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NATIONAL COOPERATIVE HIGHWAY RESEARCH PROGRAM

NCHRP RESEARCH REPORT 896

Updating Regional Transportation Planning and Modeling Tools to Address Impacts of Connected and Automated Vehicles

Volume 2: Guidance

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TRANSPORTATION RESEARCH BOARD

2018

NATIONAL COOPERATIVE HIGHWAY RESEARCH PROGRAM

Systematic, well-designed research is the most effective way to solve many problems facing highway administrators and engineers. Often, highway problems are of local interest and can best be studied by highway departments individually or in cooperation with their state universities and others. However, the accelerating growth of highway transportation results in increasingly complex problems of wide interest to highway authorities. These problems are best studied through a coordinated program of cooperative research.

Recognizing this need, the leadership of the American Association of State Highway and Transportation Officials (AASHTO) in 1962 initiated an objective national highway research program using modern scientific techniques—the National Cooperative Highway Research Program (NCHRP). NCHRP is supported on a continuing basis by funds from participating member states of AASHTO and receives the full cooperation and support of the Federal Highway Administration, United States Department of Transportation.

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The needs for highway research are many, and NCHRP can make significant contributions to solving highway transportation problems of mutual concern to many responsible groups. The program, however, is intended to complement, rather than to substitute for or duplicate, other highway research programs.

NCHRP RESEARCH REPORT 896, VOLUME 2

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FOREWORD

By Lawrence D. Goldstein
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NCHRP Report 896: Updating Regional Transportation Planning and Modeling Tools to Address Impacts of Connected and Automated Vehicles, Volume 2: Guidance includes detailed information and guidelines for state departments of transportation (DOTs) and metropolitan planning organizations (MPOs) to help update their modeling and forecasting tools to address expected impacts of connected and automated vehicles (CAVs) on transportation supply, road capacity, and travel demand components. CAVs are likely to influence all personal and goods movement level of demand, travel modes, planning and investment decisions, physical transportation infrastructure, and geographic areas.

Under requirements for long-range transportation planning established by the Moving Ahead for Progress in the 21st Century Act (MAP-21) federal statewide and metropolitan planning regulations, DOTs and regional MPOs are required to have a multimodal transportation plan with a minimum time horizon of 20 years. CAVs are developing rapidly, and manufacturers and shared fleet operators suggest that highly automated vehicles will be present on the highway system in significant numbers well before the year 2038, the minimum time horizon for plans initiated in the current year. As evidence of that commitment, there are 17 shared automated vehicle (SAV) pilots in eight states in current deployment. There will be both direct and indirect impacts of CAV deployment, and not all these impacts will be positive. Experience has shown that there are often indirect and unintended consequences from rapid changes, and the planning community needs procedures and methods to address both potentially positive and potentially negative outcomes.

In this report, the Texas A&M Transportation Institute, DKS Associates, Resource Systems Group, RAND Corporation, and Shelley Row Associates together reflect on the challenge of forecasting travel behavior in the context of CAVs; describe the technologies and the influences on their adoption timelines; present a framework for planning and modeling; present approaches for planning under uncertainty; and suggest updates to trip-based and activity-based dynamic assignment and strategic modeling systems.

This report is intended for use by experienced agency staff of state DOTs and MPOs that have greater (and lesser) planning and modeling capacity. While the modeling approach may differ among these agencies, all have in common the need to develop new planning and modeling processes that include CAVs in the transportation environment. The research team also developed a stand-alone executive summary (Volume 1) that concisely conveys the key findings of the research. It is available with this report on the TRB website (http://www.trb.org), along with a PowerPoint® presentation that can be adapted for presentations to agency decision makers.

CONTENTS

Note: Photographs, figures, and tables in this report may have been converted from color to grayscale for printing. The electronic version of the report (posted on the web at www.trb.org) retains the color versions.

CHAPTER 1

Introduction

> **Chapter Highlights**
>
> - Conveys study objective—to provide DOTs and MPOs with guidance on updating modeling and forecasting tools related to connected and automated vehicles.
> - Defines the main challenge addressed by this research—changes to the existing forecast modeling paradigm made necessary by the future presence of connected and automated vehicles in traffic streams.
> - Summarizes report contents and guides readers to specific text on the basis of their information needs.

Study Objectives

This report provides information and guidelines for state departments of transportation (DOTs) and regional metropolitan planning organizations (MPOs) on updates to modeling and forecasting tools that will be necessary to more appropriately account for the expected impacts of automated vehicles (AVs) and connected vehicles (CVs) on transportation supply, road capacity, and travel demand components.

Updates are needed because connected and automated vehicles (CAVs) are expected to prompt disruptive changes to transportation. CAV implementation is likely to influence level of demand, travel modes, planning and investment decisions, physical transportation infrastructure, and geographic areas for all personal mobility and goods movement. Planners and modelers are faced with evaluating public and private investment in roadways and other transportation facilities with only one certainty: disruptive change is on the horizon. Automated technologies in vehicles, efficient communications between vehicles and infrastructure, and a market shift toward economical and flexible shared mobility fleets will transform the current landscape of personal mobility and goods movement. The difficulty of predicting the exact timing, magnitude, type, and locations of the disruptive changes poses new risk for infrastructure investment decisions.

Both direct and indirect impacts are expected from each of the elements of CAVs, and not all impacts that come from these disruptive technologies will be positive. Experience has shown that indirect and unintended impacts often result from rapid changes, and the planning community needs methods to address both potentially positive and potentially negative outcomes. For example, vehicle automation affects the driving task by potentially altering the perceived time inefficiencies related to driving. The idea is that time spent operating a vehicle is wasted, and that time could be spent doing something more productive. People's value of time will be changed when they are converted from drivers to passengers who will be able to conduct business while in transit to and from a workplace. Another possibility is that the time gained may be spent in leisure activities (e.g., reading, watching TV). The dynamics of this change may result in a shift in the choices people make regarding destination, route, or mode. Likewise, the changes in dynamic travel time as drivers become passengers have implications for toll-road modeling and parking costs.

Planners and modelers are concerned with long-range forecasting of these types of fundamental, indirect impacts from transportation automation. Change may occur quickly for certain

This study was executed under NCHRP 20-102, a task-order support contract addressing critical issues in AV and CV development that DOTs and MPOs are facing. For information on related studies and reports, see http://apps.trb.org/cmsfeed/TRBNetProjectDisplay.asp?ProjectID=3824.

modes, while for other modes it may take decades to realize the impacts and obtain market stability. For instance, transit systems may soon be affected as shared rides and comprehensive mobility-as-a-service (MaaS) platforms grow; however, impacts on parking and land use changes may take many years. A significant determining factor in every aspect of CAV adoption and societal effect will be regulatory decision making.

The impacts of CAVs on transportation systems will have to be studied and measured as the technology is developed and deployed. However, given what is known today about the potential impact of AV technology when combined with communications systems and sharing behavior, there is clearly a new role for exploratory modeling in a planning context that deals with uncertainty. Long-range forecasts are made for 20 to 30 years into the future, so planners can expect that this system of technologies will, by that future time, have a significant impact on the transportation system and travel choices. Some preliminary attempts at modeling have been made with existing trip-based and activity-based (AB) models, but the results have been somewhat unsatisfying, posing questions instead of answering them. This report describes the need for and the gaps in planning and modeling approaches and tools and presents high-level guidelines for near-term implementations. However, the authors acknowledge that considerations in the CAV space are changing rapidly and that this report may need updating in the next 3 to 5 years.

Defining the Problem: Forecasting Travel Behavior and Technological Changes

Forecasting travel and its consequences in urban regions is a difficult prospect, given the scale of the systems and the multitude of influences on travel behavior. How, when, and if traffic congestion can be reduced is a complicated question because of the uncertainty about many factors. Forecast population growth 30 years into the future can vary significantly, depending on migration rates (natural growth is typically stable). Other factors include changes in travel behavior and choices over time, economics, and transportation costs. Potentially radical changes from new technology such as driverless vehicles, a sharing economy, and expanded communications capabilities can all play a part in forecasts as well.

In the strict sense, modeling is a mathematical representation of data using formulaic expressions. Models designed to both predict and test future scenarios can only be as accurate as the formulas calibrated to match observed data and the forecast independent variables, such as the future number of households. In addition to data, however, the model design—the structure that defines the independent and dependent variables and the process by which the mobility environment is simulated—is also critical to the effectiveness of forecasts in providing valuable information to decision makers.

CAV technology is changing the traditional travel forecasting paradigm. Not only are changes in planning approaches necessary, but the very structure and complexity of models will need to be adjusted as the technologies are deployed.

This report makes the distinction between model design and modeling (and planning) framework. A model can be designed to represent information that is reflected in observed data, while a framework is a higher-level, less-detailed presentation of procedures that reflect the anticipation of significant changes to data that are collected in the future. A framework is preparatory, while a model design is descriptive.

In the past several decades, travel forecasting models have been predicated on the assumption that past trends in travel behavior and choices will continue two or three decades into the future with only minor alterations. This paradigm of transportation modeling was effective because of relative stability being observed in travel behavior over time. Most trips are made by private auto because that mode is widely available, convenient, comfortable, and accessible. People are willing to pay for these travel experience characteristics. In cities where public transportation is readily available and serves mobility needs more comfortably and economically than private autos, ridership is robust. These two modes of personal transportation—private auto (or walking/biking) and public transportation [bus or rail, and, to some limited extent, taxis and transportation network companies (TNCs)]—remain the primary mobility choices. Models can be calibrated to observed choices reflected in surveyed data and growth can be applied. This process results in a rational forecast level of demand calibrated to observed data and validated by existing usage levels. The forecast level of demand is then compared with system supply represented by facility capacity to determine future system performance. The process of calibrating models to observed data, validating the modeling outcomes to existing (or rather, immediate past) conditions, and applying future growth to produce one potential future outcome has been a long-standing paradigm in the United States.

Recent mobility and technology innovations are prompting a change to the existing forecast modeling paradigm. Telecommunications, vehicle- and ridesharing, and robotics have begun, in varying degrees, to change the mobility landscape. With the advent of smartphones, communications technology has placed an enormous amount of information about modal availability, routing, system conditions, and other critical transportation information in travelers' hands. Information communication technologies, through telecommuting and teleshopping over the Internet, are slowly increasing their impact on the need for personal mobility. Personal trip making for access to goods is being supplanted by efficient and economical product delivery. Workplaces are becoming more flexible, allowing many employees to work from home either permanently or as needed. The ease with which someone can gain access to real-time information about vehicle location has given rise to TNCs that allow travelers to share a ride and to other services that provide shared use of a vehicle, bicycle, or scooter. These modes are now widely available in many urban areas, but planning and modeling in most regions in the United States have not kept up with the changes.

AV technologies are a new element of change expected to influence travel choices. Artificial intelligence, robotics, and connectivity/communications are being incorporated into CAVs. Connectivity is expected to become the norm, with vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) components merging with highly automated vehicles (e.g., Levels 3 to 5), creating an information-filled mobility environment. While no wide-scale deployments of CAVs exist today, this technology is expected to be widely adopted. The technical questions are ones of design, integration with the existing transportation system, and acceptable safety and security. Public policy and liability questions are expected to be more fully addressed when deployment advances.

Another aspect of the expected impact on travel of AVs and CVs is auto ownership, availability, and vehicle use patterns. The ability of AVs to run autonomously (without a driver or passengers) is expected to enhance the utility of TNCs by lowering operating costs for owners. A CAV that runs autonomously and is shared is called a shared autonomous vehicle (SAV). This technology could greatly increase the number of shared vehicles and rides and could change auto ownership patterns significantly. SAVs could be used sequentially or simultaneously (i.e., the pooled versions with high vehicle occupancies).

A limitation of the work that has been done to date in modeling CAV use is that it applies imposed or assumed changes in behavior to modeling frameworks. No behavioral data indicating trip/tour frequency, length, mode, route, time of day, or other characteristics of AV or CV operations exist, simply because the technology is new and has yet to be deployed. Any changes are assumed by the analysts and may or may not remain applicable when eventually compared with actual deployment and behavioral changes resulting from AV and CV technologies. This report refers to these noncalibrated tests as "modeling experiments." Modeling experimentation done by imposition of changes to calibrated parameters and input data (such as trip rates, lengths, and mode choice) to examine the potential impacts of AVs and CVs is testing the sensitivity of

This report provides information about how state DOTs and MPOs can begin accounting for CAVs in planning and modeling activities. It is intended for agencies both with and without significant resources to undertake new activities.

the models to imposed changes. Existing models do not have AV or CV modes, nor do they reflect behavioral impacts of deployment of AVs and CVs. Modeling parameters, such as the in-vehicle travel time coefficient in mode choice models, are calibrated to observed conditions. The observed conditions to which these types of parameters are calibrated do not include AV or CV choices for travelers, so these models do not test the actual impacts of AVs and CVs.

The needs of MPOs and DOTs may differ when they address the uncertainties posed by future CAV deployment and use. For instance, an MPO or DOT in a high-growth area with significant congestion and investment needs may adopt an aggressive approach to scenario planning and specifically wish to include AVs and CVs and other high-impact technological developments in the long-range plan for the region. Another MPO or DOT may not have growth issues, so the focus of the long-range plan may instead be on economic development and quality-of-life improvement for citizens. In such a region, the impacts of AVs and CVs could be addressed in an incremental fashion by using only data-supported modeling rather than scenario-based methods.

The planning approach that might be chosen has an impact on the type of modeling that is appropriate. An MPO or DOT may decide, as a matter of planning policy, to adopt a range of strategies that best fit the long-range requirements a region is addressing. Some regions and states have greater planning capacity to accommodate the additional resources needed to implement changes to planning processes and modeling. While the approach to development of methods may differ between regions and states, all agencies have in common the need for information and guidance on how to plan for and model CAVs.

Navigating the Report

This report is a resource for understanding and implementing updates in modeling and forecasting tools to more appropriately account for the expected impacts of CAVs on transportation supply, road capacity, and travel demand components. The content is organized in a hierarchical manner. The early chapters present foundational information, and the later chapters present more advanced knowledge that builds on the underlying concepts presented in the early chapters. The earlier chapters, that is, provide the rationale for accounting for CAVs in planning and modeling activities, as well as pertinent information about technology and regulatory contexts, and summarize uncertainties in benefits and risks. The subsequent chapters provide high-level guidance on how to practice forward-looking planning and modeling.

While CAVs represent new technologies with many moving parts, developing a strategy to begin planning for and modeling CAVs does not have to be complicated. This report provides information about how to get started. The information is geared toward planners and modelers in MPOs and state DOTs of all sizes and geographies. The content is based on reviews of the literature, the professional experience and expertise of the research team, and information gathered in a stakeholder workshop.

Table 1 provides an overview of the main sections and corresponding information contained in this report.

Table 1. Information in this report.

