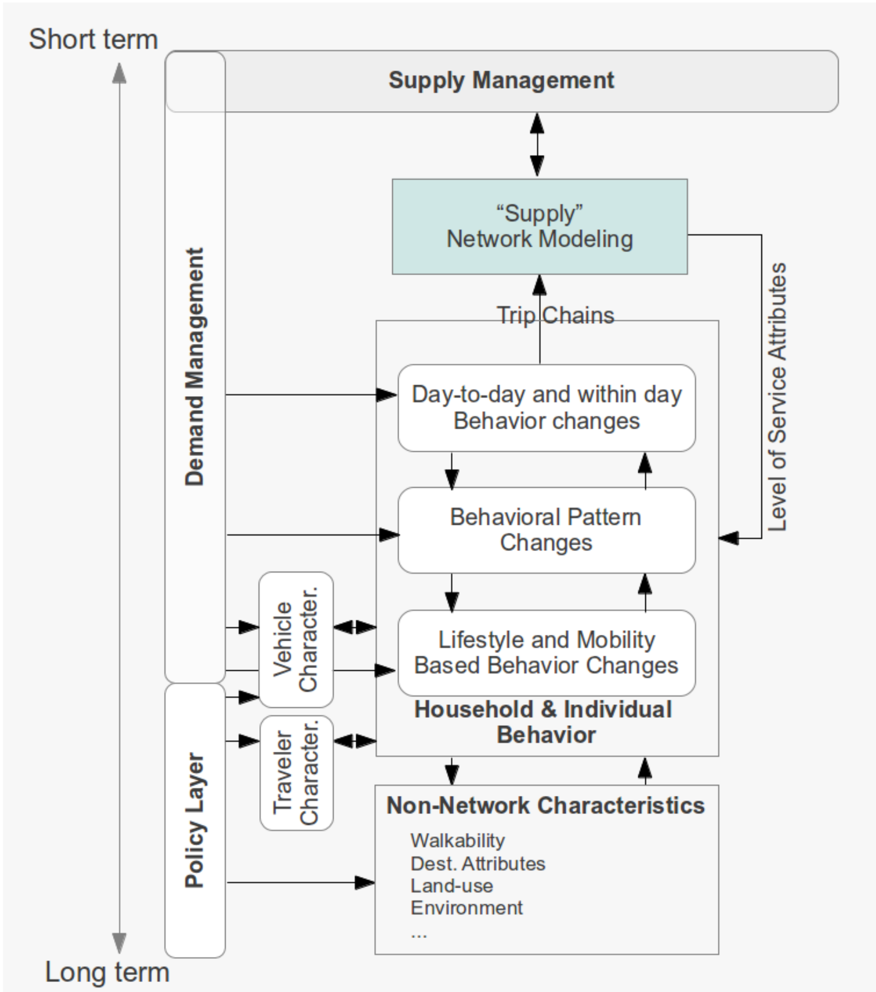


**Figure 1. Chart. Conceptual Framework.**

Household and individual behavior-change dimensions can be categorized on the basis of the time frame over which they take place, and hence, the level of analysis where a particular decision or group of decisions must be considered, as follows:

- Short-term, trip-level decisions take place within a day as well as from day to day. Trip-level decisions can be categorized further into the following types:[(3)]
    - Pre-trip (strategic) high-level traveler choices take place before departure (i.e., trip-making decisions).
    - En-route (tactical) high-level traveler choices take place during the trip (i.e., route modification).
- Medium-term decisions involve behavioral patterns such as activity chain planning and adjustments that take place over a longer period than hours or days.
- Long-term, lifestyle, and mobility decisions affecting vehicle holdings and location choices take place over weeks, months, and years.

Operational intervention programs can be categorized by the interventions or controls with which they seek to improve system operations and performance by influencing underlying traveler choices.[4] They can target the supply side by modifying the network with traffic and infrastructure access controls (e.g., ramp metering), which affect behavior through the level of service as an influence factor. Alternatively, operational interventions may affect demand directly with pricing (e.g., congestion pricing). Demand and supply management overlap as information supply (e.g., variable message signs and earlier traveler time dissemination) targets both demand and supply indirectly through demand response.

In addition to demand management, which influences household and individual behavior directly, there are further influencing factors, which can be divided into categories, as follows:

- Traveler.
    - Traveler and household characteristics that affect traveler behavior.
    - Vehicle characteristics that affect traveler behavior (e.g., type, dynamics).
- System.
    - Network characteristics (e.g., connectivity, length of route, and roadway types) and segment elements that define roadway and transit path characteristics (e.g., ride quality, lanes, and frequency).
    - Environment, events, states, or features of the network that affect traveler behavior but do not originate from system control strategies (e.g., weather, walking paths, and other characteristics of transit service besides route configuration, such as headways).

It is important to note that behavior choices are denoted as behavior changes, as they are better represented as the outcome of an adjustment process of a current choice rather than as the outcome of a choice process that does not recognize one's current state. Also, the arrows in figure 1 not only show the possible mappings of an explanatory variable on a possible outcome but also represent the perception of attributes and characteristics by the user in question.

# TRAVEL BEHAVIOR STUDIES REVIEW

This section reviews studies of different levels of traveler decisionmaking as outlined in the conceptual framework, organizing travel behavior knowledge by decision horizon. At the within-day and day-to-day levels, route and departure time choices have been the primary focus. Travelers' experiences from day to day influence their future decisions, and the line between these daily choices and a traveler's behavioral pattern quickly blurs. For example, a traveler may eliminate public transportation from his or her choice set after a bad experience, even if the utility is otherwise perceived as quite high. Since mode choice is subject to available modes, it tends to be modeled and studied as a behavioral pattern in the time horizon of weeks or months. Finally, lifestyle and mobility choices reflect the self- or otherwise-imposed constraints to which travelers are subjected (and choose) over longer time frames. Much work has been done within each area to understand how various factors influence these choices, but there is less understanding of the mechanisms that work to define these travel habits, patterns, and long-term constraints. These mechanisms and how they relate to different levels of traveler decisionmaking are discussed last.

## DAY-TO-DAY AND WITHIN-DAY BEHAVIOR CHANGES

Jan et al. found that travelers habitually follow the same route for the same trip, but route variations increase with longer travel distances.[(5)] The dominant factors for route choice are travel time and distance.[(5–7)] Significant research effort has been focused on the effects of route choice behavior under traffic information systems, the dynamic aspect of route choice behavior, and the relationships among route choice, departure time, and trip-chaining decisions.[(8–10)]

Traveler information influences route choice substantially. Abdel-Aty et al. studied route changes in Los Angeles, CA.[(7)] Only a small share of the respondents (15 percent) reported using more than one route on their commute. Of that 15 percent, 34 percent said they changed routes after actually seeing traffic conditions. Higher incomes and education levels predicted more route changes, perhaps reflecting schedule flexibility and arrival-time expectations for such workers.

Mahmassani and Herman performed a survey of commuters in Austin, TX, and yielded a binary logit model that relates route switching propensity to four types of factors: geographic and network condition variables, workplace characteristics, individual attributes, and use of information (radio traffic reports).[(11)] They found that variables describing the characteristics of the commute itself had a dominant effect relative to workplace rules or individual characteristics. Information in the form of radio traffic reports also appeared to have a strong impact. Regular listeners to traffic information were more likely to switch routes. The only sociodemographic attribute significant in the model was age.

In a similar experiment, Avineri and Prashker examined the impact of information on traveler learning, differentiated by travelers' risk aversion.[(12,13)] The results suggest that when information about travel times is provided, travelers do not always choose the route with the least expected time. Giving static information to users increases traveler heterogeneity; in this case, individuals learned more quickly to prefer either routes with less travel time or routes with less variability in travel time. When examined at an aggregate level, this combination could be seen as a "non-learning effect" or no change. Furthermore, higher variation in travel times is associated with lower sensitivity to travel time differences. Avineri and Prashker found in some cases that "increasing travel time variability of a less attractive route could increase its perceived attractiveness."[12] This underscores the need for better models of learning and reinforced habits as an alternative to utility maximization.

Beyond these dimensions, only a couple of studies have addressed destination adjustment in response to real-time information for discretionary travel (shopping).[14] The remainder of this section discusses the effects of other network and non-network factors that have been explored in more depth.

**Effect of Tolling and Other Costs on Mobility Decisions**

Travel cost as part of demand management is a powerful tool to influence travel behavior. Hensher and King examined the influence of parking costs in the central business district, a park-and-ride facility with public transit access, and the related mode choice as well as destination choice (including the alternative to forgo the trip) in Sydney, Australia.[15] Each of the participants was required to consider six alternatives in a stated preference questionnaire. In 97 percent of the responses, cost was the most significant factor in location and mode choices. Similar results were found by Handy et al., who studied whether Americans drive by choice or necessity.[16] The study found that most drivers chose the car because of the costs and a lack of alternatives. However, studies of this nature in Europe may reflect stricter land use norms that have led to denser, more compact urban form and increased use of public transit but that also decrease costs for public transit operators and increase the cost of parking.

Congestion pricing of roadways presents a valuable opportunity to rationalize road networks by helping ensure that travelers pay for the delay costs they impose on others. A study of Seattle, WA, travelers with Global Positioning System (GPS) vehicle units estimated that variable network pricing (to reflect the congestion impacts of different demand levels over space and time) would reduce regional vehicle miles traveled (VMT) by 12 percent and total travel time by 7 percent with a 6:1 benefit-cost ratio.[17] Using GPS tolling meters, the study followed participants to establish a baseline tolling routine. Participants were then given a monetary travel budget sufficient to cover the cost of their routine for the duration of the study period, creating an incentive to reduce certain forms of travel to save or make money. This policy approach is very similar to Kockelman and students' credit-based congestion pricing policy proposal. However, VMT results differed in their network simulations of the Austin and Dallas-Ft. Worth regions of Texas, where marginal social-cost pricing of freeways for all links by time of day was consistently estimated to result in VMT savings of less than 10 percent.[18,19]

Saleh and Farrell investigated the influence of congestion pricing on the "peak-spreading" of departure time choice.[20] Results suggest that non-work activities and work schedule flexibility impact departure time choice for the trip to work. Furthermore, respondents were less willing to pay a toll to depart earlier than usual.

In a similar vein, Transit Cooperative Research Program (TCRP) Report 95 discusses a number of elements that influence a traveler's decision to use a high-occupancy vehicle (HOV) lane.[21] The report concludes that because so many urban, facility, and vehicle characteristics interact with one another it is difficult to delineate the effect of HOV lanes on travelers. However, the success of

HOV lanes—both in terms of drivers served and benefits to the road network—is attributed to combinations of the following attributes:

- Urbanized population of 1.5 million or more.
- Orientation, preferably radial, to a city center, "focusing on major employment centers with preferably more than 100,000 jobs."
- Geographic barriers.
- Congestion in general purpose lanes.
- Realistic potential for 25–30 buses per hour.
- Peak-hour travel time savings of preferably 1 min/mi or more or at least 5 min of total travel time.(21)

### Walk Quality on Day-to-Day Travel Behavior and Patterns

Beyond information and pricing, the quality of the urban environment can influence route and activity timing decisions. Cervero and Kockelman examined many features of urban form that may reduce auto dependence.(22) Their gravity-based accessibility measure for access to commercial jobs was found to have an elasticity of -0.27, suggesting neighborhood retail shops and pedestrian-oriented design are more significant than residential densities in mode selection. Integrating aspects of pedestrian-oriented design such as four-way intersections and vertical mixing of land uses may result in significant VMT reductions. For example, a 10 percent increase in the number of four-way intersections in a neighborhood was associated with an average reduction of 5.19 percent of person miles traveled for non-work trips. A doubling of land use mix or variety is associated with a roughly 11 percent increase in modes other than single-occupancy vehicle (SOV) for non-work travel.

In addition to urban density, mixed land use and high-quality pedestrian-oriented urban design increase the use of public transit and non-motorized transport modes.(23) Naess and Jensen found that, in general, car use increases with increasing distance from the city center.(24,25) This could also be an indicator of self-selection or endogeneity (a topic discussed in more depth in later sections). Similarly, Cervero studied the impact of compact, mixed-use, pedestrian-friendly design on mode choice.(26) The study quantified density and diversity and estimated the influence of each on mode choice. The influences were significant but modest. Surprisingly, the most important influence factor for mode choice was the sidewalk ratio. In well-developed pedestrian areas, commuters were more likely to use public transit or join carpooling initiatives.

Information, pricing, and urban form influence day-to-day and within-day behaviors, but they are understood and applied over time such that they also influence travel patterns. These and other influences are discussed in the context of habits in the following sections.

## BEHAVIORAL PATTERN CHANGES

### Sociodemographics and Household Composition

A number of papers have studied the impact of sociodemographic variables on travel behavior patterns. Several studies found significant relationships and variables such as age, gender, household composition, and income. Newbold et al. used the General Social Survey dataset in Canada to determine the travel pattern differences of older (65+) and younger people.(27) The data are available for different time periods (1986, 1992, and 1998) and can therefore also control for generational differences. The study found significant differences in trip duration and frequency across generations. Employment level and health status were also significant predictors of trip duration and frequency.

Gender differences in trip duration and frequency as well as mode choice are significant in many studies, which attest women to be more likely to change their behavior toward more sustainable travel modes.(28,29) Moriarty and Honnery and Best and Lanzendorf found no significant differences between men and women in total number of trips and distance traveled but found differences in activity types.(30,31) Whereas men make more work trips, women make more journeys for maintenance activities. Researchers consistently find that household composition influences trip type, duration, and frequency. Key stages in households include the gain or loss of employment, children, and retirement.(32) Student, unemployed, and part-time employed households with no children are more likely to use non-motorized transportation, and high-income and retiree households are less likely to use non-motorized transportation. Car ownership, also endogenous to some model systems, is found to be significant in many studies, particularly with high-income groups, with a tendency to use cars versus public transit.(33) Guilano, Guilano and Narayan, and Guilano and Dargay studied differences in travel behavior between different sociodemographic groups in the United Kingdom and United States.(34–36) According to the studies, Americans make 4.4 trips per day with a length of 43 mi (70 km) compared to 3 trips per day and 16 mi (26 km) in the United Kingdom. In both countries, travelers over age 65 traveled roughly half the distance of younger participants. The difference between the countries was explained by the lower income and significantly higher transport costs in the United Kingdom.

Bomberg and Kockelman surveyed more than 500 Austin, TX, commuters to gather information on driving behavior during and after an abrupt increase in fuel prices.(37) For most of summer 2005, price increases were comparable to previous years; however, between August and September, prices increased 36 percent, from $2.16/gal ($0.57/L) to $2.93/gal ($0.77/L). Ordered-probit models to classify the behavior change suggest that travelers are most likely to respond by reducing overall driving through increased use of other modes or trip chaining. A traveler’s built environment characteristics were more influential in behavior change than even income, education, and average driving. Some drivers adapted their driving style, suggesting the use of a series of strategies to cope with system changes. Respondents were surveyed again in 2006 to gather information about response to transportation policy measures. Though there was substantial support for alternative modes and reduced fuel dependency, respondents’ willingness to pay for driving increased ($1.45/gal ($0.38/L)) as distance from the central business district increased by one standard deviation from the mean (3.74 mi (6 km)).