Section	Description
Chapter 1: Introduction	• Presents the report purpose, rationale, and organization.
Chapter 2: Definitions of CAVs and Current Status	• Offers a simple description of CAVs and their enabling technologies. • Defines AVs and CVs. • Describes six levels of AVs. • Summarizes current states of development and deployment for AVs and CVs.
Chapter 3: Uncertainties Associated with CAVs	• Summarizes uncertainties in CAV adoption timelines and potential benefits and risks. • Describes the uncertainties associated with adoption of the technologies. • Presents a framework of three phases of adoption: (1) testing and early deployments, (2) consumer initial adoption, and (3) system-level organization as CAVs become predominant. • Discusses potential impacts related to safety, congestion, and land development. • Examines critical considerations for planning and modeling in five areas of impact: (1) transportation costs, (2) transportation safety, (3) vehicle operations, (4) electrification (fuel), and (5) personal mobility.
Chapter 4: Framework for Planning and Modeling CAVs	• Provides a high-level framework for accounting for CAVs in the planning and modeling processes. • Provides a conceptual framework for planning and modeling CAVs. • Discusses the individual elements of the framework: data, planning context, modeling, CAV adoption timeline, and communicating uncertainty.
Chapter 5: Planning in the Context of Uncertainty	• Discusses approaches for accounting for uncertainty in the planning process. • Reviews how uncertainty is managed in current transportation planning. • Describes the unique challenges in managing uncertainty posed by CAVs. • Identifies methods suited to managing decision making under deep uncertainty: (1) scenario planning, (2) assumption-based planning, (3) robust decision making, (4) info-gap, and (5) dynamic adaptive pathways planning.
Chapter 6: Adapting Trip-Based Models to Address CAVs	• Provides high-level guidance on accounting for CAVs in trip-based models. • Identifies potential modeling changes. • Discusses the contexts and approaches for (1) land use modeling, (2) auto availability and mobility choices, (3) trip generation, (4) trip distribution, (5) mode choice, and (6) routing and traffic assignment.
Chapter 7: Adapting Disaggregate/Dynamic Models to Address CAVs	• Provides high-level guidance on accounting for CAVs in AB travel demand models and dynamic traffic assignment methods. • Identifies potential model improvements. • Discusses the modeling contexts and approaches: (1) sociodemographics, (2) land use/built environment, (3) auto ownership/mobility models, (4) activity generation and scheduling, (5) destination/location choice, (6) mode choice, (7) routing and traffic assignment, (8) pricing, and (9) truck and commercial vehicles.
Chapter 8: Adapting Strategic Models to Address CAVs	• Provides high-level guidance on accounting for CAVs in strategic models developed to supplement more sophisticated modeling efforts as screening tools for evaluating policies. • Depicts the typical strategic model components. • Identifies potential modeling changes. • Discusses the modeling contexts and approaches: (1) sociodemographics, (2) built environment, (3) mobility, (4) accessibility, (5) pricing, (6) travel demand, (7) mode choice, and (8) truck and commercial vehicles.
Chapter 9: Communicating in an Uncertain Environment	• Provides guidance on how transportation planners and modelers can communicate about the uncertain future. • Distinguishes certainties from uncertainties in a CAV future and presents tips for talking about both.
Appendix: Regulatory Context for CAVs	• Discusses federal regulatory context for CAVs and state legislation.

CHAPTER 2

Definitions of CAVs and Current Status

Chapter Highlights

- Defines AVs and CVs.
- Describes six levels of automated vehicles.
- Summarizes the current state of AV and CV development and deployment.

Definitions of AVs and CVs

AV technologies represent a switch in responsibility for the task of driving from human to machine. They encompass a diverse range of automated technologies, from relatively simple driver assistance systems to fully automated vehicles. An autonomous vehicle is one in which there is no human driver and the levels of vehicle automation are higher.

A fully automated vehicle does not require a steering wheel, accelerator, or brake pedal (see Figure 1). All driving functionality is handled through onboard computers, software, maps, and radar and light detection and ranging (lidar) sensors (see Figure 2). Because most traffic crashes are caused by human error, the safety benefits AVs could provide are compelling—although incontrovertible empirical proof that AVs deliver safety benefits has yet to be produced. Other potential benefits are related to congestion mitigation, air pollution, greenhouse gas (GHG) reduction, and mobility enhancement for underserved populations, such as low-income people, older adults, persons with disabilities, and rural residents. With advancements in artificial intelligence—particularly in areas of big data analytics, machine learning, and knowledge management—rapid progress is being made in terms of AV development and deployment.

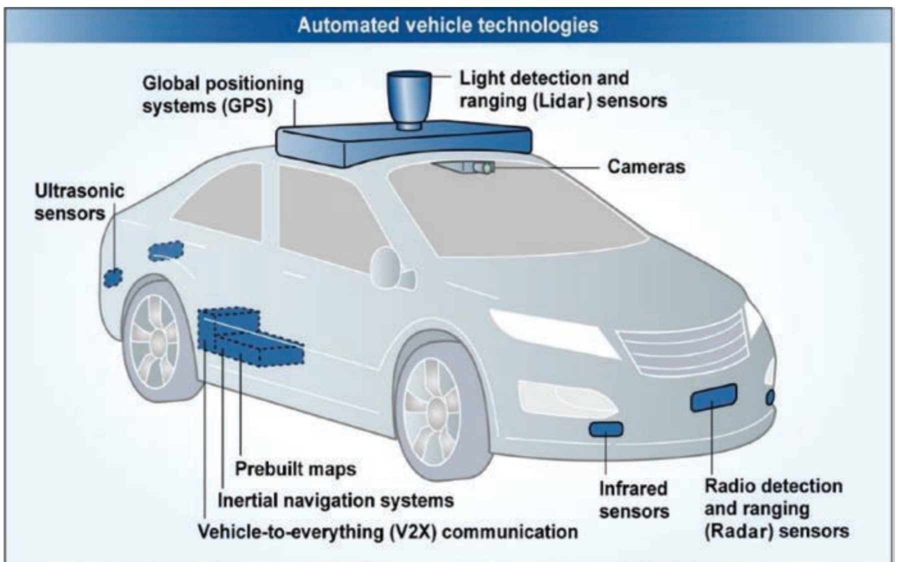
AVs can be further distinguished as being connected or not. Connectivity is seen by many to be a major enabler for driverless vehicles in the medium term.

AVs encompass a range of automated technologies, from relatively simple driver assistance systems to fully autonomous or self-driving vehicles.

CVs have internal devices that connect to other vehicles, other road users, or back-end infrastructure.

A CV, in contrast, has internal devices that enable it to communicate wirelessly with other vehicles, as in V2V communication, or with an intelligent roadside unit, as in V2I communication. V2V applications enable crash prevention, and V2I applications enable telecommunication, safety, mobility, and environmental benefits. The acronym V2X is sometimes used to designate vehicle-to-everything (including pedestrian and bicyclist) communication. Data communications that enable real-time driver advisories and warnings of imminent threats and hazards on the roadway are the foundation of CVs (Hong et al. 2014). At present, V2I and V2V applications solely provide driver alerts; they do not control vehicle operations. Dedicated short-range communications (DSRC) and 4G-LTE are two candidate schemes for CV applications, and 5G is on the horizon.

Figure 1. Interior of a fully self-driving vehicle.



Levels of driving automation adopted by Department of Transportation

Level	Name	Definition
0	No automation	Human driver controls all aspects of dynamic driving tasks, even when enhanced by warning system
1	Driver assistance	Automation controls one vehicle function (e.g., steering or speed)
2	Partial automation	Automation controls both steering and speed with driver responsible for monitoring and immediate reengagement
3	Conditional automation	Automation controls both steering and speed and monitors environment; driver may be notified to reengage
4	High automation	Automation performs all aspects of dynamic driving tasks in some driving modes; driver not required to reengage
5	Full automation	Automation performs all aspects of dynamic driving tasks under all roadway and environmental conditions

Sources: GAO and GAO analysis based on U.S. Department of Transportation information. | GAO-18-132

Technology Definitions

Lidar uses laser remote sensing to map the vehicle's surroundings.

Radar uses radio waves to determine the range, angle, or velocity of objects.

GPS uses navigational satellites to provide precise positional and velocity data.

Inertial navigation systems use gyroscopes and accelerometers to track the vehicle's position and improve GPS accuracy.

Infrared sensors are capable of measuring the heat being emitted by an object and detecting motion.

Ultrasonic sensors can measure the distance to an object by using sound waves.

V2X encompasses communication between other vehicles, other road users, and infrastructure.

Figure 2. AV technologies and levels of automation.

Levels of Automation

The National Highway Traffic Safety Administration (NHTSA) has adopted a framework for automated driving developed by SAE International (2016) that categorizes automation into six levels. Vehicles with Levels 0, 1, and 2 technologies are already available for private ownership and currently operate on public roadways. Some observers believe that current Level 1 and Level 2 technology could have a major impact on safety. Levels 0, 1, and 2 are defined as follows:

- Level 0 involves no automation at all. The driver executes all tasks involved in operating the vehicle.
- Level 1 is referred to as "driver assistance." At this level, the driver is in control but has the option of assistance with some tasks, such as steering or braking and accelerating. However, the automated driving system cannot operate both steering and speed at the same time. Basic cruise control falls into Level 1.
- Level 2 is referred to as "partial automation." At this level, the automated driving system can execute both steering and braking or accelerating at the same time. The driver is responsible for monitoring the driving environment at all times and taking control of the vehicle when needed.

NHTSA categorizes vehicles with Levels 3, 4, and 5 technologies as automated driving systems (ADSs). Vehicles with ADSs are still in development, and automakers and technology firms are actively testing them on public roads. Levels 3, 4, and 5 are defined as follows:

- Level 3 is referred to as "conditional automation." The automated driving system can operate the vehicle in certain conditions, but the driver is a necessity. The driver can take his or her hands off the wheel and perform other activities, such as reading text messages, and the vehicle can drive for an extended period of time on its own. However, the driver must be ready to take control when alerted by the system.
- Level 4 is referred to as "high automation." When a vehicle is operating at this level, it can do everything, and the driver is not expected to take control. However, the automated driving system can only be in control in certain geographic areas or on specific road types, such as in a particular area within the city limits or in a designated self-driving vehicle lane on a highway. The driver might still need to control the vehicle when the vehicle is outside of these areas.
- Level 5 is referred to as "full automation." ADSs are fully autonomous in any condition or environment without a human driver or occupant. The driver is completely optional. Because drivers no longer need to control the vehicle, some Level 5 ADSs do not have a steering wheel, brake, or gas pedal.

Current AV Context

Many people believe that highly automated vehicles will first be available to consumers as SAVs (Reinventing Wheels 2018). Cost is a main factor. Lidar sensors are still too expensive to be used in mass-produced vehicles. The cost of this technology is considered less of a barrier for fleet vehicles because they generate revenue throughout the day to cover the expense, whereas the typical privately owned vehicle is used for a small fraction of a day. Related to this is the fact that the global shared mobility market was $54 billion in 2016 (Grosse-Ophoff et al. 2017). The United States is one of the largest shared mobility markets, at $23 billion.

As of February 2018, testing of SAVs on public roads in the United States was occurring through 17 active pilots in eight states—Arizona, California, Florida, Massachusetts, Michigan, Pennsylvania, Texas, and Washington—by companies such as Waymo, Uber, EasyMile, Ford, Navya, GM Cruise, and Drive.ai (Stocker and Shaheen 2017). After the fatality caused by an Uber vehicle in Arizona in March 2018, Uber suspended testing in North America. The majority of these pilots are targeting Level 4 technology in which a human operator does not need to control the vehicle as long as it is operating in a suitable design domain given its capabilities. The pilots have been implemented as two types: (*a*) on private roads and in planned communities and (*b*) on public roads and city streets.

Many original equipment manufacturers (OEMs) have made bold claims about when highly automated vehicles will be available to car-buying consumers (Fagella 2017). Renault–Nissan, under a new partnership with Microsoft, plans to release 10 different Level 4 vehicles by 2020. Volvo hopes to have a car that can drive fully autonomously on the highway by 2021. It envisions that full autopilot will be a highly enticing option on a premium vehicle and will initially be priced at $10,000. In 2015, Volvo became the first car company to promise to accept full liability whenever one of its cars is in autonomous mode. Hyundai is working on self-driving vehicles, but with more focus on affordability. It is developing a low-cost platform that can be installed in models the average consumer can afford and is targeting highway driving in 2020 and urban driving in 2030. BMW has a high-profile collaboration with Intel and Mobileye to develop autonomous cars, with the goal of getting highly and fully automated driving into series production by 2021. Still, due to regulatory, legal, or infrastructure readiness issues, the actual timeframe for deployment and adoption of these highly automated privately owned vehicles is hard to project. For example, associated research under the NCHRP 20-102(07) rubric, "Implications of Automation for Motor Vehicle Codes," provides guidance concerning legal changes that will result from the rollout of AVs.

Current CV Context

Several manufacturers, including Kapsch, Savari, Cohda Wireless, DENSO, and Arada Systems, are actively developing and testing CV devices and applications. Other companies (e.g., Qualcomm, Savari) are developing V2X equipment that uses other forms of wireless communications, including cellular, Wi-Fi, and Bluetooth. However, the U.S. Department of Transportation (U.S. DOT) and others have been committed to DSRC being the primary mechanism for vehicle safety applications under the expectation of new Federal Motor Vehicle Safety Standards (FMVSS) to mandate V2V communications for new light vehicles and to standardize the message and format of the V2V transmissions. Nonetheless, as of 2018, such rulemaking has not advanced. In November 2017, NHTSA issued a statement that it had not made any final decision on the proposed rulemaking concerning a V2V mandate.

The key enabler for CAVs is communication of location and status data and an ability to analyze and interpret data intelligently. While emerging forms of connectivity (e.g., DSRC, 5G mobile communications) offer promise for new communication services, many practical benefits of CAVs can be achieved over existing mobile networks. Coupling the development of CVs with the deployment of emerging communication standards may delay the societal benefits that CAVs can offer.

The federal government has played a significant role in supporting the research, development, and piloting of CV technology. The U.S. DOT Connected Vehicle Safety Pilot Program sought to demonstrate that DSRC-based CV technology was ready for large-scale deployments. Executed in Ann Arbor, Michigan, this program equipped vehicles with vehicle awareness devices, aftermarket safety devices, and retrofit safety devices, and it deployed DSRC infrastructure to assess the functional performance of V2V and V2I safety applications (Bezzina and Sayer 2015). The U.S. DOT is also currently sponsoring three additional CV pilot deployments in New York, Wyoming, and Florida that are being rigorously evaluated to assess benefits:

- The pilot program in New York is evaluating the use of CV technology in a dense urban environment with significant pedestrian and cyclist traffic in addition to vehicular traffic. In-vehicle

equipment has been installed on up to 10,000 city and fleet vehicles to test V2V applications such as intersection movement assist and forward collision warning, and on roadside infrastructure in Manhattan and Brooklyn to test V2I applications such as detection of pedestrians in signalized intersections and a red-light violation warning system (Galgano et al. 2016).
- The pilot program in Wyoming focuses on applying CV technology along freight-intensive corridors that experience significant weather-related incidents and delays. DSRC onboard equipment is installed in a combination of maintenance vehicles, emergency vehicles, and private trucks, and roadside equipment is installed along Interstate 80 to communicate road conditions, variable speed limit zones, and detour information (Gopalakrishna et al. 2015).
- The pilot program in Tampa, Florida, is evaluating CV technology deployed in a suburban-to-urban corridor with managed lanes that experiences significant congestion and delays while bringing thousands of vehicles to and from a dense urban center with high pedestrian traffic. V2V safety applications such as forward collision warning and intersection movement assist are being evaluated, as are V2I applications such as curve speed warning and transit signal priority (Waggoner et al. 2016).