In these studies, some urban form variables were evaluated in addition to traveler characteristics. Residents of less dense urban areas tend to travel farther. Thus, density influences the price of travel and therefore travel behavior.[38] In the United States, urban form is thought to reinforce car use and dependency.[35]

### Effect of Travel Demand Management Measures and Parking Pricing on Mode Choice

TCRP Report 95 indicates that eliminating minimum parking space requirements and charging market rates for residential parking spaces could reduce vehicle ownership per household enough to reduce household VMT by 30 percent.[39] In the same report, charging employees for parking at work was linked to a 10–30 percent decrease in SOV mode share, depending on the quality of transit alternatives. In Portland, OR, establishing maximum parking ratios and a "parking lid" appeared to reduce the downtown parking ratio by half, from roughly 3.4 long-term spaces per 1,000 $ft^2$ (93 $m^2$) of commercial space in 1973 to 1.5 per 1,000 $ft^2$ (93 $m^2$) in 1990.[40] These parking policies along with some travel demand management measures and transit enhancements are credited with increasing Portland's "downtown transit share from 20–25 percent in the early 1970s to a downtown commuter transit share of 30–35 percent in the 1980s and 1990s."[40] Many urban design variables influence mode share. For example, cities with few parking spaces per employee tend to have higher transit mode share, as expected, since limits on parking are implicitly reflected in the shadow price associated with parking.[40]

Using the 6-week Mobidrive study, Schlich and Axhausen explored repetitious travel behavior.[41] As humans rarely evaluate all their options anew at each opportunity and constraints are relatively similar from day to day, habits are formed but mediated by each day's changing needs. Schlich and Axhausen found that behavior is more variable on weekend days than working days.[41] Variability declines over time, and for each individual in the study, variability was sharply reduced and constant after 2 weeks (i.e., the respondent looked similar over 3 weeks and over 5 weeks). They recommended that participants be observed over 2 weeks.

### Learning, Experience, and Inertia

Inertia, a traveler's propensity to continue making the same choices based on past experience, is not yet well understood. Recently, Cherchi and Manca demonstrated that the significance of inertial effect varies substantially with model specification, and this effect is not stable during a stated-preference (SP) experiment.[42] Depending on a participant's past experience and exposure to options, the inertial effect also varies, pointing to a need for well-designed and controlled experiments.

Using a regret-based model employing Bayesian perception updating, Chorus et al. determined a perceived value of acquiring travel time information as the difference between expected regret induced by a choice before and after acquiring information.[43] Simulations revealed that this value, even for drivers who consider transit as an alternative to driving, is influenced by three factors: information irrelevance, information unreliability, and preference for driving. These same factors also limit the effect of received information on mode choice when the information is highly favorable toward transit. The authors suggested only transit information that is freely provided and easily accessible has the potential to be used by drivers. This information should also be reliable and include aspects of comfort, dynamic conditions, convenience, and perhaps even environmental friendliness. Given the difficulty in meeting these conditions of low-cost, high-quality information, Chorus et al. suggested it may be more efficient to demonstrate the car's limited attractiveness in certain conditions, such as inclement weather or road accidents.

## LIFESTYLE- AND MOBILITY-BASED BEHAVIOR CHANGES

This section primarily examines urban form variables and the self-selection phenomenon to understand travelers' lifestyle choices. The influence of added network capacity on travel behavior is briefly discussed as it relates to traveler characteristics.

The effects of price and traveler characteristics on utility are well understood, but attitudes about mobility and lifestyle and how these attitudes manifest in behavior are still not well understood. There are studies that examine the influence of psychosocial attributes besides income on car ownership.[44] Hiscock et al. in Scotland and Cullinane in Hong Kong found psychosocial benefits in car use, especially for young males.[45,46] Car owners in these studies felt car use improves prestige, protection, autonomy, and self-image.

For decades, the supply-oriented approach to transportation planning revealed that network equilibrium will always result in increasing travel in response to increased capacity such that adding additional capacity only alleviates congestion in the short term. Furthermore, adding freeway capacity is thought to induce additional travel, so Fujii and Kitamura explored the relationship between individuals' activities and the travel environment to determine whether this is the case for commuters between the times they leave work and the times they go to sleep.[47] The authors used structural equations to analyze the impact of hypothetical freeway lanes in Japan's Osaka-Kobe metropolitan area on residents' time use and travel. The model examined the number of trips during this period, the total out-of-home activity and travel durations, the number of home-based trip chains, and the total amount of time spent at home after arriving for the first time until going to sleep. Their model of travel preferences suggested that older, married individuals tend to have a lower preference toward both in-home and out-of-home activities, meaning they have lower preferences toward all activity types. Individuals with higher incomes have large preference indicators for both in-home and out-of-home activities but more so for out-of-home activities. Because time-use and travel variables were treated as endogenous in this study, the impacts of supply changes cannot be thoroughly addressed. However, the results suggest that additional freeway lanes induce very little traffic, indicated by only slight increases in number and duration of out-of-home activities. Much of the time savings from added capacity is allocated to in-home activities.

### Effect of Transit-Oriented Development/Density on Behavior Patterns and Long-Term Choices

Much of the available research on travel behavior and land use interactions is aggregate analysis. The focus on the relationship between urban form and aggregated travel patterns provides little insight into the underlying factors and mechanisms by which urban form influences individual choices.[48] Disaggregate analysis using analysis of variance or regression to study household- and individual-level behaviors suggests that behavior differences are greater among neighborhoods than among individuals within neighborhoods and that attitudes play a very important role in decisionmaking. Handy noted there is a need to understand how urban form shapes choice sets, since discrete choice theory is only able to illustrate how factors influence choices within a given choice set.[48]

Holtzclaw et al. attempted to determine which factors most influence home location selection and associated transit use.[49] Using odometer readings from emissions systems inspections in

San Francisco, CA, Chicago, IL, and Los Angeles, CA, the authors predicted a household's VMT as a function of home-zone density, proximity to jobs, transit service and access to jobs by transit, availability of local shopping, and pedestrian and bicycle friendliness (i.e., the attractiveness of these options compared to driving).[(49)] The elasticities for vehicle ownership with respect to density for Chicago, Los Angeles, and San Francisco were -0.33, -0.32, and -0.35, respectively. Elasticities for VMT (per capita) with respect to density were -0.35, -0.4, and -0.43. Since residents of these cities have above-average access to transit and the model did not control for costs of parking, income, and other relevant variables, applying this model across more cities may not yield such results. For example, the model does not control for attitudes toward driving and public transit, differences in living or vehicle-ownership costs, or the cost and quality of transit. These variables differ significantly in most major U.S. cities, and attitudes are typically a very strong influence on travel patterns. However, the magnitudes are surprisingly similar for three urban areas that differ significantly in terrain and climate. Density often acts as a strong proxy for other urban characteristics.

Equally important to the understanding of how these factors reduce VMT is an understanding of what factors individuals most prefer in neo-traditional developments. In Lund's survey, California residents were asked to identify their top three reasons for choosing to live in a transit-oriented development. Only 33.9 percent cited transit accessibility as a top reason.[(50)] More often, residents preferred type or quality of housing (60.5 percent), cost of housing (54 percent), or quality of neighborhood (51.7 percent). Lund also found that residents who listed transit as one of their top three reasons were 13–40 times more likely to use transit than those who did not, suggesting significant effects of self-selection in such developments. This endogeneity is the topic of the following section.

**Residential Self-Selection and Vehicle Ownership**

Researchers have sought to disentangle the impact of travel preferences and self-selection in home location choice and how this choice ultimately impacts differences in observed travel patterns across distinct neighborhood designs. Cao et al. suggested that attitudes and sociodemographics are confounding influences in such studies.[(51)] While definitive conclusions have not emerged, general neighborhood design distinctions (e.g., walk-oriented versus auto-oriented, existence of bicycle lanes, distance to work and non-work locations) appear responsible for at least half of the observed VMT differences. (See references 51–53 for discussions of literature and results.)

Surveys conducted in Atlanta, GA, by Frank et al. revealed that despite driving preferences, residents living in a walkable neighborhood tended to drive far less than those living in auto-oriented neighborhoods.[(54)] The least walkable neighborhoods generated roughly 45.5 mi (73.3 km) of travel per worker per day while the most walkable generated only 28.3 mi (45.6 km). Furthermore, those who preferred an auto-oriented neighborhood but happened to live in a walkable neighborhood tended to drive significantly less (25.7 mi (41.4 km) per day per worker) than their counterparts in auto-oriented neighborhoods (42 mi (67.6 km)), despite their stated preference. Of those who preferred walkable neighborhoods, the VMT per day per worker values averaged 25.8 and 36.6 mi (41.5 and 58.9 km) for residents of walkable versus auto-oriented neighborhoods, respectively. Thus, while someone may prefer to live in a different neighborhood, it appears that he/she will conform to the travel opportunities of the home neighborhood. Households residing in suburban settings (versus more traditional neighborhoods) tend to be older and have more members. As expected based on VMT patterns, they also own more vehicles per household member (see, for example, reference 55). The neighborhoods in the Frank et al. study had similar densities but differed in household size and income.[54]

More recently, Aditjandra et al. applied dynamic (quasi-longitudinal) structural equation models to understand residential self-selection in the United Kingdom.[56] This method was demonstrated in a U.S. context by Cao et al.[57] In the United Kingdom study, 219 participants who had moved to their current residence in the last 8 years were asked how they drive now compared to before they moved on a 5-point scale from “a lot less” to “a lot more.” Results suggest that sociodemographic characteristics are the main influence on changes in car ownership, but changes in neighborhood characteristics—in particular, safety factors and shopping accessibility—had an important influence. These findings corroborate Cao et al.’s suggestion that, controlling for residential self-selection, neighborhood design impacts on travel behavior “may be similar in different geographical settings despite different planning contexts.”[56,57] In the United States, car ownership is associated with yard size and availability of off-street parking, whereas in the United Kingdom, shopping/facility accessibility and safety of residential neighborhoods most influences vehicle ownership. Again, such variables can often proxy for other characteristics; for example, yard size could indicate home lot size or that the residence is a single-family dwelling.

These proxy issues point to the need to better understand human interactions and the mechanisms that drive behavior. After all, if a family moves, friends may still live in the old neighborhood and exhibit the former travel behavior, and as many studies have shown, geography is one of the best indicators of frequency and duration of social contact.

## BEHAVIORAL MECHANISMS

Besides all the influencing factors and characteristics that explain travel behavior changes, it is important to understand the underlying process of the perception and manifestation of these characteristics, which then lead to a behavior adjustment. That is, how do patterns become lifestyle choices? Even though there are day-to-day travel variations, travel patterns repeat themselves, which suggests that parts of travel behavior are habitual and influenced by inertial effects.[58] Furthermore, the effect of information depends on whether travelers comply with the prescribed information. Inertia, information compliance, travel experience, and learning determine system outcomes that feed back into supply and demand models.

Behavior adjustment implies that behavior is an outcome of experience or new information about current conditions. This can be seen as a learning process that leads to an adjustment of behavior. Mahmassani and Chang studied adjustment- and experience-based models of perceived travel time for departure time choice.[59] Under the myopic adjustment rule, the perceived travel time is only a function of the latest day’s outcome. In laboratory experiments conducted to study the effectiveness of different information strategies on user responses to information, Srinivasan and Mahmassani found that route switching model specifications, which predict whether a user will switch paths in a given time interval, consistently outperformed models that view the process as a new choice at every opportunity.[60] These mechanisms are neither mutually exclusive nor collectively exhaustive, meaning they can operate simultaneously and in conjunction with other mechanisms. The authors designed an experiment whereby virtual commuters were given trip times on three facilities (at decision locations), real-time information about congestion on the facilities, a message alerting the driver when he or she was stuck in a queue, and post-trip feedback consisting of departure time, arrival time, and trip time on the chosen path. Their empirical findings suggest that an individual's negative experience with advanced traveler information systems (ATIS) has mixed effects on inertia, but congestion and information quality tend to reduce inertia. Drivers who experience lower switching costs and increased trip time savings tend to comply with information. In the sequential treatment, past negative experience relative to preferred arrival time seemed to increase likelihood of compliance. Inaccurate information decreased drivers' compliance propensity.

Bayarma et al. examined multiday travel behavior as a stochastic process using 6-week travel diary data, exploring how travel patterns vary and persist among heterogeneous individuals.(61) The authors classified weekday travel patterns into five representative patterns: public transport commuting; extensive car use involving three or four visits to a location; three to four shopping, leisure, and social trips; high fraction of trips that serve to transport another person; and mostly work visits and time spent on work-related activities. The authors found that transitions from a pattern to itself are frequent, especially for non-workers, but transitions from pattern to pattern vary substantially across individuals. Individuals with a driver's license tended to have a higher level of day-to-day variability in their travel patterns. Residential location type also influenced variability in daily travel, with individuals living in a central area regularly pursuing more shopping and leisure activities. Gender, marital status, and number of household vehicles were insignificant in this study—age, household type, and employment status explained much of the variation.

A seminal work on attitude-behavior theory addressed the interrelationships between attitudes and behavior from multiple modeling perspectives, including multiattribute, hierarchical, market segmentation, and, to a lesser extent, structural equation models.(62) Simple models provided empirical support for behavioral feedback mechanisms, and attitudes and behavior were found to simultaneously influence one another. The concept of simultaneous influence has been explored in greater depth since the study, and market segmentation and structural equation models are still used to explore psychosocial influences in travel behavior. Beyond attitude, perception and intention have a substantial influence on behavior. While attitude and perception have been explored in great depth, less attention had been paid to traveler intention until recently. Bamberg found that forming an implementation intention (when, where, and how to perform an action) increases the probability that a goal intention is manifested in behavior.(63) In a study of 90 university students, forming an intent to ride a new bus route was the best predictor of whether a student rode the new bus route, even more so than current bus- and auto-use habits. While habit exerted a strong negative effect on whether one would test the route for the control group, habit did not strongly influence the experimental group. Thus, Bamberg points out that influencing behavior involves not only influencing the decisionmaking process but also the formation of implementation intention.(63)

## Household Interactions

The dominant paradigm in travel behavior is the individual satisfying needs while maximizing the utility derived from the activities undertaken. That this undersocialized understanding severely limits the scope of its work has been understood since the mid 1970s, but only in recent years have researchers developed a set of methods and models that can replace the previous generation in practical application.(64) Even though the social context of traveling is underresearched, the importance of joint activity participation is evident and has been studied. Kostyniuk and Kitamura analyzed time-use data and found that joint activities tend to have a longer duration than other similar non-work activities.[65] Furthermore, people participating in joint activities travel farther to perform an activity. Household level and social network size influence traveler choices at all levels, from departure time and route to residential and employment location selection.