Significant research and standardization have gone into the development of CV technology specifically related to DSRC. SAE and IEEE have been actively working on standards for DSRC (SAE J2735; IEEE 1609.2, IEEE 1609.3, and IEEE 1609.4) and V2V performance (SAE J2945/1). The various DSRC manufacturers will be required to certify that their equipment conforms to these standards to ensure interoperability of vehicles from different OEMs using different hardware. The U.S. DOT has organized several CV PlugFests throughout the country at which CV vendors have been able to test their devices' performance, interoperability with other equipment, and conformance to the aforementioned standards (Abuelhiga 2013).

The U.S. DOT has indicated that CV technologies could be critical to the success of AVs' safety. For example, connected technologies could help AVs maintain or improve situational awareness by communicating traffic control messages that camera- and radar-based crash avoidance technologies may not be able to detect because of obstructions such as buildings or fog. Additionally, CVs have other potential benefits, including congestion mitigation and reduction of air pollution and GHGs. The U.S. DOT's research and other efforts related to CVs historically have been largely independent of vehicle automation, but recent departmental efforts have sought to study the potential interactions and synergies between the two concepts.

CHAPTER 3

Uncertainties Associated with CAVs

The transition from travel by horse and buggy to mass adoption and use of motor vehicles was a major socioeconomic transformation of the 20th century. This transformation helped to produce huge gains in economic productivity and quality of life but also spawned negative externalities of vehicle use such as congestion, crashes, and inequalities in access to jobs. Likewise, the transition from travel by conventional motor vehicles (e.g., automobiles, trucks, and public transit) to adoption and use of CAVs will be a defining mobility transformation of the 21st century. Huge positive changes are possible in the economy, environment, and society, but only if the transition is managed effectively by DOTs and MPOs.

Chapter Highlights

- Describes the uncertainties associated with adoption of CAV technologies.
- Presents a framework of three phases of adoption:
  - Testing and early deployments,
  - Consumer initial adoption, and
  - System-level organization as CAVs become predominant.
- Discusses potential impacts related to safety, congestion, and land development.
- Examines critical considerations for planning and modeling in five areas of impact: transportation costs, transportation safety, vehicle operations, electrification (fuel), and personal mobility.

Uncertain CAV Adoption Timelines

When CAV adoption timelines are being considered, it is important to separate the hype from the reality. Many reports have been made through the blogosphere about the potential roll-out dates of CAVs. Each manufacturer comments about the release of its first products, many of which appear to be speculative and aggressive. As noted in the previous chapter, while OEMs may be publicizing information about product releases to gain market share, other conditions surrounding the technology remain even more uncertain. Conditions related to the market penetration and consumer adoption of CAV technology include the following:

- The cost of the technology will certainly drive the rates of adoption.
- Whether the technology is used in privately held vehicles or through private corporations supplying fleet services will drive the rate of market penetration.
- On-road testing of CAVs continues, but actual usage safety statistics and experience will drive public attitudes about the technology.
- Comfort and convenience, in addition to cost, will drive consumer preferences regarding AVs.
- Roadway and parking infrastructure will need to be adapted to CAVs.
- Government policy and traffic laws, including tests of liability in the court system, will undoubtedly drive market penetration scenarios.
- Finally, the technology will certainly advance and change, and features will be added or subtracted on the basis of cost effectiveness in the market.

Several studies have focused on deployment and adoption timelines and scenarios. These range from scenario-based assumptions defining “evolutionary” to “revolutionary” development and market penetration (Zmud et al. 2015), to modeling approaches based on existing vehicle adoption and turnover rates (Fagnant et al. 2015). Because of the high uncertainty in published deployment scenarios, the only thing that can be said for sure is that deployment will occur in three eras:

1. CAVs are developed and tested.
2. Consumers begin to adopt CAVs.
3. CAVs become the primary means of transport.

There will be three to four decades (or more) of a mix of human-driven vehicles and CAVs on the roadways. This intervening period will be challenging, with many safety, security, and privacy issues. Transportation agencies need to be thinking and planning ahead.

The industry does not have enough information to provide exact timing and details for the start and end of these eras. The highest levels of uncertainty pertain to the gray area between the second and third eras. The transition from a human-driven world to a world with only CAVs will not happen overnight. There will be a long period of time (perhaps three to four decades or more) with a mix of human-driven vehicles and CAVs on the roadways.

This intervening period will be challenging, with many safety, security, and privacy issues to be resolved. Governments and transportation agencies need to plan ahead, anticipate potentially unintended consequences, and formulate policies to facilitate the movement toward a new way of traveling and to reduce the potentially offsetting effects of CAVs. For example, cybersecurity vulnerabilities associated with CVs could compromise safety. Energy use and suburban sprawl could increase with the proliferation of AVs as driving becomes less onerous and persons without a driver license have more opportunities for travel. Combining AVs and CVs with the practice of sharing vehicles could modify these effects. Both the expected development path for these technologies and their potential impacts are uncertain, but AV and CV technologies will clearly influence the transportation system and travel demand going forward.

For the purposes of this report on planning and modeling tools, three general phases or categories of adoption were assumed. While the information below suggests evolutionary growth of CAVs, the authors acknowledge that this is not a consensus view.

- Testing and early deployments:
  - Currently, most vehicles on the road are at Level 1. The transition to Level 2 or Level 3 vehicles will be influenced by fleet turnover rates. With people keeping their vehicles on average for about 7 years, and with an average age of vehicles on the road of 11 years, it will take decades to obtain saturation of Level 4 or 5 vehicles.
  - Automation will be vehicle specific (i.e., AVs) with limited V2V connectivity (due to absence of mandate) and no systematic enhancement.
  - Lidar sensors are still too expensive to be used in mass-produced vehicles and will be costly for private ownership. This cost of technology is considered less of a barrier for fleet vehicles because they generate revenue throughout the day to cover the expense, whereas the typical privately owned vehicle is used for a small fraction of a day.
  - Regulation will limit usage to specific geographies. Early stage deployments will need to be near perfect in operations to engender trust among the public and policy makers. Testing on controlled roadways so that these technologies are as foolproof as possible is important before their introduction on public roadways.
  - SAV services will be introduced first in limited geographies, following the current models of TNCs such as Uber and Lyft or small shuttles such as Drive.ai and Navya vehicles. They can also take the form of carsharing services, such as Zipcar and car2go.
- Consumer initial adoption:
  - Growth in Level 4+ to 50% or more of the overall vehicle fleet will take time. Level 4–5 vehicles entail self-driving operations. Road operators need to implement coordinated rules

of the road for their safe operation. An owner of a private vehicle may not want to pay a high purchase price for a vehicle that is initially geographically constrained in its sphere of operations.
  - With expansion of operating geographies, adoption will increase for suburban and commuter usage.
  - Shared automated services will continue to grow in denser core urban areas of metropolitan regions.
  - Some systematic organization of flow and automated route optimization will occur, but overall, optimization will remain limited because of the substantial number of non-CAVs still on the roads.
- System-level organization as CAVs become predominant on the road:
  - Traffic will be predominantly Level 4+ CAVs. Usage will be widespread enough to achieve systematic route and flow optimization, practically eliminating delay due to congestion.
  - Shared AVs may become the predominant mode, mostly because of operating cost. If high-occupancy SAVs predominate, passenger miles traveled (PMT) may become a more important measure of performance than vehicle miles traveled (VMT).
  - It is also possible, however, that privately owned CAVs will predominate, particularly in less urbanized areas.
  - The eventual mix of private and shared CAVs is currently unpredictable because it will depend on consumer preferences, on pricing and supply decisions by OEMs and TNCs, and on future regulation and pricing of vehicle ownership and insurance.

On the basis of this paradigm of market adoption, modeling and planning tools can be developed to address the short-, mid-, and long-term impacts on travel behavior that each of these conditions promulgates:

Because of adoption timeline uncertainty, modeling and planning tools should be developed to address the short-, mid-, and long-term impacts on travel behavior.

- In the short term, many existing planning and modeling tools will suffice, as travel behavior changes will not be significant, other than increasing use of new modes, such as TNCs, and perhaps new types of access and egress options for public transportation systems.
- In the mid-term, the operational characteristics of CAVs will become more widespread, and non-AVs will be either organically minimized in the fleet (by natural attrition) or regulated in such a way that their usefulness and attractiveness to buyers and riders are limited. The existence of non-AVs in the fleet becomes a problem for system operations because AVs can be controlled by route and operational functions while competing for roadway maneuvering space with manual vehicles that are unpredictable in their behavior. Modeling and planning tools will need to address this important phase of market penetration and must be able to present the problems related to having mixed fleets of CAVs and non-CAVs.
- In the longer term, the technology will be pervasive and require a complete set of new assumptions about urban form, land use, parking requirements, and other indirect impacts in addition to the direct impacts on travel behavior and choice. Planning tools and the models that support them will need to be based on scenario assumptions for this longer-range timeframe.

Monitoring and Surveying AV and CV Adoption

SAVs could soon be freely operating on public roads, so it is important to examine creative approaches for assessing their potential impacts on the transportation system. Transport and land use impacts will vary significantly, depending on extent to which AVs are used as privately owned vehicles, sequential ride-hailing fleets, or pooled ridesharing fleets. Policy makers, public road operators, and transportation service providers need empirical data (not modeled simulations) on potential behavioral responses. However, capturing accurate answers to what people might do in the future is tricky; preferences change as policies, society, and technology mature. Research participants today are in a situation vastly different from the one people will be in years from now, when the technology has become widespread. For example, asking an 18-year-old today about his or her likely use of AVs is wildly different from asking a future 18-year-old who has grown up with highly automated technologies available since birth.

Perhaps the best researchers can do in the short term is to track and monitor. Researchers need to better understand current trends in vehicle ownership and vehicle usage, and, through such insights, better forecast likely impacts. However, such understanding has to be based on empirically derived data, not on arbitrary assumptions and mechanical simulations. True insight will be achieved by research focused on better understanding behavior through attitudes, lifestyle issues, adoption behaviors, situational influences, and foundational activity and travel pattern choices. Ultimately, planners and modelers need to begin to answer the following question: How might behavioral trends change when the driver is removed?

Uncertain Benefits and Risks of AVs and CVs

AVs and CVs are potentially transformative technologies with benefits and risks that are still highly uncertain. While great promise for substantial benefits exists, the technologies are still in the development and testing stages, and the rules under which they should be safely operated are yet to be fully defined, so the possibility of harm or damage exists. This section highlights benefits and risks in three key areas: safety, congestion/pollution, and land use.

Safety

CV Applications

When individuals drive a vehicle, they increase not only their own risk of a crash and related costs, but also crash risks and costs for other motorists as well as pedestrians, cyclists, and society in general. V2V safety applications can enhance safety by addressing a majority of vehicle crash types if the V2V communication is successfully interpreted and acted upon (Najm et al. 2010). This outcome necessitates that CV applications are demonstrably effective and widely used and that the driver–vehicle interface performs well. More testing is necessary to reach a satisfactory level of certainty in effectiveness and usage. Research has indicated that a marginal increase in benefit can be obtained through V2I safety applications, depending on the extent to which V2I infrastructure exists widely (Eccles et al. 2012).

Highly Automated Vehicles

Even without V2V and V2I, AVs can reduce a majority of driver-related errors, which account for 94% of traffic crashes according to NHTSA (2015). To achieve this outcome, certain mechanisms need to be in place. As more of the driving task is switched to AVs (as is the case with Levels 3–5), many technologies (i.e., sensors, motion control, trajectory planning, driving strategy, situational awareness) need to operate effectively so that the vehicle performs at least as well as a human driver (Trimble et al. 2014).

The Casualty Actuarial Society's Automated Vehicles Task Force (2014) reevaluated the results of the National Motor Vehicle Crash Causation Survey in the context of an AV world. This reevaluation found that about half of all accidents could be addressed by AVs. The study concluded that driverless cars may be safer than human drivers, but that flawed hardware or software could cause accidents, and liability could then fall on manufacturers or installers. In such cases, the insurance pricing would fall to product liability actuaries for coverage. Recent fatal crashes in 2018 involving ADSs reflect the uncertainties that exist in the readiness of such vehicles to operate on public roads [e.g., Tesla Autopilot in Florida and California (Levin 2017) and Uber vehicle in Arizona (Griggs and Wakabayashi 2018)]. Vehicle errors could be introduced because hardware or software could be insufficiently tested, prematurely released, or inadequately maintained by owners or manufacturers, resulting in decreased safety benefits.

Safety benefits are enhanced through widespread use of AVs and concomitant reduction of human errors. However, a factor limiting the safety benefits of AVs is that AV applications may only operate under specific conditions, and these conditions can be constrained by vehicle location, speed, or dynamics (Smith et al. 2015). On the basis of these constraints, AVs may only address certain precrash scenarios. For instance, Smith and colleagues identified GM's Cadillac CTS Super Cruise technology (Level 3 automation for motorway environment) as working well in both bumper-to-bumper traffic and on long road trips in light traffic but cautioned that more complicated driving conditions might be challenging. Staying centered in a lane on a highway is much less demanding than staying centered on a road in a crowded city where lane markings can be less visible, other vehicles may block a camera's view of them, and bicyclists and pedestrians travel alongside cars and trucks.

A related uncertainty pertains to whether AV technology can match the learning while driving of a human driver, who exercises the aggregated wisdom of predictive knowledge from many drivers. The ADS is learning from the driving it experiences as an iterative process, so the vehicle is learning from itself. Thus, the automation system may not know how to behave in unknown situations, and in some cases, the vehicle's response may lead to a crash situation (Sivak and Schoettle 2015). For example, the system may fail to respond to a hazard. Conversely, it may respond inappropriately to a nonhazard (e.g., braking hard for a piece of paper in the road).

Cybersecurity

Cybersecurity issues are another potential source of safety error. Cybersecurity, in the context of vehicle systems, refers to security protections for systems in the vehicle that actively communicate with other systems or other vehicles (Garcia et al. 2015). While cybersecurity issues are a challenge for CVs, security becomes a bigger concern with Level 4–5 vehicles, in which software and connectivity play a much bigger and more critical role for the safe driving of vehicles. Unlike traditional vehicles, AVs may be vulnerable to cyberattacks that can spread from V2V. Hackers could potentially stop a fleet of AVs, halting the transportation system and reducing safety (even though no real case of malicious car hacking has yet been reported).

Congestion

The true implications of AVs on congestion and pollution may not be known for a long time. However, on the basis of past studies, assumptions about possible impacts of this new technology are possible. AVs and CVs are likely to affect factors that contribute to congestion—potentially in both positive and negative ways—resulting in an uncertain and likely mixed net overall effect.

System Efficiency

CAVs could potentially drive with greater precision and control than humans (Smith 2012). Various V2V- and V2I-enabled mobility-focused applications could increase the efficiency of the vehicle system (U.S. DOT 2015). For example, dynamic speed harmonization and cooperative adaptive cruise control are two applications that could increase system efficiency by enabling vehicles to coordinate their actions in certain circumstances. This ability could plausibly enable infrastructure operators to redesign aspects of their facilities to accommodate more traffic in various ways. By reducing lane size and shoulder width, an agency could restripe a road and add a lane, thus effectively increasing the supply of roads. If this were to occur, it would likely be over the long term, as it would require all (or nearly all) vehicles to be capable of driving with a high level of control. Because the vehicle fleet turns over slowly, even in optimistic projections, this is likely a distant proposition, but it is possible that fleet services and privately owned vehicles may turn over faster in the future. Additionally, new lanes may only be possible in areas with sufficient spacing, so roads that are already lane dense may benefit less than locales with existing excess space. Rural areas, and less-dense areas in general, would likely benefit more than dense urban areas.

Vehicle Occupancy

Congestion impacts are dependent on the future demand for and supply of public transportation. AVs combine the advantages of public transportation (e.g., not having to pay attention to the driving task) with those of traditional private vehicles (e.g., flexibility, comfort, and convenience). Much research has focused on whether the use of ride-hailing services has led to increased congestion and reduced use of public transportation in some urban areas (Hughes-Cromwick 2018). If AVs were to be made available as autonomous ride-hailing fleets, public transportation ridership would likely suffer and congestion would increase, particularly in urban areas. Regulations (or lack thereof) will undoubtedly have a large effect on the potential outcomes by encouraging travelers to choose higher-occupancy mode choices. In such conditions, AVs might offer benefits for congestion by providing first-mile/last-mile linkages to mass transit systems.

Induced Demand

Pricing will be a critical component in how travelers will choose new modes or new technologies. AVs and CVs could decrease the cost of driving, thus inducing additional VMT (Anderson et al. 2014). CAVs are likely to reduce the costs (both direct and indirect) associated with driving, namely the opportunity cost of a motorist's time, fuel costs, and crash-related costs. Opportunity costs are related to factors of convenience and flexibility as well. For example, demand may increase because traveling to downtown is more convenient when driving and parking are automated. When the cost for an activity decreases, all things being equal, demand for that activity will increase. It is unclear how much or how quickly the cost of driving will decrease, or how much a change in price will change the demand for driving. When the costs associated with driving changed in recent years, motorists were relatively unresponsive in the short term, indicating that large changes in prices (or a long time horizon) may be required to alter consumer driving behavior. The U.S. Energy Information Administration found, for example, that large changes in gasoline prices created minimal change in VMT (Morris 2014). This evidence indicates that short-term changes in the cost of driving will likely have minimal effect on VMT; how changes from AVs and CVs over the longer term will affect VMT is less clear.

Congestion outcomes are also related to the fact that SAE Level 5 AVs could alter demand by enabling persons who were previously unable to drive to do so (Smith 2012). Persons under the legal driving age and those who are unable to drive because of disabilities are two potential sources of increased demand. If these populations were legally and otherwise empowered to independently operate a motor vehicle, they could dramatically increase VMT. It is unclear exactly how many people in these groups would choose to take advantage of increased mobility services or options, or how much they would drive given the opportunity, but this could represent a large share of the U.S. population. For example, the U.S. Census Bureau estimates that one in five people in the United States has a disability, and more than half of those have a severe disability (U.S. Census Bureau 2012). Stated differently, about 56.7 million people have a disability, and more than 23.4 million have a severe disability. These groups are much more likely to be unemployed than the general population, and they are likely to have a lower income as well. Moreover, the U.S. Census Bureau (2017) estimates that about 26% of the U.S. population (or about 83 million people) is less than 16 years of age. If this population were capable of riding unescorted in personal vehicles, they could add significantly to VMT as well.

Traffic Incidents

AVs and CVs are likely to decrease the frequency of crashes, which should result in decreased congestion from nonrecurring sources of congestion. Yet, how or whether AVs will alleviate or contribute to congestion resulting from work zones is still unclear. Thus far, AV designers have already given construction zone navigation careful thought. Some image recognition systems are capable of identifying warning signs or cones, understanding that these symbols connote a work zone, and acting on this information to drive more cautiously to navigate a changed road configuration (Amadeo 2014). How these behaviors will change over time, and what impact—if any—automated driving will have on work zone–related congestion, is unclear.

There will be a period during which AVs will operate on roads alongside conventional vehicles. Traffic crashes will likely result from the interaction of human-driven cars and AVs as they share the road.

Several V2V- and V2I-enabled CV applications are also envisioned to address driving in or near work zones or in inclement weather conditions. These applications and their associated warnings focus on safety and would likely decrease crashes, but whether they will decrease congestion related to inclement weather is unclear. How well AVs will be able to drive in poor weather is also unclear. According to media reports, some current automated systems are incapable of driving in inclement weather conditions, such as snowstorms (Trudell 2015). Under such conditions, these vehicle systems will often cede control to the human driver.

Pollution

Congestion and air pollution are inextricably related. Automobiles emit local air pollutants (e.g., particulate matter, hydrocarbons, nitrogen oxides, and carbon monoxide) and global air pollutants (greenhouse gases) when they combust fuels, primarily fossil fuels. Thus, when people drive a vehicle, they reduce the air quality of the surrounding area and impose the costs of climate change—a global effect—on everyone. Vehicles are also loud. When people drive, they add to the noise pollution of those who live and work in the area. Noise and air pollution are related to vehicle factors (e.g., type of vehicle), travel factors (e.g., number of trips), driver behavior (e.g., driving style), and infrastructure (e.g., operation of transportation infrastructure). CAVs have the potential to affect each of these categories in uncertain ways.

Land Development

Urban land development has always been influenced by transportation technologies. As U.S. cities expanded to provide housing for a growing population in the 20th century, the introduction and proliferation of the personal automobile reduced transportation costs and facilitated the spreading out of urban populations, resulting in what is commonly termed "sprawl." Investments in transportation infrastructure that increased transportation capacity and consequently reduced travel times (or, more broadly, the disutility of travel), have largely been met with an increasing tendency for low-density land use development, with both population and employment moving out of central cities and into suburban locations where land is less expensive and more plentiful.

While automobile travel has enabled the rapid growth of cities and their economies, it may have distorted the market for land to produce development patterns with unintended external consequences. Land development is a complex process: the effect of automobile use on development patterns is complicated by many market and policy factors. A cyclical relationship exists between current development patterns and automobile use, such that each may reinforce the other. This relationship is still highly debated in academic literature (Burchell et al. 2002; Glaeser and Kahn 2003; Ewing and Hamidi 2015). Yet, current development patterns in the United States undeniably allocate a large portion of land for automobile use in the form of highways, streets, and parking.

Economic Factors

In terms of market forces, transportation costs (both monetary and nonmonetary) currently moderate the distance one is willing to travel to access lower-priced land for development. Automobile availability has greatly increased mobility and improved accessibility outside of the central city core (Glaeser and Kahn 2003). As with the introduction of the automobile, AVs and CVs have the potential to decrease the nonmonetary costs of driving. AVs and CVs could increase safety and the convenience of vehicle travel, thereby lowering transportation costs. Consumers might travel more miles and take more trips to access lower-priced land and rural locations. With fully automated Level 5 AVs, time and other nonmonetary costs of vehicle travel would be further diminished. Owners could send vehicles on pick-ups, to accomplish errands, or to drop off a passenger without having to devote time or energy to the trip. An AV equipped and allowed to drive unoccupied and return home after each trip may more easily allow shared use among household members, which could lead to a decrease in the number of vehicles per household. Sivak and Schoettle (2015) estimated that this shared use could reduce average vehicle ownership rates by 43%. However, the same authors also concluded that travel per vehicle would increase by 75% (Schoettle and Sivak 2015). Thus, individual vehicle costs may decrease, but the related impact on land development is uncertain.

Parking effects will be experienced differently in urban and rural areas. In urban areas, AVs may reduce the need for parking adjacent to destinations. AVs and CVs may be able to park in smaller spaces with more precision than human drivers, and higher-level AVs are expected to have the ability to drive and park at home or in remote parking areas. This capability would allow for more cars to fit in less space and in nonadjacent locations to free up centrally located land for other uses. Changes to parking needs will only occur with high levels of CAV adoption and will require changes to parking requirements, which currently mandate parking minimums for new development. In the long term, this may stimulate infill development as existing parking infrastructure in high-rent areas is no longer needed. If vast expanses of central city land devoted to parking can be reclaimed for housing and other uses, then a move to urban centers may be accelerated because housing in central cities may be more affordable and expansive than it is today. In contrast, in rural areas, the unbundling of parking adjacent to activity centers could lead to the construction of parking on cheaper, undeveloped land, following the same patterns seen with previous sprawl development.

Lifestyle Factors

Other land use impacts remain largely unknown in the context of an AV future. For example, would parents feel comfortable sending their kids alone in an AV? If yes, then it is plausible for households to live farther away in more sprawled settings because chauffeuring children to and from school is no longer a major constraint. However, if parents do not have such trust in the technology, then households may be more restricted in their location choices as they strive to remain within a reasonable travel time and distance of good schools and recreational and after-school activities for their children. Recent trends have seen many older households move into urban centers to access opportunities more easily. Would the introduction of AVs slow down this trend, with older households comfortable residing in suburbs well past retirement age because automated urban mobility service fleets can easily transport them to and from activity destinations?

Regulatory Factors

Policy and regulatory frameworks will play a major role in shaping future land use development patterns and residential and work location choices. Land use policies and zoning regulations strongly affect various location choices, and the extent to which regulatory authorities and city councils will alter policies and relax or tighten zoning restrictions in response to the introduction of AVs in the marketplace remains unclear. Another key question in this context is the extent to which different stakeholders and players will wield influence in shaping land use and location decisions. How will real estate developers, financiers, city councils and policy makers, and consumers interact, and what will be their relative influence in shaping future urban spaces?

However, the main question is whether the changes brought about by AVs will be structural (highly disruptive) in nature or whether they will merely magnify or reduce effects that have already been observed over the past several decades? A nonstructural change may simply lead to a modest increase or decrease in the rate of sprawl, for example, while a structural change may either dramatically increase the rate of sprawl or kill the suburbs and promote significant densification in urban centers.

Will the changes in CAV influence be structural (highly disruptive) in nature or simply a continuance of effects that have already been observed over past decades?

Critical Considerations for Planning and Modeling

The prior discussion of uncertainties is only important insofar as it provides context for areas of impact by CAVs on travel behavior, and, by extension, on modeling and planning tools. These areas of impact can be categorized as follows:

- Transportation cost,
- Transportation safety,
- Vehicle operation,
- Electrification (fuel), and
- Personal mobility and convenience (including shared, owned, or rented vehicles).

Table 2 summarizes the potential of these impact categories to influence travel behavior and choice. Transportation cost is a very uncertain impact area. Costs of vehicles that include highly automated technology will need to be recouped by OEMs, so the cost per vehicle is likely to increase. However, the cost per trip may decline if fleet services of driverless vehicles prevail in the market. Thus, the overall transportation cost to the consumer is uncertain and is most likely tied to vehicle ownership versus distributed vehicle ownership, vehicle club membership, or ridesharing.

The safety impacts of CAVs were discussed earlier in this chapter. A reduction in crashes would improve the reliability of travel times and reduce property damage, injuries, and fatalities. Improved reliability would increase the utility of AVs, which would increase their market share. Improved reliability would also increase the utility of the network performance itself by encouraging users to travel farther as trip and tour planning becomes more consistent.

Impacts of CAV operational characteristics are perhaps the most discussed in the industry to date. Much research has focused on the impact of connecting vehicles through DSRC into platoons of vehicles, which would dramatically shorten headway space and thereby improve coordinated acceleration and vehicle throughput. The overall impact would be to increase capacity, with most estimates arriving at a doubling of existing roadway capacities. However, because platooning requires increased space, the prospect of increased capacity where formation and dissolution of platoons is frequent may be diminished.

In the longer term, the prospects of positive impacts from vehicle operations of an automated fleet are expected to be impressive. While groups of platooned vehicles may or may not improve

Table 2. Critical considerations for travel behavior impacts of CAVs.

		Transportation Cost Uncertain impact. Transportation cost in CAVs could rise for some and decrease for others, depending on the prices for privately owned vehicles and TNC services and the relative use of those options. For private AVs, prices could be high initially and then come down if market penetration increases.		**Transportation Safety** Crashes are expected to decrease, saving personal operation cost and public agency cost. Incident delay would be reduced, increasing travel time reliability.		**Vehicle Operations** CAV is expected to increase capacity by reducing headway, particularly when AV-only facilities begin operation. Coordinated flow (through V2V and V2I communications) could further increase effective capacity and reduce congestion.		**Fuel Type** Fleet could be electrified and refueling automated, reducing personal time requirements and commercial fuel delivery. Electrification could reduce vehicle operation cost.	**Personal Mobility and Convenience** SAVs (and private AVs) could increase independence of young, old, and limited-mobility populations by increasing their access to auto and auto-to-transit modes. Reduced disutility of travel time could reduce perceived auto in-vehicle times and have an effect on choices similar to that of reducing actual travel times.	
Category	**Modeling Element**	**If Cost Increases . . .**	**If Cost Decreases . . .**	**Crash Avoidance Increases Travel Time Reliability**	**Crash Avoidance Increases Personal Safety**	**Capacity Increases from Reduced Headways**	**Coordinated Flow Reduces Congestion**	**Fleet Is Increasing in Electrification**	**Greater Mobility for Current Nondrivers**	**Relief of Driving Task (Reduced Disutility of Travel Time)**
Land use	Work, housing, retail location	Shifts growth in housing/work/retail location choice to denser areas (increase in densification)	Shifts growth in housing/work/retail location choice to less-dense areas (increase in sprawl)	Increase in sprawl	na	Increase in sprawl (possibly offset by urban parking land being available for other uses; see below)	Increase in sprawl (possibly offset by urban parking land being available for other uses; see below)	Increase in sprawl	na	Increase in sprawl
Land use	Parking land use needs	na	na	na	na	Zero-occupancy trips reduce need for central parking (on-street and garage)	Automated/stacked parking reduces parking space needed per vehicle	na	na	na
Trip generation	Trip and tour making	Fewer trips, but possibly more home-based tours with fewer stops per tour	More induced trips, but possibly fewer tours because of more trip chaining	More induced trips, but possibly fewer tours because of more trip chaining	na	More induced trips, but possibly fewer tours because of more trip chaining	More induced trips, but possibly fewer tours because of more trip chaining	More induced trips, but possibly fewer tours because of more trip chaining	na	More induced trips, but possibly fewer tours because of more trip chaining
Trip time/length	Trip distance (VMT)	Shorter trips	Longer trips	Longer trips	na	Longer trips	Longer trips	Longer trips		Longer trips
Transit	Use of scheduled transit (bus, rail, bus rapid transit)	Transit use increases	Transit use decreases (perhaps offset by TNCs offering better first- and last-mile connections to transit)	Transit use decreases	Transit use decreases (relative safety effect)	Transit use decreases	Transit use decreases	Transit use decreases	Transit use decreases (fewer captive riders)	Transit use decreases