Many researchers have studied the effect of household attributes on joint activity travel. For example, Jones et al. and Kostyniuk and Kitamura found that adults are strongly affected by the presence of children.[64,65] Couples with children perform most joint activities at home, whereas couples without children are more likely to perform joint activities outside the home. Employment status influences the starting point of joint activities; couples in which both are employed tend to choose a starting location outside the home. The same research also found that the availability of a car positively influences individual time-use patterns of couples. Fujii et al. found that people rated time spent in non-work joint activities higher than non-work activities spent alone.[66] Time spent in joint activities was rated more "satisfying," and people chose to allocate time to joint rather than independent activities if possible. Freedman and Kern researched the implications of two-worker household status on location choices and concluded that wives' commute burdens influence home and workplace location decisions.[67]

In a similar study of time use via detailed in-person interviews with 30 dual-career households in the United Kingdom, Green found that residential site selection depended more on the working male's job location, even in households that had recently moved.[68] The interview results and census data suggested male worker commute times in the United Kingdom in 1995 were declining with respect to 1980 commute times, while those of female workers were increasing in dual-career households. Men's commute times were still longer, with roughly two-thirds of males commuting more than 30 min to work and about half of females commuting more than 30 min. Green expected the long-run convergence of male and female commute patterns in the United Kingdom, and American Time Use Survey data suggest this happened in the United States as of 2007 or earlier.[68,69]

Srinivasan and Bhat found that wives' in-home maintenance durations were the most susceptible to change based on household attributes and husbands' activity choices.[70] Out-of-home work duration and commute time negatively impacted husbands' in-home maintenance time, while the number and age of children had no effect. To accommodate this, wives' in-home maintenance time increased with their husbands' out-of-home work durations, the number of children under age 5, and the availability of a personal vehicle. Females' commute times were not found to affect their in-home maintenance times.

Lee et al. used simultaneous Tobit models for Tucson, AZ, data to model household time expenditures.[71] Their results suggest that the number and work status of household heads are primary determinants of trip chaining and time allocation. Interestingly, income and vehicle ownership levels were not found to be strong predictors of chaining behavior. More recently, Lee et al. used 2001–2002 Atlanta, GA, survey data and land use files. As expected, they found that people with children over age 6 spend less time traveling and those with very young children (under age 5) spend less time in out-of-home subsistence and discretionary activities.[71]

Hence, time and task allocation at the household level were incorporated in the models. (See references 72–75.) However, individuals are part of social networks, and behavior is influenced by others' attitudes and behavior. Thus, joint activities do not only involve household members but may also include the social network. Axhausen noted that in addition to the generalized costs of travel and the hedonic utility of a location (as modulated by the sociodemographics of an individual and perhaps his/her values, attitudes, and lifestyle), the geography of the social network of the person should be included in models.[76]

## Social Networks

More studies, including surveys and data collection efforts, have recently focused on the influence of social networks on travel behavior. (See references 77–81.) A number of new models and simulations have also shown this influence.[82,83] These studies mostly explored the cross-sectional relationships between characteristics of social networks and physical and virtual travel. Van den Berg et al. used a social interaction diary to study the factors influencing the planning of social activities.[84] The researchers found that social activities scheduled later in the day are less likely to be routine. In contrast, social activities of longer duration and taking place on weekends are more likely to be routine or preplanned. Harvey and Taylor studied the influence of work location on joint activities with time-use data.[85] They argued that people who work at home spend more time alone and therefore show a tendency to travel more to fulfill their needs for social interaction. Carrasco and Miller described joint activity participation with egocentric social structure effects (degree of a person), the use of communication technology, and sociodemographic variables.[77] They found that people with a high egocentric social network degree are more likely to perform joint activities. The availability of communication technology such as telephones and the Internet reduces the cost of coordination and influences participation in joint activities. Further, information dissemination within a social network could change attitudes and perceptions, leading to changes in travel behavior.[86,87] To date, information dissemination in a travel behavior context has not been examined further than numerical experiments. The complexity and lack of data have hindered the incorporation of social network concepts into full transportation demand models. This issue is discussed further in later sections of this report.

Market researchers and behavioral scientists have examined how new behaviors are adopted and to what extent adoption may be a function of a personal identity and social norms, particularly social acceptance. A great body of work is concerned with adoption of new technologies and purchasing behaviors, but little research has been done regarding adoption of modes and transportation behaviors of one’s close or extended social networks.

# TRAVEL BEHAVIOR MODELS REVIEW

## ACTIVITY-BASED MODELS

The advantages of activity-based models are diverse but can be organized in to the following four categories, which are later discussed in more detail:

- They can identify the influence of time, destination, and mode on trip attributes.
- They capture long-term behavior, overcoming the limitations of tour-based models by including activity patterns outside the daily schedule in addition to time dependency, destination, and mode.
- They capture certain characteristics of individual-based decisions beyond aggregate traffic analysis zones.
- They capture short-term decision shifts that may have substantial impacts at the network level. Linkage of interpersonal decisions that are crucial to policies such HOV lanes can be taken into account.

These are also the main reasons to incorporate an activity-based framework rather than a trip- or tour-based framework.

Within activity-based travel demand models, there are two primary modeling paradigms: utility-based econometric models and rule-based computational process models. These models are not exclusive but have different philosophical approaches and are therefore fundamental in how the travel generation process is understood. Combinations of the two models can be found within agent-based simulation models, which are discussed later in this report.

### Utility-Based Econometric Models

Utility-based econometric models have their roots in economic consumer choice theory, which says that individuals maximize their utility from the choices they make. These models consist of a number of different choice-based models for the individual's activity-travel decisions. These models can be enriched by other utility-based models, such as hazard models for time durations. The set of economic equations builds the structure to model the relationships among the traveler characteristics, the network characteristics that allow the individual to travel, and the environment characteristics that describe the place to perform activities and further restrictions on the traveler's behavior.

The following are existing utility-based econometric activity-based model systems:

- Greater Portland METRO.[88]
- San Francisco County Transportation Authority.[89]
- New York Metropolitan Transit Council.[90]
- Mid-Ohio Regional Planning Commission (Columbus, OH).[91]

- Sacramento Area Council of Governments.[92]
- Atlanta Regional Commission.[93]
- Comprehensive Econometric Micro-Simulator for Daily Activity-Travel Patterns.[94]
- Florida Activity Mobility Simulator.[95]

All of the listed models can be categorized as full individual day pattern models or linked full individual day pattern models. The full individual day pattern models follow the concept of an overarching daily activity-travel pattern proposed by Bowman and Ben-Akiva.[96] These models are based on an underlying system of multinomial logit or nested logit models in a particular hierarchy. The linked full individual day pattern models enhance the models previously described by allowing intrahousehold interactions in activity-travel engagement models. The Columbus, OH, and Atlanta, GA, models are examples of such models.

### *Types and Advances*

To meet expectations and improve analyses, one of the natural responses from transportation modelers is to develop more sophisticated modeling forms, ranging from simple logit and probit to nested and mixed logit to Bayesian procedures and so on. The travel behavior model evolved from simple regressions based on aggregate, revealed preference (RP) data to more sophisticated mathematical functions based on disaggregate, SP data.[97] For example, the logit family of models progressed from the binary logit model to the multinomial logit model or the conditional logit model and then to the nested logit model and the mixed logit model. As early as 1972, the binary logit model was utilized in intercity travel mode choice. The multinomial logit model was primarily used to model multiple choices. Ben-Akiva derived the nested logit model that is designed to capture correlations among alternatives.[98] At the time of this report, mixed logit is considered the most promising discrete choice model that is intuitive, practical, and powerful. It combines the flexibility of probit with the tractability of logit.