Transit	Auto access to transit and multimodal tours	Access to transit by auto decreases	Access to transit by auto increases (use of longer-distance commuter bus and rail could increase)	Access to transit by auto increases	na	Access to transit by auto increases	Access to transit by auto increases	Access to transit by auto increases	Access to transit by auto increases	Access to transit by auto increases
Time choice	Variability in choice of time of day to travel	Peak spreading is reduced	Peak spreading is increased	Uncertain—peak demand and reliability both increase	na	Uncertain—peak demand and capacity both increase	Uncertain—peak demand and reliability both increase	Peak spreading is increased	na	Uncertain—peak demand increases but sensitivity to delays decreases
Vehicle occupancy	Carpool formation	Increase in shared ride	Increase in riding/driving alone	na	Increase in riding/driving alone (fewer people afraid of using auto)	na	na	na	Increase in riding/driving alone (fewer people dependent on others for rides)	Increase in riding/driving alone (less stress/disutility of using auto alone)
Vehicle ownership/availability	Access to private or shared vehicles; number of autos per household; zero-car households	Lower in general—mix depends on relative costs of private vehicles and TNCs	Higher in general—mix depends on relative costs of private vehicles and TNCs	Safety may be a motivator to purchasing a CAV	na	na	na	Hybrid/electric may affect buying behavior choices	Increased availability of both	na
Intercity travel	Intercity work and recreational trip generation	Intercity trips decrease	Intercity trips increase	Intercity trips increase	Intercity trips increase	Intercity trips increase	Intercity trips increase	na	Intercity trips increase	Intercity trips increase
Intercity travel	Intercity work and recreational trip distance	Intercity trip distance decreases	Intercity trip distance increases	Intercity trip distance increases	Intercity trip distance increases	Intercity trip distance increases	Intercity trip distance increases	Depends on vehicle range and recharging time	Intercity trip distance increases	Intercity trip distance increases
Freight and commercial	Long-haul freight	Fewer and shorter trips	More and longer trips	More and longer trips, more during peak times	More and longer trips	More and longer trips, more during peak times	More and longer trips, more during peak times	Cost of fuel is significant	na	More and longer trips (platoons with driverless vehicles lower costs)
Freight and commercial	Residential and commercial delivery	Reduced home/commercial delivery trips	Increased home/commercial delivery trips	Increased home/commercial delivery trips	Increased home/commercial delivery trips	Increased home/commercial delivery trips	Increased home/commercial delivery trips	na	na	Increased home/commercial delivery trips (use of driver-less vehicles could lower costs)
Freight and commercial	Residential and commercial service calls	Reduced home/commercial service trips	Increased home/commercial service trips	na	na	Increased home/commercial service trips	Increased home/commercial service trips	na	na	na

Note: na = not applicable.

intersection and freeway operations, the coordination of flow through the concept of synchronized arrivals and reserved time and space may indeed prove to reduce queuing and congestion. This type of coordinated fleet would require a significant saturation of AVs communicating and adjusting speed to optimize flow across the roadway network. For a typical commuter or shopper, this type of system would practically guarantee reliability.

Electrification is also discussed frequently in conjunction with vehicle automation. If shared fleet services are used, the user would not need to be concerned with refueling the vehicle because the fleet owner/operator would use optimizing algorithms to reduce cost. As the need for a personal vehicle that performs both intercity travel for hundreds of miles and daily short trips diminishes, the use of electricity directly may remain the most economical fuel choice. This would have an enormous impact on the petroleum industry, but also on fuel delivery services, gas station land use, and the need for strategically located electric refueling stations.

Impacts on personal mobility and convenience are perhaps the most uncertain aspects of CAVs. If shared-use fleet services prevail in the marketplace as the population of the United States ages, the prospect of older adults, young teens, and persons who currently struggle with independent mobility gaining greater transportation freedom could greatly improve. However, these individuals could also benefit in a scenario of privately owned CAVs if the cost of the vehicles is not prohibitive.

The impact on the (dis)utility and (in)convenience of travel time—a key component of the value of travel time—from CAV technology is also somewhat uncertain. A key modeling issue is how the perception of travel time will change as drivers become passengers. It is expected that being relieved of the driving task will allow users to perform productive activities in the car, thereby reducing the disutility of in-vehicle travel time and, thus, decreasing the value of travel time savings. The extent to which this will be true and how it might vary according to journey duration, trip purpose, lifestyle, and other factors remain uncertain. It is also conceivable that there will be a novelty effect of riding in a CAV that will diminish over time, although this may be positive or negative. Some riders may be wary of the technology at first and gradually become used to it, while others may find the ability to perform other activities in the vehicle exciting at first but more commonplace over time.

Finally, robotics may help produce a new age of a sharing economy in place of an owning economy. This would have an enormous impact on the auto finance industry because the need for personal loans would decline. However, from a transportation point of view, a complete replacement of the entire owned fleet with a shared fleet would have a dramatic impact.

CHAPTER 4

Framework for Planning and Modeling CAVs

This chapter builds on the information presented in the preceding chapters and provides a conceptual framework for planning and modeling CAVs. Subsequent chapters provide high-level guidance for planning and modeling practice.

Chapter Highlights

- Provides a conceptual framework for planning and modeling CAVs.
- Discusses the individual elements of the framework—data, modeling, planning context, timeline for CAV adoption, and communicating uncertainty.

Elements of a CAV Planning and Modeling Framework

A framework for forecasting CAVs and the technologies and associated changes in travel behavior that might occur includes five elements:

- Data,
- Planning context,
- Modeling,
- CAV adoption timeline, and
- Communication of uncertainty.

The first three elements—data, planning, and modeling—combine to create a forecasting environment. The typical planning process includes developing a vision for transportation in a region, setting goals and performance measures as targets, collecting data, building models from the data, and using models in either a predictive or an exploratory mode to evaluate alternative transportation investments. The planning context depends on the timeframe and the level of uncertainty that stakeholders and planners have about the future within a specific time in the future. More certainty leads to the application of predictive models to analyze facility alternatives (e.g., capacity, alignment, and mode), while greater uncertainty leads to the application of scenario-based planning or other methods for addressing deep uncertainty.

The basic tenet of the CAV planning and modeling framework is the uncertainty that is fundamental to forecasting. Data, by definition, always describe a past condition; they relate information from the time the data were collected. Models that are calibrated to data describe the relationship between independent variables, such as households and employment, and the impact those independent variables have on dependent variables, such as total VMT. The models describe the conditions depicted by the data. A forecast application of data-calibrated models changes the value of the independent variables by adding growth but keeps the relationship to the outcome—the dependent variables—the same.

For instance, a trip rate is calibrated to observed trip-making frequency based on a household travel survey. A forecast application of the rate of travel may remain constant, even while the overall population grows, and the outcome of the application of the fixed trip rate is a

Data-supported modeling does not forecast behavioral changes; instead, the process forecasts growth in presently observed behavior—as it should.

greater number of trips, even though the rate of trip making stays the same. Data-supported modeling does not forecast behavioral changes; instead, the process forecasts growth in presently observed behavior—as it should.

The further out in time a forecast application is made, the less certainty an analyst has about the accuracy of the modeling outcome based on the relevancy of the data used to calibrate the model. Data relevancy is the inherent validity of the data as time passes. In a rapidly changing transportation environment, models calibrated to data become less useful for longer-range planning. Conversely, in a stable and unchanging environment, data and models built upon the data retain their relevancy for a longer period.

The relevancy of data and models is a subjective determination. No fixed guidelines exist to determine the amount of time that data remain relevant and can be used for predictions to support transportation plans. Decisions regarding data relevancy and the use of predictive modeling versus exploratory modeling need to be made at the outset of a planning process. As data and models become less predictive, the planning process used needs to change. Alternative analysis (choosing one outcome as the best) can be done by using predictive models, while exploratory modeling can support scenario-based planning, which keeps several future scenarios in play when making decisions.

Decisions regarding data relevancy and the use of predictive modeling versus exploratory modeling need to be made at the outset of a planning process.

The fourth element of the framework for forecasting CAVs concerns the timeline within the planning horizon and the level of advancement and adoption of automated transportation technologies. The level of advancement and adoption can be built into the definition of scenarios in long-range analysis or viewed as a static prediction for predictive analysis of alternatives.

The last element, communication, involves the need for the analyst to convey the level of uncertainty associated with the model results to decision makers and stakeholders. A situation that analysts commonly face in using this framework is a de facto interpretation of results as predictive. A better method is to determine at initial project scoping whether the analysis is going to be based on predictive, data-supported modeling or on exploratory techniques, which should not be taken as a prediction.

Framework for CAV Planning and Modeling

Figure 3 depicts the framework for a system of planning and modeling for CAVs. The framework displays a planning and modeling timeline at the top showing that data are collected in the past and planning occurs in the present. The CAV adoption timeline arrow indicates that an agreement needs to be made on the level of adoption/advancement of CAV technology—and the rate of adoption of the technology—over the planning/modeling timeline period. No assumed time period is indicated in the figure. The total time period could be 20 years or 50 years, depending on the application.

The assumption in the diagram is that all modeling is done in the present time. As time passes, the relevancy of data becomes less. Therefore, predictive modeling is more valid for the shorter term, while exploratory modeling is useful for long-term planning. However, the diagram does not indicate the time when modeling should be done within the planning timeframe. The intent of the diagram is to show that predictive modeling can be used when more confidence in the relevance of the data occurs, while exploratory modeling should be used if greater uncertainty exists about the relevance of data and the models that are calibrated to the data.

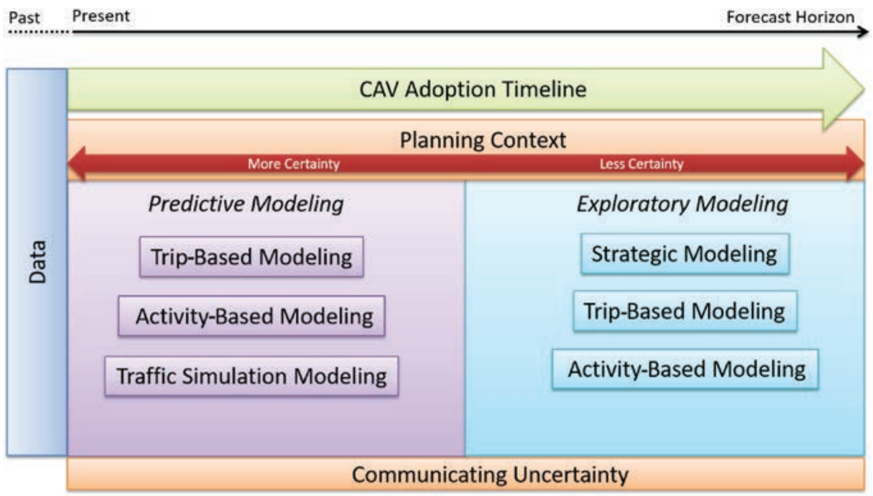


Figure 3. Framework for CAV planning and modeling.

Framework: Data

Data are not available to build predictive long-range travel models of CAVs, or any of the technologies and applications that will be promulgated in the future. However, deployment of preliminary versions and types of CAV technology is expected to increase within just a few years. As data that include AVs, CVs, and related applications become available, predictive models may be constructed.

Data are not available to build predictive long-range travel models of CAVs, but as data become available, predictive models may be constructed.

A move is occurring in many cities to develop smart city technology. A smart city is predicated on generating and sharing data with the desire to develop greater efficiencies with physical infrastructure, citizens, multiple levels of government, and business crossing all economic sectors including transportation. Municipal leadership hopes that opening data access will stimulate creativity that will result in more efficient and equitable cities with a reduced impact on the environment and a better quality of life for regional residents and visitors.

Two main types of data will become important as CAV technology gains a foothold: archival data and real-time data. Archival data can be used to build informative descriptions and models about the existing transportation choices people are making and the trends in those choices. Real-time data describing immediate changes in system performance, vehicle tracking, route planning, infrastructure status (such as traffic signal timing), speed, direction, occupancy, and other statistics are being used to enhance the efficiency of transportation system operations.

Because data to build forecast models of CAVs will be scarce in the short term, models of longer-range futures must be used in exploratory mode by imposing reasonable changes to the parameters that describe travel behavior and choices based on the judgment of analysts, leadership, and stakeholders. Rather than rely solely on the judgment of analysts, however, the planning process must also include a method to define which changes are reasonable and which are not acceptable to the planning community. A scenario-based planning process can accomplish this.

Note that the quality of the data, such as avoiding sampling bias and the underreporting of trips, remains important. A judgment about the relevancy of data must be made, based not solely on the age of the data but also on the applicability of the data to the questions being asked. For example, data collected currently (in 2018) from TNCs may inform, but may not reflect, travel behavior changes of later, more intense market penetration of shared CAVs and an interconnected trip-planning environment.

Stated preference data should be caveated, particularly in the case of CAV technologies, since respondents probably do not have any experience with the technology.

Similarly, stated preference data should be caveated, particularly in the case of CAV technologies, because respondents probably do not have any experience with the technology. Models calibrated to data collected in today's transportation environment cannot simply be applied with an additional mode representing the CAV technology because the chosen mode needs to be present in the environment at the time the data are collected for the individual choice to be valid in the model. There is a difference between making a choice on the basis of a lived experience versus the imagined qualities of an experience.

Data quantity and quality will develop alongside smart mobility advances. Most models are built from data that are collected by survey sampling. This method is useful to modelers, because individual characteristics, such as income level, can be used as a stratification of the independent variable (person or household). Passively collected movement data from connected devices such as smartphones are gaining in popularity because the data are broad—meaning the data are collected across a wide spectrum of the sample universe—but individual characteristics are suppressed to protect privacy. Survey sampling is expensive but valuable because it gathers data that are "deep" in terms of joining respondent characteristics with travel behavior. In the future, as automation and digitalization become commonplace, data that are both broad and deep will likely become available, making the data much more useful for calibration of models. Planners and modelers need both broad data—or big data—to capture small but impactful nuances and deep data—or survey data—to describe motivational factors (independent variables) that can be used to predict behavior. However, the basic tenet of the planning and modeling framework—that data relevancy passes with time—still applies, regardless of the span or depth of the data collection methods.

Framework: Planning Context

The purpose of modeling systems and other tools and processes used for travel forecasting is to inform analysts, agency leadership, stakeholders, and the public about potential outcomes of planning decisions. The context of planning for CAV technology is one of deep uncertainty about the impacts, infrastructure needs, deployment timeline, market penetration, design, engineering, and many more aspects of automation. CAVs are expected to be disruptive and impactful, but that is the only certainty about which the planning community generally agrees. The framework for CAV modeling and planning suggests a simple idea within the context of deep uncertainty: the longer the planning horizon, the less certainty about predictive processes.

The basic method for planning under deep uncertainty across many fields of study, including transportation, has been scenario-based planning. Scenario planning can be applied to transportation as a step incorporated in performance-based planning at various stages throughout the process (Twaddell et al. 2016). Also, many MPOs, DOTs, and other planning agencies have conducted visioning processes for the specific purpose of evaluating a larger set of alternative futures than those that are typically studied in federally required metropolitan transportation plans.

Scenario planning arose from the business problem of products becoming obsolete as markets and technology changed over time. Businesses needed a process to protect their business lines against disruptive changes in the future. They realized that prediction of only one future, or selecting one alternative from a set of futures and pursuing only that one, was causing a sort of blindness to change. Being prepared for change was the key to being able to adapt quickly to changes in the markets. To prepare for change, a set of plausible scenarios had to be developed as a part of the planning process, which enabled adaptability and lowered the risk associated with changes in the marketplace.

Similarly, the transportation planning community is facing the problem of adaptability and risk associated with an uncertain future, one based on advanced technology that is not currently well defined. While the one-best-alternative method that has been established over decades in transportation planning may suffice for short-term plans, it is becoming abundantly clear that long-range plans are facing increasing risk of being invalid because of CAVs and other disruptions to the transportation space.

It is becoming abundantly clear that long-range plans are facing increasing risk of being invalid because of CAVs and other disruptions to the transportation space.

The Federal Highway Administration (FHWA) recently published a scenario-planning guidebook for practitioners titled *Next Generation Scenario Planning: A Transportation Practitioner's Guide* (Ange et al. 2017), which describes the process of scenario planning for transportation. FHWA is also pending production of report guidance on scenario planning for CAVs.

Framework: Modeling

Modeling in this framework is divided into two parts: predictive modeling and exploratory modeling. Predictive modeling is used to describe models that are calibrated with historical data, validated by system performance (traffic counts) for a past year, and tested for short-range forecasting accuracy. Predictive modeling is the way travel forecasting has been done traditionally because past data have usually been good for predicting future outcomes, even in the longer term, under a stable transportation environment. In fact, the ability of travel demand models to forecast in the short term, and in most cases simply validated by the parameter calibration year without forecasting at all, has been commonly held as the indicator of the accuracy of the model for forecasting. This is patently a false assumption.

Exploratory modeling is the use of models for testing various scenarios that do not match the trends seen in the historical data archive. Models calibrated to recently measured travel behavior in surveys or from passively collected data are used in predictive mode. When analysts change the calibrated parameters to reflect a change in behavior—as is expected with CAV impacts—they are using exploratory models. However, the changes in parameters are not done for the purposes of testing the sensitivity of the calibrated model to changes. Sensitivity testing is done by changing the independent input variables, such as forecast households. Analysts often create ranges of values for input parameters. For CAVs, the ranges would need to be plausible. For instance, it would not be plausible to increase trip generation per household to a rate, which would occupy all household members all day in travel activity. Analysts may use professional and rational judgment to set ranges for exploratory modeling.

Several types of modeling processes exist for conducting exploratory modeling and planning. Scenario-based planning may require simply adjusting models to match the assumptions generated as part of a workshop process. These scenarios may differ widely in model inputs, such as demographic forecasts, but they may also assume varying levels of technology adoption. Assumption-based planning, quantitative risk analysis, and exploratory modeling and analysis/robust decision making (RDM) are other techniques that may prove useful to CAV modeling efforts. These techniques are discussed in detail in Chapter 5 of this report.

Exploratory modeling can be done with process models (such as trip-based and AB models), or it can be done with various strategic models that use a wide range of plausible inputs, distributions, elasticities, and outputs. While process models use a finer level of detail, the time required to process details may limit the usefulness of these models for exploratory analysis. More generalized strategic models may be more useful because of the ability to run many iterations and create distributions of outputs that are helpful in analyzing scenarios in the several scenario-planning processes. At an appropriate point in time, planners and modelers in a region should agree on whether models can be taken as predictive tools that extend trends found in observed data or should be discussed as exploratory tools that are not based on observed data.

The framework provides three types of modeling systems that can be applied in an exploratory modeling context:

- Trip-based models developed as aggregate models of population and employment in a region with disaggregate measures of transportation supply and an aggregate assignment process,
- Activity-based and dynamic traffic assignment models developed as disaggregate models of persons and firms in a region with disaggregate measures of transportation supply, and
- Strategic models developed as disaggregate models of persons and firms in a region with aggregate measures of transportation supply.

Strategic models are intended to be applied in a scenario planning context to evaluate the impacts of a variety of policies and investments. Often, these are used as a screening analysis, where hundreds of combinations of different policies can be tested and prioritized. Trip-based and AB or DTA models are applied for a more limited set of scenarios to explore the more detailed impacts of policies and investments on the transportation system.

Framework: Adoption Timeline

The timeline for adoption of CAV technology is debatable and is complicated by the definition and functionality of the technology. However, in this planning and modeling framework, it is important to include a description of potential phases of deployment where specific modeling and planning tools may be warranted. For example, early adoption may be with shared automated fleet services operating in a limited range or geography, and may involve relatively little private ownership of highly automated AVs. Over time, as the transportation fleet transitions to high automation and reaches a tipping point, more data about behavior will become available. The overall shift is expected to be toward exploratory modeling and planning in the early years of deployment, and then back to predictive modeling and planning as the fleet becomes saturated with AVs and behavioral outcomes can be measured.

Predicting CAV adoption involves many uncertainties. First, technology develops in controlled laboratory conditions but needs extensive real-world testing to bring it to fruition. Many individual technologies need to converge and be tested for driverless cars, and there have already been setbacks from crashes. Computing and communications systems that CAVs depend on are advancing in parallel. CAV system adoption is also dependent on public acceptance and desirability, most notably operating cost, which has not yet been determined in an open market. Public policy and governance may eventually adapt and control the technology to address societal health, safety, and welfare issues, including equitable access to services.

The framework for CAV modeling and planning suggests that the planning process include a thoroughly developed timeline. Consent among stakeholders about the timing of deployment will ease the process of scenario development.

Framework: Communicating Uncertainty

Framing the conversation about uncertainty is part of the CAV planning and modeling framework because in transportation planning, decision makers typically look to transportation planners to provide robust predictions. With so much uncertainty surrounding CAV and its potential impacts, planners need to be knowledgeable about how to communicate uncertainty without introducing doubt and a lack of confidence in forecasts. In this framework, it is critical to communicate with leadership about uncertainty but without under- or overstating outcomes.

Personality preferences vary among planners, modelers, and leadership. Analysts presenting information about CAVs to leadership and to other planners and modelers will need to understand various perspectives and preferences when collecting information describing deep uncertainty. Most leaders feel it is their responsibility to act, but with the inherent risk that automated technology poses about the long-term future, it may be a time for contemplation, not action. Planners need to learn to talk confidently without misleading the audience about the level of certainty.

Plans and models are communication tools. Understanding how to communicate under uncertainty is fundamental to a conceptual framework for planning and modeling CAVs. The processes and tools are used to inform leadership about the usage and character of transportation facilities and the development of and impacts to the urban and rural transportation environment.

Today, CAVs loom large as deeply uncertain and potentially transformative transportation technologies. Deep uncertainty exists when parties to a decision do not know, or do not agree upon, the system model that relates action to consequences, the probability distributions to place over the inputs to these models, or the relative importance of different consequences (Lempert et al. 2003). The ultimate design of the technologies, the timing and pace of their adoption, and their impacts on transportation goals are unknown but need to be included in forward-looking planning efforts, since they will become fully mature within most planning horizons.

CHAPTER 5

Planning in the Context of Uncertainty

Chapter Highlights

- Reviews how uncertainty is managed in current transportation planning.
- Describes the unique challenges in managing uncertainty posed by CAVs.
- Identifies methods suited to managing decision making under deep uncertainty:
  - Scenario planning,
  - Assumption-based planning,
  - Robust decision making,
  - Info-gap, and
  - Dynamic adaptive pathways planning.

Forward-looking planning activities typically seek to evaluate and choose from among a set of candidate decision options. For transportation planners, this can include choices about expanding highway capacity, extending or enhancing transit service, creating bike lanes, and prioritizing system upgrades and maintenance. Planners often use models, along with expert judgment and other techniques, to assist in the evaluation and selection of decision options. The task is difficult because there may be many and sometimes competing criteria by which the options must be evaluated, such as the safety, transportation demand, service quality, equity, greenhouse gas emissions, local air pollution, and cost. Moreover, how each option performs for those criteria depends on very hard-to-predict and often-disputed future conditions. These can include long-term demographic and land use changes, economic growth or decline, energy prices, consumer behavior, and new transportation technologies.

Dewar and Wachs (2008) noted that transportation planning does not manage uncertainty particularly well:

> Travel demand forecasting as widely practiced today deals inadequately with uncertainty. . . . The current transportation modeling process is demanding in the sense that it employs a great deal of data to a large number of interconnected models having many parameters. The complexity of the modeling process, however, does not extend to the accurate representation of complex economic and social phenomena, and point estimates of many quantities are used that make it difficult to analyze or even to represent the uncertainty that characterizes transportation systems and traveler decision making.

Uncertainty in Transportation Systems

The extent to which uncertainty exists in the performance of transportation systems and in systematic responses to uncertainty in those systems through the planning, decision making, operations, and management processes is an important and complex problem. Urban transportation systems include extensive networks of massive, immovable, and long-lived physical facilities. The extent, location, and physical condition of the current system in any geographic location are, in the short run, among the least uncertain of all the elements of the physical environment. Bridges, tunnels, highways, and rail lines are unchanging for decades or centuries, are dominating features of the landscape, and are difficult to alter physically.

What is important to structure the discussion here is not the stability of the physical transportation network but rather the variability of travel on that network and, consequently, the variability and uncertainty of the network's performance under different circumstances. Travel that takes place on transportation facilities is highly variable, flexible, and malleable. People and goods use the transportation system rationally, but they employ many and highly individual criteria when deciding how to fulfill varying needs. The complexity of travel decision making by people and firms is fundamentally reflective of social, economic, and cultural patterns that are themselves quite complex, and these are compounded by the complexity of physical flows in transportation networks.

Because of the complexity in the modeling process, point estimates are used, which makes it difficult to represent the uncertainty that characterizes transportation systems and traveler decisions.

Yet, when society taken together makes all of its travel decisions by using many different rational choice processes, the outcome is clear patterns that seem regular and repetitive, and this in turn leads to the notion that uncertainty is less important to planning than it actually is. Traffic peaks almost every day at the same times and places; roughly the same number of people use public transit versus highways between certain origins and destinations at a certain hour of the day. When looked at by an engineer, traffic on a facility has certain predictable characteristics like volumes, densities, starting times, and concentrations at certain origins and destinations that recur on a predictable, daily basis. However, the engineer looks at the performance of the system and not of the thousands of people who are using it. When looked at as a social phenomenon rather than as traffic flows, trips can be made by different modes, at different times, at different vehicle occupancy rates, for different purposes, from different origins to different destinations, and, in at least some cases, can be postponed or cancelled.

Transportation modelers are no strangers to uncertainty, although it is typically left unaddressed. CAVs exacerbate many of the existing uncertainties, such as the cost of driving, the elasticity of travel demand to this cost, and the greenhouse gas emissions per mile traveled. If these aspects were previously treated as uncertain, the range of potential values for these parameters might need to be widened, and if they were previously not treated as uncertain, they certainly must be now.

There is also a host of other ways that CAVs create new challenges for managing uncertainty. AVs in particular can be thought of as a new transportation mode and may fundamentally change the future of mobility and its associated effects (DOE 2016). As just one example, AVs are expected to fundamentally change land use in the decades to come, not only because people's preferences for urban versus suburban living may change, but because significant changes in urban environments may occur. Urban dwellers may give up their personally owned vehicles in favor of SAV services, which means the large fraction of urban space devoted to parking may be converted to other uses (Zmud et al. 2016). Housing shortages in many cities could be alleviated if garage space previously devoted to vehicles could be repurposed for housing. If AVs prove to be extremely safe and efficient, redesigned lanes may free up space for other modes.

These types of changes are enormously difficult to anticipate. Just as it was not possible to predict in 1990 how the Internet would change communication methods and frequency 20 years later, so it is not possible today to confidently predict how AVs will change travel modes and frequency 20 years from now. Yet, the uncertain future will shape the answers to questions that transportation planners are trying to address now. Should a particular light rail line be expanded, or will that expansion become obsolete in a future with AVs? Should urban planners consider purchasing satellite parking for AV fleets? Should an AV lane be included in future highway capacity expansions? These questions are difficult to answer with traditional methods of planning. The next section examines how these questions can be addressed with a new class of methods for managing deep uncertainty.

Overview of Planning Processes

Predictive Analysis, or Agreeing on Assumptions

Most traditional planning methods seek to (*a*) reduce uncertainty by requiring agreement on assumptions about the current and future conditions under which a plan must perform, and (*b*) analyze the decision options. Transportation planners would first characterize the future urban form, economic growth, and other factors that affect travel demand. These characterizations are often, but need not be, single numerical values; they could also be distributions around future trends. For example, instead of predicting an increase in VMT of 10%, a planner could predict a normally distributed increase in VMT with a mean of 10% and a standard deviation of 2%. In this case, a Monte Carlo simulation would be used to estimate the most likely future given the assumptions that were adopted, and to identify the near-term policy actions that would maximize the likelihood of the desired outcomes (Adler et al. 2014).

Transportation planners would then evaluate the merits of various plans or investment choices (e.g., highway capacity expansion) under these assumptions. A sensitivity analysis could help assess how much influence each assumption has on the outcome. Such approaches have been termed "agree-on-assumptions" (Kalra et al. 2014), "predict-then-act" (Lempert et al. 2013), or "science first" (Dessai and Hulme 2007).

When faced with disagreement and deep uncertainty (e.g., about the deployment and impact of AV technology), these traditional processes are vulnerable to bias and gridlock. First, many important assumptions are buried in models rather than in front of decision makers. This makes it difficult for decision makers to understand and assess potentially critical assumptions on which their decisions hinge. Second, many factors are difficult, if not impossible, to predict. Stakeholders also know that the choice of assumptions drives the choice of investment option. They may press for assumptions that will lead to the options they already favor and thereby make consensus difficult (Lempert et al. 2003). Decision makers risk losing stakeholders' buy-in early if the foundations of the decision process lack transparency, appear arbitrary, or do not include their beliefs.

Agree-on-assumption approaches are also vulnerable to reaching brittle decisions—ones that are optimal for a particular set of assumptions but that perform poorly or even disastrously under other assumptions. Sensitivity analyses are often not sufficient for exploring the full range of plausible assumptions and future conditions (Bonzanigo and Kalra 2014), and agree-on-assumptions create little opportunity for exploring the performance of decision options under unexpected conditions. They yield no information about how an optimal solution performs if the future is surprising, and they do not guide decision makers to solutions that might work well if the predicted future does not happen. Yet, a significant need for understanding the effect of surprises and unexpected conditions exists; repeated studies have shown that human beings have a widespread tendency toward overconfidence, with strong belief in our ability to predict the future when we cannot (Kahneman 2011).

Exploratory Analysis or Agreeing on Decisions

It is possible to manage deep uncertainty by seeking a robust decision—one that performs well across a wide range of futures, preferences, and worldviews, though it may not be optimal in any particular one. Robust decisions are often flexible—designed to be modified over time as new information becomes available. It is possible to identify robust strategies by inverting the traditional steps (i.e., by using agree-on-assumption processes).

These strategies, also sometimes called "context-first" methods (Ranger et al. 2010), begin with laying out the decision options (as opposed to first laying out predictions of the future) and then stress-test the options under a wide range of plausible conditions, without requiring a decision or agreement upon which conditions are more or less likely. They evaluate the decision options repeatedly, under many different sets of assumptions. Planners can evaluate options under low-likelihood but high-consequence events, can treat as uncertain the assumptions buried in models, and can use every stakeholder's beliefs about the future; agreement on assumptions is not required. This process reveals which of the options are robust, meeting needs under a wide range of conditions rather than performing well in only a few. Analytical tools can then help identify the specific conditions in which each option no longer meets its goals.