At the same time, a large number of transportation professionals have devoted effort to identifying and evaluating major utility factors besides time and cost to improve the predictability of utility functions. Hensher used an early example to incorporate comfort and convenience in a travel mode choice model.[99] Algers et al. included comfort and convenience in a study on the value of travel time.[100] Later, Liu et al. proposed a conceptual framework that includes travel time, monetary cost, comfort/convenience, and safety/security in the travel choice models.[101] In a recent choice model, Ben-Akiva et al. integrated latent variables to model attitudes and perceptions and their influence on choices.[102]

The underlying concept to understand behavior changes from operational interventions has to account for the problem that behavior switching is not the same as observation of a certain behavior. Behavior switching is less rational, as travelers tend to stick with what they are used to, which can be described as inertia. The decision rule is no longer based only on maximizing the utility but includes a switch if the utility of switching exceeds a threshold. The generalized indifference band framework is shown in figure 2.

$$Pr(X = 1) \Longleftrightarrow Pr(U \geq 0)$$

**Figure 2. Equation. Generalized Indifference Band Framework.**

The random utility formulation has to account for time and location at different days and can be formulated as shown in figure 3.

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}$$

**Figure 3. Equation. Random Utility Formulation.**

Where:

$V_{ijt} = f\,(Z_i, N_{\mathrm{ijt}}, NN_{\mathrm{ijt}}, V_{ijt})$.

$Z_i$ = Traveler characteristics.

$N_{ijt}$ = Time-dependent network attributes by decisionmaker $i$ at decision location $j$ at day $t$.

$NN_{ijt}$ = Time-dependent non-network characteristics by decisionmaker $i$ at decision location $j$ at day $t$.

$V_{ijt}$ = Time-dependent vehicle characteristics by decisionmaker $i$ at decision location $j$ at day $t$.

$\varepsilon_{ijt}$ = Error terms correlated over different times of day, locations, and days.

To incorporate interpersonal interactions, a utility maximization approach can be included. Each individual's utility is calculated jointly and singly, and a joint decision is made if the difference of the best alternatives exceeds a certain threshold, as shown in figure 4 and figure 5.

$$\Delta U_{si} = \sum U_{ijt_{single}} - \sum U_{ijt_{joint}}$$

**Figure 4. Equation. Joint Versus Single Utility Threshold.**

$$\Delta U_T = \sum (\alpha_i U_{si} + \ldots + \alpha_k U_{sk})$$

**Figure 5. Equation. Weighted Sum of Joint Versus Single Utility Threshold.**

Where:

$\alpha$ = Each individual's weight of influence.

**Rule-Based Computational Process Models**

Rule-based computational process models are developed on the premise that individuals do not always act rationally and so do not maximize their utility. Instead, individuals rely on a process that contains complex if-then rules to solve a task, similar to a production system model. These models have problems describing the statistical significance of the factors that affect the rules and are therefore not always best for understanding behavior changes based on experiments or for predicting future changes. The following are existing rule-based computational process activity-based model systems:

- CARLA: Combinatorial Algorithm for Rescheduling Lists of Activities.[103]
- STARCHILD: Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions.[104]

- SCHEDULER.[105]
- AMOS: Activity-Mobility Simulator.[106]
- SMASH: Simulation Model of Activity Scheduling Heuristics.[107]
- ALBATROSS: A Learning-Based Transportation Oriented Simulation System.[108]
- TASHA: Travel Activity Scheduler for Household Agents.[109]

### Agent-Based Modeling Systems

The Transportation Analysis and Simulation System (TRANSIMS) and the Multi-Agent Transport Simulation Toolkit (MATSim) are agent-based activity-based modeling systems that were originally designed to account for the full disaggregate representation of individual travel behavior.[110,111] They were mainly developed to capture characteristics of individual-based decisions beyond aggregate traffic analysis zones and short-term decision shifts that may have substantial impact at the network level in conjunction with dynamic traffic assignment. Thus, the feedback is based on aggregated system information, not on specific agent information. If one is not interested in the Nash equilibrium, traditional dynamic and non-dynamic traffic assignment approaches fail because there is no access to human behavior.[112] Since these agent-based systems do not find a clear equilibrium, it is unclear what solution they produce. Further, by decoupling the demand side (activity-based models) from the supply side (either assignment or simulation models), the activity models typically compute probabilities for a large number of alternatives, which demands an explicit choice set. Accounting for such alternative sets in real-size networks would result in very long computation times.[113]

## MODEL INTEGRATION

As previously discussed, the development of advanced travel behavior and demand models and the development of transport supply models have been relatively independent of one another. Thus, the demand and supply models are each formulated to use forecast outputs from the other model without feedback. As a result, the level of service input to demand models is not necessarily the same as that output from the supply models nor is the demand input to supply models necessarily the same as that output from the demand models. Thus, it is important to integrate demand and supply models to ensure consistency between supply and demand. Efforts to integrate demand and supply models have been made in recent years. Lam and Huang presented a mathematical formulation for dynamic traffic assignment for modeling simultaneous location, route, and departure time choices.[114] Their model can be used as a simplified travel demand analysis tool but cannot capture travel behavior complexity. Lin et al. proposed an integration of an activity-based model simulator with a dynamic traffic assignment model, where feedback convergence is measured by aggregated travel time and number of trips.[115] The authors showed that the initial differences are substantial and can be reduced dramatically on an aggregated level. Lu and Mahmassani presented a “joint route and departure time network equilibrium assignment model explicitly considering heterogeneous users with different preferred arrival times at destinations, values of time, and values of early and late schedule delays.”[116] Their “multicriterion simultaneous route and departure time user equilibrium” determined both changes in route choice in response to dynamic pricing as well as temporal shifts toward less congested periods. Application of this model in a large network setting remains limited by computational capabilities, but the model can realistically be applied to alleviate congestion by finding optimal dynamic pricing schemes by location, pricing periods, and toll charges.

On a completely disaggregate level, some agent-based simulations also incorporate demand and supply models. Esser and Nagel and Rieser et al. developed a multiagent microsimulation module that integrates activity generation, route assignment, and network loading.[117,118] Generated daily activity-based plans are executed by agents and assigned to the route. The traffic simulation is then used to evaluate those activity plans. Changes in activity start times, route choices, etc. are randomly adjusted and high-scoring activity plans are executed.

Although the need for integration of transportation demand and supply has been accepted for years, much of the research is still in the conceptual stage.