Analyses performed in this way do not make the decisions for decision makers. Instead, they help decision makers debate important questions:

- Are the conditions under which our option performs poorly sufficiently likely that we should choose a different option?
- What trade-offs do we wish to make between robustness and, for example, cost?
- Which options leave us with the most flexibility to respond to changes in the future?

This inverted process promotes consensus around decisions and can help manage deep uncertainty around transportation technology, climate change, and a host of other factors.

Qualitative Methods for Managing Deep Uncertainty

The most common qualitative method for addressing uncertainty is scenario planning. Scenario planning is a response to the limits of predictive agree-on-assumptions analysis. In scenario planning, analysts develop diverse and often divergent views about the long-term future. Rather than tell a single story, the planners craft a suite of different tales. Classical scenario planning involves a small set of handcrafted scenarios aimed at facilitating broader thinking about potential future outcomes. Yet, it has limitations in ensuring that a wide enough range of futures is considered and in linking scenarios to near-term policy choices. A newer group of methods has evolved in response. These methods typically use vast numbers of computer-generated scenarios to identify actions that are robust in performing well across a wide range of potential futures.

Qualitative methods include scenario planning and assumption-based planning. The former has limitations in the range of futures considered and in linking to near-term policy choices. Thus, the latter has evolved in response.

Classical Scenario Planning

Scenario planning constructs diverse and often divergent narratives about the long-term future. A family of scenarios, often three or four, aims to span the range of plausible futures relevant to the decision at hand. The aim is for planners to use those scenarios to consider how near-term policies might shape and be shaped by those futures. Nearly all the work described earlier uses scenario planning to assess CAV impacts. In addition, FHWA is pursuing a study to develop scenarios for CAVs. The Task Order Proposal Request describes the study (FHWA 2016) as follows:

> The purpose of this study will use the transportation scenario planning process to develop approximately three to five descriptive futures (scenarios) of the deployment, market uptake, use, and impacts of CV and AV technologies. The U.S. Department of Transportation (DOT) is planning to provide the outcome of this study to State, regional and local transportation agencies. The deliverables of this study shall include the future scenario outcomes, a high level assessment of these futures, and an illustration of how agencies can use scenario

planning to develop their own, more localized future CAV scenarios. State and regional agencies may use this illustrative scenario planning process to anticipate likely issues and challenges they will face due to CAV adoption, and therefore to help visualize and understand their planning options, including developing or changing institutional and operational responses and policies.

The Department of Energy also recently engaged in a scenario planning exercise to identify trends that would lead to different greenhouse gas emission scenarios in transportation. Members of this team were part of workshops that resulted in the paper *The Transforming Mobility Ecosystem: Enabling an Energy Efficient Future*, which has several goals (DOE 2016):

> The intent of this paper is to provide the Energy Department's forethought, along with public and private stakeholder input, on the future of mobility and subsequent impacts on energy. It introduces four possible mobility futures, or narratives, defined by two factors chosen for their transformative potential and pertinence to the discussion: vehicle control (from driver-only, to self-driving, and fully automated defined as Level 4 or 5 functionality by SAE International), and vehicle ownership (from personal ownership to fully shared vehicles). This paper, however, does not offer policy recommendations, or provide strategies that would enable one future narrative over the other. Additionally, it does not set target expectations for low-carbon technologies (e.g., battery costs), but observes a range of factors that, ultimately, could shape each future narrative and determine the impacts on energy and GHG emissions. Other factors may emerge in the future that could have a significant energy impact.

An MPO in a high-growth area with significant congestion and investment needs may implement scenario planning and include CAV and other technological impacts in the long-range plan.

Scenario planning does have shortcomings. First, the choice of any small number of scenarios to span a highly complex future is ultimately arbitrary. A scenario exercise will inevitably miss many important futures that do not make the cut into the top few. Second, scenario-based planning provides no systematic means to compare alternative policy choices. With a small set of divergent scenarios, it can be unclear which if any scenario to use for planning purposes, and how to choose from among competing policy options that make sense in some but not all the scenarios. Thus, scenario planning is a powerful tool for imagining the uncertain future and constructing collective ideas of desirable and undesirable futures, but these ideas may be difficult to use in decision making to shape those futures (Lempert et al. 2003).

Assumption-Based Planning

Assumption-based planning is another qualitative approach to managing uncertainty. All plans must make assumptions about the future because of the presence of uncertainty. Many assumptions are explicitly identified and planned for, but most plans also contain implicit or hidden assumptions. These implicit assumptions can cause significant problems and weaken robustness of plans when not made part of the planning process. In the presence of uncertainty, assumption-based planning (Dewar 2002) can help organizations systematically identify explicit and implicit assumptions and ensure they are part of the process of planning actions to achieve defined strategic goals.

Assumption-based planning hinges on identifying load-bearing assumptions (assumptions that, if broken, would require major revision of the course of action) and, subsequently, the vulnerability of those load-bearing assumptions. For example, a plan to expand light rail to a planned development area hinges on the assumption that the proposed development will succeed. This assumption might be vulnerable if the development hinges on an optimistic level of economic growth. Assumption-based planning guides organizations in determining a course of action to deal with the vulnerability of load-bearing assumptions once they are identified.

Quantitative Methods for Managing Deep Uncertainty

In response to the difficulty of linking scenarios to policy choices, many have turned to alternative methods for decision making under deep uncertainty. As described earlier, deep uncertainty exists when decision makers do not know or do not agree on the models that describe relationships between key drivers and outcomes, the probabilities of key variables, or how to value the desirability of different outcomes. These characteristics hold true of CAV technologies, for which it is not clear how the different technological, social, economic, and other trends will interact to shape CAV adoption or their outcomes. A new class of methods—which includes but is not limited to RDM (Lempert et al. 2003), dynamic adaptive policy pathways (Haasnoot et al. 2013), and info-gap (Ben-Haim 2006)—all seek to use multiple (often hundreds or thousands) of computer-generated future scenarios to identify decisions that are robust—that is, decisions that work well in many future scenarios even if they are not optimal in any one future. Such decisions are often no regret (i.e., they make sense no matter what the future brings) and adaptive or flexible (i.e., they enable changes as new information becomes available).

Quantitative methods include robust decision making, info-gap, and dynamic adaptive pathways. Rather than ask, "What will happen?" these methods ask, "What should we do today to most effectively manage the range of events that might happen?"

These methods and bodies of work have been brought together by a recently formed professional organization called the Society for Decision Making Under Deep Uncertainty (www.deepuncertainty.org), which updates its website with publications and reports describing these methods. As the website shows, these approaches have been widely applied to water resource planning, defense planning, energy investments, health, and a variety of other fields but have not been extensively applied to transportation planning. There is clear value in doing so, and it is to be hoped that the deep uncertainties that CAVs present will encourage such work.

Robust Decision Making

RDM rests on a simple concept (Lempert et al. 2003). Rather than use models and data to assess decision options under a single set of assumptions, RDM runs models over hundreds to thousands of different sets of assumptions to describe how plans perform in many plausible conditions. Unlike Monte Carlo analysis, which attaches probabilities to those assumptions to estimate expected outcomes, RDM uses simulations to stress-test strategies and helps decision makers identify robust strategies—those that perform well regardless of the assumptions or future conditions—and identify the key trade-offs between potential robust strategies. Often, the robust strategies identified by RDM are adaptive, that is, designed to evolve over time in response to new information.

Info-Gap Theory

Info-gap theory is another approach that helps decision makers identify robust options, but it takes a somewhat different tack. RDM uses models to assess the performance of options in a wide range of potential future conditions and then identify conditions that result in poor performance (i.e., conditions to which the system is vulnerable). In contrast, info-gap uses models to compute how options perform as a function of uncertainty. An info-gap analysis defines robustness as "the maximum uncertainty in our estimates that can be tolerated while still guaranteeing a particular desired result" (Irias and Cicala 2013). An info-gap analysis produces a graph showing the performance that planners can robustly achieve on one axis as a function of uncertainty on the other axis. Like RDM, info-gap does not provide decision makers with the solution; rather, it seeks to inform decision makers on trade-offs, risks, and vulnerabilities.

Dynamic Adaptive Pathways Planning

Another approach is dynamic adaptive pathways planning (DAPP; Haasnoot et al. 2013). With the DAPP approach, a plan is conceptualized as a series of actions over time (pathways). The essence is proactive planning for flexible adaptation over time, in response to how the future actually unfolds. The DAPP approach starts from the premise that policies and decisions have a design life and might fail as the operating conditions change (Kwadijk et al. 2010). Once actions fail, additional or other actions are needed to achieve objectives, and a series of pathways emerges; at predetermined trigger points, the course can change while the objectives are still achieved. By exploring different pathways and considering the path-dependency of actions, planners can design an adaptive plan that includes short-term actions and long-term options. The plan is monitored for signals that indicate when the next step of a pathway should be implemented or whether reassessment of the plan is needed.

Institutional, Resource, and Other Considerations for Managing Deep Uncertainty

While scenario planning and other qualitative methods for managing uncertainty have been around for many decades, quantitative methods may be particularly unfamiliar, since they have been enabled only recently by the growing availability of computational resources. Thus, institutional challenges to mainstreaming new approaches exist, even if they may be better suited to a particular analytical problem. This section presents some of those considerations. These observations are adapted from Lempert et al.'s (2003) comments on the application of RDM in developing country contexts.

Quantitative methods are generally designed to employ existing models and data. Thus, in cases where decision makers are already using quantitative analysis to inform their choices, these methods can augment such activities to provide a richer understanding of uncertainty and the best ways to respond to it. The models used in these analyses can be simple or complex. For instance, an analyst using a simple spreadsheet model to compare the cost–benefit ratios of alternative investments could use these methods to run the spreadsheet over many thousands of combinations of assumptions and to identify those futures where one investment is consistently more cost effective than another. Analysts with a large, complex model could similarly use these quantitative methods to stress-test the strategies that emerge from their analysis.

As one potential implementation barrier, compared with a traditional approach, quantitative methods in particular require more computer processor time to conduct hundreds to thousands of runs and more computer storage to save the results. In practice, these are not significant constraints. Analysts with spreadsheet models will generally have more than sufficient storage and processing power on a laptop to run the spreadsheet thousands of times. Analysts running a complicated model may require hundreds or thousands of processors to run their models over numerous cases. These are increasingly available (for instance, Amazon now rents time on its huge stock of multiprocessors), and those with the skills to build complicated models can also access such multiprocessor systems.

Configuring a model to run hundreds to thousands of cases often represents the greater challenge. For instance, staff skilled at developing cost–benefit spreadsheets may not know how to run the spreadsheet automatically for thousands of cases. Complex models may have an input file structure that makes it difficult to run thousands of cases efficiently. Both situations may require training and some reworking of computer code to enable analysts to generate and batch runs. Fortunately, this software, along with related training, proves to be a sound investment because it is generally useful for a wide range of analyses.

Perhaps the most significant challenges to implementing quantitative methods of managing uncertainty arise because these methods represent a new way of thinking about how near-term actions can best manage future risks. Analysts are generally trained in predictive thinking, and the decision makers they inform often expect predictive quantitative information. Methods of managing uncertainty answer a fundamentally different question. Rather than ask, “What will happen?” they allow analysts and decision makers to ask, “What should we do today to most effectively manage the full range of events that might happen?” Using these methods requires training for analysts and a path by which organizations become comfortable using new and more effective types of quantitative information. One successful path involves conducting a demonstration project parallel to an organization’s regular planning activities. Once the demonstration is complete, the organization can use this experience to begin to fold the new methods into its planning.

CHAPTER 6

Adapting Trip-Based Models to Address CAVs

Chapter Highlights

- Provides high-level guidance on accounting for CAVs in trip-based models.
- Identifies potential modeling changes.
- Discusses the context and approaches for
  - Land use modeling,
  - Auto availability and mobility choices,
  - Trip generation,
  - Trip distribution,
  - Mode choice, and
  - Routing and traffic assignment.

This chapter presents critical considerations related to accounting for CAVs in trip-based models. Along with the subsequent chapters on disaggregate/dynamic models and strategic models, Chapter 6 provides the context for the modeling adaptations and then an approach for implementing them. These chapters do not provide prescriptive rules for including CAVs in models but, rather, ways to use existing models for quantitative visualization of feasible alternative outcomes.

Overview

Trip-based models are long-range travel demand models that follow the conventional four-step process of trip generation, trip distribution, mode choice, and traffic assignment. Additional steps, feedback loops, and postprocessing often enhance trip-based models. These models have been calibrated, validated, and tested throughout the world, and they are used extensively across most MPOs and state DOTs in the United States.

Table 3 summarizes potential changes to the trip-based modeling system from CAV impacts. Successfully modeling CAVs will require several changes to existing modeling processes, including

- New modes or submodes:
  - CAVs,
  - SAVs, and
  - SAV access to transit (submode);
- Additional submodels:
  - Auto availability models that reflect the level of market penetration of CAVs and
  - Market penetration models to determine fleet composition changes over time;
- New algorithms and processes:
  - Routing routines to model dynamic ridesharing (e.g., uberPOOL),
  - Coordinated multimodal mobility services modeling (e.g., MaaS; automated tour planning), and
  - Network flow coordination (real-time speed governing and predicted arrival rates); and
- New supply models to reflect CAV impacts on roadway space.

Applying Exploratory Models in the Context of Stable Travel Behavior

When models are being applied in an exploratory manner, it is important for modeling analysts to note the stability of trip rates and lengths in the United States. Adjustment of parameters

Table 3. Potential trip-based modeling changes.

Model Component	Trip-Based Model Improvement
Sociodemographics	
Land use/demographic model	Adjust accessibility measures
Land use/demographic model	Account for parking reuse
Land use/demographic model	Estimate levels of expanded mobile populations
Market/Fleet	
Fleet composition models	Estimate and forecast types of vehicles and technology
Auto Ownership	
Auto ownership model	Estimate and forecast CAV or manual vehicle ownership
Auto availability model	Estimate and forecast availability of SAVs and carsharing
Trip Generation	
Trip rates	Estimate and forecast rates for expanded mobile populations
Trip rates	Account for zero-occupant vehicle trip generation
Trip rates	Adjust rates within reason for improved accessibility
Trip Distribution	
Impedance to travel	Estimate network cost matrices reflecting CAVs
Impedance to travel	Estimate new friction factor matrices if CAVs affect trip lengths
Mode Choice	
Mode choice model	Design new nesting structure including CAVs, SAVs, and SAV access to transit
Mode choice model	Account for MaaS impacts on multimodal tour plans
Value of time	Account for improved value of time for CAV modes
Network Assignment	
Supply models	Estimate CAV-enhanced capacity on signalized arterial systems
Network capacity	Estimate CAV-enhanced capacity on grade-separated facilities
Path costs; pricing and tolling	Estimate value of time including discounts for CAV passengers

such as trip rates and lengths, per person, needs to be done in the context of reasonableness as compared with historical trends. While trip rates and lengths may vary because of an urban area's characteristics and size, as a whole, trip making and the time spent in mobility activities is relatively stable.