# TRAVEL BEHAVIOR DATA REVIEW

## STANDARD SOURCES

Most travel behavior studies use surveys and travel diaries as data sources. There are only a few laboratory and field experiments that have been used for collecting data to capture travel behavior. The most widely used resources are national travel surveys that many countries collect. These surveys typically collect individual information (socioeconomic, demographic), household information (size, structure, relationships), vehicle information (age, make, model), and a diary of journeys on a given day (start and end locations, start and end times, mode of travel, accompaniment, purpose of travel). Recent and continuously collected national travel surveys are summarized in table 1. Armoguum et al. gave an overview of the different national travel surveys.[119]

**Table 1. Recent and Continuous National Travel Surveys.**

| Country | Source | Years |
|---|---|---|
| United States | Federal Highway Administration | 2009, 2001, 1995 |
| Germany | German Mobility Panel | 1994–2011 |
| Denmark | Danish Transport Research Institute | 2006 |
| Netherlands | Institute for Road Safety Research | 1978–2011 |
| United Kingdom | United Kingdom Department for Transport | 2009 |
| Switzerland | Federal Department of Environment, Transport, Energy and Communications | 2010, 2005, 2000 |
| Sweden | Sika Institute | 2006 |

A number of papers accessed data from secondary sources such as the American Housing Survey 2001 or relied on specific surveys designed for the research. For example, Srinivasan and Rogers used a random stratified sample of 500 households in two suburbs of Chennai, India; Ampt et al. interviewed 102 participants in their survey of household travel behavior; and Rose and Ampt included only 46 participants in their study of car use reduction strategies in Sydney and Adelaide, Australia.[120–122] Thus, the number of participants in research projects varies considerably from less than 100 to many thousands in the case of national travel surveys. Methods of data collection also vary considerably, including face-to-face structured or semi-structured interviews, postal questionnaires, telephone surveys, and, more recently, online questionnaires.

## TRAVEL DIARIES

Most studies of travel behavior use travel diaries, which include data from trips and the activity behavior that is collected with the trip. The most common practice with travel diaries is to collect data from a 1- or 2-day time span, which has a relatively low response burden and gives full information about trip frequencies, mode choice, and other decisions for aggregated models. Boarnet and Crane, Bowman and Ben-Akiva, Giuliano, Kunert and Follmer, and Newbold et al. all used 1-day travel diaries. (See references 38, 96, 34, 123, and 27.) A number of other projects used 2-day travel diaries.[23,124,125] However, to observe behavior changes and habitual travel and record data about how to influence and change travel behavior, a longer reporting period would be useful. Only a small number of research projects used 7-day or longer diaries, including Garvill et al., Kenyon, and Schlich and Axhausen.[126,127,41] In Schlich and Axhausen's study of travel behavior in Karlsruhe and Halle (Saale), Germany, participants were required to keep a travel diary for a period of 6 weeks, recording all travel movements during that time. A total of 52,273 trips were recorded by the 361 participants.[41] Garvill et al. used the German National Travel Survey, a panel survey where participants are required to complete a travel diary several times during different periods.[126] Kenyon required 100 participants to complete a 7-day travel diary three times at 6-month intervals in March 2004, October 2004, and March 2005.[127]

Not all surveys state the day of the week and season for the trips reported. Often, the day is only differentiated between weekdays and weekends/holidays. It is surprising that the season and day of the week are not discussed, as seasonality and associated weather has an influence on travel patterns, and travel patterns vary from day to day and week to week.

Larson and Poist provide an interesting overview of all papers using a postal questionnaire included in *Transportation Journal* between 1992 and 2003.[128] The authors report a total of 106,300 mailed questionnaires and that response rates have declined significantly since 1992.

## STATED PREFERENCE AND REVEALED PREFERENCE

To analyze likely behavior changes in response to changes in the transport system and other influence factors, RP data are often unavailable and SP data have to be used. As a result, significant literature has been developed around survey methods for estimating individuals' behavior adaption in the absence of revealed system variation. These methods are widely used for developing optimal pricing strategies, forecasting responses to price changes, and modeling demand functions.

Although longer time studies might have information about system changes, there are often limitations to RP data. For example, observation of choices might not occur and changes take time for adoption. These limitations could be overcome with real-life controlled experiments; however, opportunities for such experiments have been limited. The Federal Highway Administration provides some opportunities to design and collect data from such field experiments through the integrated environment at the Saxton Transportation Operations Laboratory, which has a data resources test bed, a concept and analysis test bed, and a cooperative vehicle-highway test bed. If such experimental environments are not available, SP surveys provide an approximation by asking questions about hypothetical situations. The design and configuration of such questions is not trivial and has been the subject of research in recent years. Bliemer and Rose proposed an approach to generate an efficient experimental design that minimizes standard errors in estimating the parameters from the utility function that underlies travel behavior decisions.[129]

Because SP data may not include the history of individuals, which is needed to assess the effect of habits, models estimated with SP data often overestimate the impact of changes in the system on behavior adaption. Questions included in SP surveys such as car use and trip frequency can give hints about the history so that models can capture inertia. Mixed RP/SP data include more likely inertia indicators, as they are constructed based on previously chosen alternatives and real situations are used to construct the hypothetical SP survey response.[130] Since such data is vulnerable to serial correlation, Cantillo et al. proposed discrete choice models with both inertia and serial correlation with mixed RP/SP data. They found that inertia and serial correlation in mixed RP/SP data are significant.[131]

## EMERGING POTENTIAL IN DATA COLLECTION

In 1997, Kitamura and others pointed to the need for more extensive data and improved methodologies for understanding travel behavior.(132) The case for collection of such data has strengthened in the last 15 years as others have called for more comprehensive transportation modeling and planning contexts.(58) Beyond trips and travel networks, analysts need data to understand "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."(132) If travel is assumed to be a derived demand, then sociodemographics and attitudes are thought to be the primary inducements for observed travel. When travel for its own sake is evaluated, attitudes and perceptions become even more important.(133) From this perspective, travel control measures and travel demand measures affect urban quality of life more than facility expansion.(133) Thus, any effort to understand the impact of demand-side interactions must examine human time use. This requires improved data collection and methodologies that are able to evaluate both induced and suppressed travel as well as the implications of this travel on perceived quality of life.(132) Time-use data are particularly useful for understanding location substitution of activities (e.g., telemobility alternatives) and activity and departure timing. Jara-Diaz noted that as the utility of travel depends on activities as a result of time and monetary budget assignments, then travel must be understood in the context of human activities and the nature and perception of time use.(134) Thus, meaningful models require linking data, methods, and knowledge from sociology, psychology, and economics.(134)

Kwan's review of time-use research, time-geographic research, and studies on human activity-travel patterns in space-time discusses the integrated nature of time, space, and information technology (IT).(135) Transportation research has explored the implications of IT on time use and travel behavior, noting that telemobility alternatives may be complementary, substitutive, or synergistic to traditional travel behaviors.(136) Furthermore, mobile devices allow for en-route or continuous adjustment of travel plans. A significant amount research on the dynamics of route choice behavior is based on laboratory-like experiments that repeatedly ask the participants to respond to hypothetical route choices. Because of the lack of detailed, disaggregate spatial and temporal data, much research has focused on two dimensions at a time (e.g., location and time use, time use and IT, or location and IT).(137,138) Though the availability of such data represented a significant challenge in the past, the current challenge lies in the design of postprocessing algorithms to enable analysis of the massive quantities of data available from smartphones and increased Internet use. Methods for analysis of complex space-time data are also needed.(135)

IT presents an opportunity to relax the time-space constraints often imposed in travel behavior studies. The ability to mingle work and non-work activities and locations using mobile devices blurs the distinctions between home and work and between public and private.(139) Kwan suggested that these time-space constraints will not disappear altogether, since IT accessibility and quality of service is often constrained by location.(140) Future research should examine how social and geographical contexts shape the impact of IT on specific social groups and, in particular, urban areas.(135) Furthermore, analysts should examine interactions among household members within social groups and evaluate within-household variations of IT use. IT provides additional data sources such as social networking sites that can be used for a variety of detailed destination attributes and trip purposes that were previously unavailable.

## GROWING ROLE OF EXPERIMENTS AND GAMING METHODS

Experimental methods have an increasing role to play in the study of complex activity and travel behavior dynamics, especially as information and communication technologies increase the realm of spatiotemporal opportunities available for individual and household activity engagement. In a synthesis of experimental economics approaches to travel behavior, Mahmassani identified the following situations for which laboratory experiments may be needed in the study of the relevant behavior and system properties:[141]

- Complex dynamics and collective effects are essential aspects of the system under consideration, making joint measurement in the real world considerably complicated or costly.
- Situations or policies of interest are not available in the real world (e.g., new technologies) or are mutually inconsistent in the same system.
- Control for extraneous factors is desired.
- Understanding of dynamics and learning processes is of concern.

Experiments that entail varying degrees of sophistication in context design, task design, and delivery environment and that contain different scales of experimentation in terms of number of participants and environmental perturbation are common in many disciplines concerned with the study of human systems. Transportation planning professionals and travel behavior-activity researchers have been slow to adopt experimental methods in research or practice (with the exception of stated response methods and full-scale operational tests). However, from modest beginnings in the early 1980s, there appears to be growing interest in experimental methods for the study of human behavior in transportation decision situations. The following reasons can be surmised for this phenomenon:[141]

- Growing interest in experimental economics as an approach for the study of economic systems.
- Related development in complexity science and its application to human, economic, and sociotechnical systems.
- Advancement in computing capabilities and networked environments, especially the Web, and interest in large-scale collective phenomena in networks.
- Continued development of travel behavior as a focus of interdisciplinary research, with entry of professionals from varying disciplinary backgrounds.
- Increased sophistication in methods, theories, and intellectual constructs in travel and activity behavior research.
- Significance of policy questions and concerns that require better understanding of behavioral dynamics and multiagent interactions (e.g., environmental sustainability, vehicle use, and congestion mitigation).
- Technological advances in information and communication technologies that enable improved simulation/gaming environments, delivery platforms, and multiplayer interactions.

In the mid to late 1980s, Mahmassani and Herman conducted a series of three experiments involving actual commuters in a simulated congested traffic corridor.[11] Those experiments were conducted before the widespread availability of personal computers and the Internet and entailed overcoming significant logistical challenges. The participants were all actual daily commuters who responded to traffic conditions with their selection of a particular time to depart or route to use in a commuting corridor. The experiments provided a basis for articulating a theory of departure time and route switching decision mechanisms in repeated decision situations such as work commuting. The experiment results were indirectly validated with 2-week diary surveys of commuters in Austin and Dallas, TX.[142,143] An important methodological question is the extent to which behavioral findings from laboratory experiments are indeed representative of actual behavior in real traffic systems. The main conclusion from the comparative analyses was that behavioral mechanisms developed on the basis of laboratory experiments provided a good explanation of observed behavior, with essentially similar model specifications and correct signs but different coefficient magnitudes.[143]

An extensive set of experiments was conducted by Mahmassani and colleagues to investigate user dynamics under real-time information of varying types. In contrast to earlier experiments, which addressed only the day-to-day dynamics of user decisions, the ATIS investigation addressed both real-time and day-to-day dynamics. As such, these experiments required a special purpose simulator that allowed real-time interaction between respondents and the traffic system. The interactive simulator provided ATIS information that was consistent with the traffic conditions on the network. The prevailing traffic conditions, in turn, were the result of collective decisions of individuals on the network, whose interactions in traffic were modeled using a dynamic traffic simulation model. Thus, the simulator ensured mutual consistency between user behavior, experienced traffic network conditions, and real-time information.[144]

Three sets of experiments were performed over a 3-year period: (1) en-route path choice and day-to-day departure decisions under a given overall congestion level, (2) effect of congestion and experimental exposure sequence, and (3) effect of information type, quality, and feedback to users on user decision processes.[145,146] An overview was presented by Mahmassani and Srinivasan.[147]

In the past decade, interest has grown in the potential role of experimental economics approaches in travel behavior research. Methodologically, the following guidelines are generally followed in experimental economics:[141]

- Use real monetary payoffs to incentivize subjects; in other words, the payoffs should be designed so as to induce the same behavioral response as the experienced consequences in a natural context.
- Publish complete experimental instructions.
- Do not use deception. There is considerable debate regarding this matter in the field; experimental evidence suggests that deception (false consequences to deny participants monetary payoffs) leads to unreliable responses and loss of goodwill.
- Avoid introducing specific, concrete context (i.e., keep the decision context stylized and generic and hence transferable and generalizable).

The precepts of experimental economics differ from prevailing practice in transportation and travel behavior research because the latter have generally sought to elicit responses to the actual attributes that influence choices in the real world, rather than some monetary surrogate that may be of questionable realism.

Selten et al. conducted laboratory experiments of a highly stylized day-to-day route choice game with two route alternatives (a main road and a side road) and two experimental treatments corresponding to feedback about one's own travel time and feedback about the travel times of the alternative route in addition to one's own route.[148] Each experiment consisted of 18 players at a time (equilibrium consisted of 12 players on the main road and 6 on the side road). Methodologically, the payoffs increased according to a simple linear formula with decreasing travel time, itself related linearly to volume. The researchers ran 200 iterations, considered a long time in experimental economics, but they still encountered large fluctuations. The results seemed to converge toward equilibrium but not perfectly, as fluctuations persisted under both treatments (fluctuations appeared to be smaller under the full-information treatment). Both direct and contrarian response modes could be identified among the players, with direct players changing routes after a bad payoff and contrarians changing routes after a good payoff.

An important element in experimental economics that is of considerable relevance to travel behavior dynamics is the role of learning and judgment in repeated decision situations (e.g., day-to-day adjustment). Psychological studies have examined some of these questions through experiments on individual subjects but have typically ignored the effect of other decisionmakers and different information environments. Information availability plays an important role in determining which theories are feasible in different environments. Economists have investigated learning behavior both experimentally and theoretically but on a macroscopic scale, studying how simple information adjustment rules drive equilibrium processes in games under different information environments.[149]

More recently, opportunities offered by online gaming environments have emerged as a promising approach for studying individual activity and travel choices.[150] Activity and travel behavior in virtual environments is of interest for the following reasons:

- It is a manifestation of human behavior in a domain that is occupying a greater share of the time and resources of a growing segment of the population and increasingly cutting across social, demographic, and economic lines.
- Virtual world engagement is integrally linked to physical world behavior and, as such, becomes essential in studying and predicting behavior in the latter.
- It is likely to provide insight into activity and travel behavior in the physical world and to help identify fundamental mechanisms underlying such behaviors.
- It may eventually provide a laboratory for observing behavior under controlled experimental conditions (e.g., in response to contemplated policies).

However, designing games to address the questions of interest while retaining the players' engagement remains a challenge.

## CONCLUSIONS, RECOMMENDATIONS, AND FUTURE RESEARCH

This review reflects the diversity of travel behavior research. Nevertheless, a number of topics raised in many studies will shape the future of travel behavior research and the way we understand and model the mechanisms of travel behavior. These topics cut across all areas of analysis and understanding, from general knowledge to models and data, as each section cannot be used to draw conclusions by itself. It has been widely accepted that activity-based models are needed to model the complexity of travel demand, and many activity-based models have been implemented. However, most national travel surveys conduct travel diaries of 1 day, which account for neither the details desired to understand short-term behavior nor the extended time period to capture long-term effects.

Topics that should influence the nature of project methodology, data collection, and models include behavior mechanisms, model integration, environmental impacts, and information in new data opportunities and how to use them. These appear in research quite often, but they have not been explored enough and are not ready to be implemented in today’s tools. The lack of general knowledge, difficulty in capturing and measuring behaviors, and complexity in modeling behavior are formidable challenges.

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