Table 4 shows the change in travel statistics in the National Household Travel Survey between 1969 and 2009. While trip making (person trips per person per day) more than doubled between 1969 and 1995—most likely from women entering the workforce—the two most recent surveys show similar rates of trip generation per person (3.74 and 3.79 in 2001 and 2009, respectively). Average person and vehicle trip length per trip also shows relative stability, in miles, although travel times have most likely increased as urban areas have become more congested and travel times are more unreliable because of congested conditions.

Table 5 summarizes travel trend excerpts from several American Time Use Surveys conducted annually by the Bureau of Labor Statistics (n.d.). Total time spent traveling for various activities, on average, varied by less than 3.6 minutes per day from 2003 to 2016. Other interim years of 2010 and 2015 are also shown and display little variation.

Because travel activity on average has remained relatively stable over time, particularly in the recent decade, modeling analysts must use reasonable judgment when adjusting travel behavior parameters in travel demand models.

Table 4. Summary of travel statistics, National Household Travel Survey, 1969–2009.

Travel Statistic	1969	1977	1983	1990	1995	2001	2009	95% CI
Per person								
Daily person trips	2.02	2.92	2.89	3.76	4.3	3.74	3.79	0.03
Daily PMT	19.51	25.95	25.05	34.91	38.67	36.89	36.13	1.35
Per driver								
Daily vehicle trips	2.32	2.34	2.36	3.26	3.57	3.35	3.02	0.03
Daily VMT	20.64	19.49	18.68	28.49	32.14	32.73	28.97	0.71
Per household								
Daily person trips	6.36	7.69	7.2	8.94	10.49	9.66	9.5	0.09
Daily PMT	61.55	68.27	62.47	83.06	94.41	95.24	90.42	3.38
Daily vehicle trips	3.83	3.95	4.07	5.69	6.36	5.95	5.66	0.06
Daily VMT	34.01	32.97	32.16	49.76	57.25	58.05	54.38	1.34
Per trip								
Average person trip length (miles)	9.67	8.87	8.68	9.47	9.13	10.04	9.75	0.36
Average vehicle trip length (miles)	8.89	8.34	7.9	8.85	9.06	9.87	9.72	0.22

Source: Santos et al. 2011 (https://nhts.ornl.gov/2009/pub/stt.pdf).
Note: CI = confidence interval.

Table 5. Travel minutes of activity from American Time Use Survey.

Activity	2016	2015	2010	2003
Travel related to personal care	1.8	1.2	1.2	0.6
Travel related to eating and drinking	6.6	6.6	7.2	7.2
Travel related to household activities	3	3	2.4	2.4
Travel related to purchasing goods and services	17.4	16.8	16.2	17.4
Travel related to caring for and helping household members	4.8	4.8	4.8	5.4
Travel related to caring for and helping nonhousehold members	3.6	3.6	3.6	5.4
Travel related to work	16.2	16.2	16.8	17.4
Travel related to education	1.8	1.8	1.8	2.4
Travel related to organizational, civic, and religious activities	2.4	2.4	2.4	2.4
Travel related to leisure and sports	12.6	12.6	13.2	13.8
Travel related to telephone calls	0.6	0	0	0
Total	70.8	69	69.6	74.4

Source: Bureau of Labor Statistics.

Land Use Modeling

Context

A land use/demographic allocation process is usually added prior to running the four-step trip-based modeling process. Linkage to the travel demand process, if it is done, uses measures of accessibility derived from the trip tables and roadway/transit networks. CAVs would present changes to accessibility and affect land use modeling in this way. In transportation modeling, land use modeling may be a misnomer for this important step in the process. Land use usually refers to the type of activity occurring or allowable, while typical travel demand models use socioeconomic data directly. Population, households by size, income, and other categories, and employment by category represent the level of activity in a location. These inputs, aggregated to traffic analysis zones (TAZs), become the independent variables in the trip generation step.

Land use models and methods vary considerably between U.S. planning agencies. In many planning regions, ad hoc methods ranging from local stakeholder consensus meetings to formal scenario generation processes are used. Generalized growth patterns in residential and employment locations are gleaned from workshops and converted to rational allocation of growth based on densities. Quantitative methods for forecasting the level of activity in TAZs are gaining in application. Aggregate quantitative methods are based on rational densities and predetermined allowable or desired uses, usually from a municipal comprehensive plan for future land use. Aggregate allocation of activity to TAZs may also use accessibility calculated from a travel demand model process as an indicator of readiness for a parcel to be developed.

Disaggregate residential and employment models are applied in many larger metropolitan regions. Bid rent models that simulate competitive bidding for land among residents and employers are applied by using discrete choice models. These models also use transportation accessibility from travel demand modeling processes to represent valuation (i.e., cost) of land.

Approach

Accessibility is a measure that uses the aggregate relative distance, time, or cost of a TAZ to separate it from other TAZs. Accessibility could change after widespread introduction of CAVs to the transportation system. Accessibility is a common parameter used in both aggregate and disaggregate land use models to represent the relative cost of travel from residence to work or other activities. As the relative accessibility of a parcel or TAZ of land increases, it becomes more desirable for development. Measures of accessibility are calculated from existing and forecast distribution of trips or other activity at each TAZ combined with network costs.

CAVs will potentially have significant impacts on travel costs and therefore would change the input accessibilities in most quantitative land use models. Travel costs can be categorized into personal travel time costs and vehicle operating costs. Vehicle operating may be affected by CAVs through depreciation, changes in insurance costs, changes in vehicle technology, and behavioral shifts toward vehicle sharing. Insurance costs for CAVs may decline because of a reduction in crashes. If CAV fleet service providers move toward electrification, both fuel and maintenance costs may decrease. Additionally, cost sharing from shared vehicle usage would divide operating costs, including tolls, among riders. Finally, under a shared usage CAV scenario, the capital cost of vehicles would decline significantly because CAVs may be used for many more hours compared with the typical privately owned vehicles that sit idle up to 23 hours per day.

CAVs will potentially have significant impacts on travel costs and therefore would change the input accessibilities in most quantitative land use models.

Travel demand model network shortest-path procedures are used to determine trip cost and travel time between TAZs. Composite measures that include both auto and transit costs are also used (logsums from the mode choice step). These times and costs, combined with the level of population and/or employment in each TAZ, are used as inputs to land use allocation models. Often, land uses are part of comprehensive municipal city plans, in which land use is tied to zoning ordinances. These city plans usually indicate the expected land use in all parcels within the extraterritorial jurisdiction of the city. These can be a guide to the location of future population and employment and can be an input to a land use allocation model used as part of a travel demand modeling process.

Factors to Consider for Land Use Modeling and CAVs

Factors to consider when forecasting land use and demographic allocation that includes CAV scenarios include

- Geographic distribution of growth—densification and/or urban sprawl,
- Reuse of land formerly dedicated to parking, and
- Demographic changes (aging and household composition).

Changes in relative accessibility between TAZs derived from changes in transportation cost and travel time owing to CAVs may result in either densification or sprawl or a combination of both. The relief of the driving task may change the value of time for drivers commuting to work or for other trip purposes. Time spent driving can be viewed as wasteful. Drivers would be converted to passengers with time to perform other activities such as sleeping, reading, working remotely, or engaging in social activity. At a minimum, drivers would need to retain the function of piloting the CAV and monitoring systems, even at Level 4 technologies.

Modelers may need to estimate and locate the amount of space dedicated to parking and forecast the conversion of the space to other uses or to open space. In the early years of CAV adoption, parking will remain a needed land use. In the longer term, land needed for parking may decline. Analysts will be able to model the trends in the reuse of parking facilities over time on the basis of observations, but in early years, scenarios of changes will need to be envisioned.

Modelers will also need to account for more detailed demographic characteristics to model the potential increase in availability of CAVs to population segments not currently considered for trip-based models. CAVs may provide independent mobility for younger people not currently eligible to legally operate a vehicle, probably between ages 12 and 18, through ridesharing and vehicle sharing. Levels of elderly and mobility-limited persons will need to be forecast in TAZs as ride and auto availability increase from the introduction of CAV technology. Household composition, including age categories and mobility limitations, will be important in the estimation of trip making, so these variables will need to be included in demographic forecasting models.

Alternate Work Locations

Alternate work locations are places where business can be conducted outside of home residences but are not a usual place of work. These locations include formal alternate work locations such as branch business offices, informal offices where meeting rooms can be leased, or even coffee shops. Future peer-to-peer sharing of commercial office space may also surface as significant alternate work locations for many commuters, much in the way that peer-to-peer residence sharing has entered the temporary and vacation housing marketplace.

If trends point to alternate work locations becoming more prevalent, or analysts wish to create exploratory scenarios, including increased sharing of commercial office space, trip lengths for work trips may decline in the future. This trend would have an impact on trip generation. More trips may be generated with reduced trip lengths. The ability to work closer to home and other daily activities may spawn increased work trip rates as the alternative workplace option competes with telecommuting. Efficiencies created by CAVs may enhance or take from these options. A reduced impedance to travel created by CAVs could compete with alternate work locations, just as it would compete with the choice to remain working at home.

Gaps in Current Land Use Models

Regions will need to gather input for addressing long-range considerations for land use modeling with impacts from CAVs. Forecasting based on current trends in the growth of land use patterns may lead to omissions about changes in residential and commercial location decisions. Growth should be assessed in at least four scenarios: a continuation of past trends, more densification than current trends, more significant sprawl to exurban areas, and a combination of infill and sprawl growth in focused geographic subareas of a metropolitan region.

Efficiencies gained from CAVs and related technologies such as comprehensive mobility sourcing (i.e., MaaS) could lead to choices in residential location that fill in and densify urban cores. The market for urban living space could grow if mobility services create a quality of life that some residents may be searching for in place of long commutes, separation from entertainment options, relief from yard maintenance, and a desire for greater active transportation options. Researching and quantifying current land developable as infill is important when increased densification impacts from CAVs are being considered. Also important is quantifying the amount of potential infill development that could occur if parking facilities become available for residential and commercial redevelopment. Studies of convertible parking space versus space that would require more costly demolition would further enable forecasters to quantify redevelopment properties for input to land use models. If operating costs decline as a result of CAV deployment, and the share of household budgets dedicated to mobility declines in parallel, the effect could be a greater share of household budgets dedicated to housing. This may make inner-city housing more affordable and create densification.

When inputs for land use modeling scenarios are being designed, careful consideration should exercised in speculation about commuting time increasing as a result of the driving task being relieved by CAV. As shown in Table 5, the time spent in travel has on average remained stable for many years. Although CAVs may have an impact on activity that can be performed while in transit, time spent traveling will not necessarily increase. Relief of the driving task indicates that the in-vehicle time may be spent more productively or used for entertainment purposes. However, the strong desire to minimize travel time may remain a common behavioral attribute into the future.

Auto Availability and Mobility Choices

Context

The availability of autos to household members is used in trip-based models to indicate a propensity for use of the vehicles because they are costly, and most people would want to use something that takes a large share of household budgets. Households with no owned vehicles are used as an indicator of a requirement for public transportation or ridesharing. Some models use a ratio of number of household members of driving age to the number of autos available for use in a household as a measure of these modal propensities.

Auto ownership can also be used as a factor in calculating vehicle trip frequency. More often, household income has been used as a variable indicating that no impediment to trip generation from the lack of availability of vehicles exists. Changes in ownership patterns under CAV scenarios indicate the need for a different schema to address vehicle availability and its indication of modal preference and ease of trip generation.

Approach to CAV Auto Availability Estimation

Although auto ownership is the preferred parameter in many travel demand models, CAVs could potentially shift the current pattern of individual ownership of vehicles. If the cost per trip—or mile traveled—decreases with the introduction of efficiently shared CAVs, many people may move away from current auto ownership patterns. Schemas for household transportation choices resulting from CAVs could include the following:

- A household has roughly one car per household member of driving age, continuing the current pattern.
- A household keeps a mix of owned CAVs and non-CAVs or vehicles equipped with only Level 1 or 2 technologies.
- A household is within an area that has high accessibility to shared CAV services, and vehicle sharing is common at the household income level or in the geographic location.

Several combinations of auto availability can be designed around observed data as they become available. Assumptions about auto availability will need to be made when exploratory modeling scenarios are being designed.

Table 6 is an example of an auto availability table that could be developed for scenarios or from observed data over time. Auto availability should become a common parameter to supplement auto ownership for most travel demand models that include CAV forecast scenarios. These types of household mobility classifications will need to be determined or theorized as part of scenario modeling to dissect the complexity of mobility options that will become available in the future.

Mobility as a Service

The objective for measuring auto availability for trip-based models is to reflect the propensity for trip making and modal choice with higher levels of vehicle availability. CAVs could also be implemented in a MaaS transportation environment. With MaaS, the cost of transportation could be paid through a single system, most likely wireless and automated, such that a combination of trips into a daily pattern could be planned and optimized to minimize cost and involve easy transfer between autos, public transportation, and bicycling or walking. A single transportation card that pays for all modes seamlessly could be issued.

Table 6. Example CAV availability schema.

		Vehicle Ownership						CAV Sharing			
		CAV-Enabled			Non-CAV			Ridesharing Potential		Vehicle-Sharing Potential	
Household Size	Household Income Group	1	2	3	1	2	3	Low	High	Low	High
1	Low	*Number or percentage of regional household totals*									
	High										
2	Low										
	High										
≥3	Low										
	High										

Trip Generation

Context

Trip generation is the process used in trip-based travel demand models to estimate and forecast the number of trip ends generated by residential or commercial activity in TAZs. Trip ends refer to each end of a single trip: the origin or the destination. In travel demand modeling, each end of a trip, before the ends are joined or linked together in the trip distribution step, is classified as either a production or attraction trip end. Persons in households generate trips, and therefore production trip ends are calculated from the number of households in a TAZ. Attraction trip ends are calculated from employment levels in TAZs with commercial activity—retail, office and other work locations, schools, and entertainment venues.

Approach to Capturing CAV Effects on Trip Generation

As shown in Table 5, total time spent traveling for different activities varied, on average, by less than 3.6 minutes per day between 2003 and 2016 in the United States. Because travel activity has remained relatively stable over time—particularly in the recent decade—modeling analysts must use reasonable judgment when adjusting travel behavior parameters in travel demand models.

As Table 4 illustrated, trip rates per person and time spent in travel activity have also remained stable. Although CAVs may provide a more efficient and less costly mode of travel, analysts should be cognizant of the trend toward stabilizing and minimizing total per person time spent in travel activities. Overall, CAVs may change the need for travel, the efficiency with which it is performed, and the aggregate total travel by enabling trip making by populations whose mobility currently is limited.

Telepresence and CAV Scenarios

Several factors should be considered when modeling futures are being forecast, including the effects of telecommuting, alternate work locations, and other telepresence. These factors include the

- Cost of travel,
- Availability of vehicles or rides,
- Efficiency and reliability of travel,
- Quality of telepresence technology, and
- Culture of workplaces.

The greater efficiency, lower cost, and improved availability of travel under CAV scenarios creates an impetus to increase trip generation rates. The effects of the quality of telepresence technology and workplace culture can have either positive or negative impacts on the decision to telecommute or perform other activities through telepresence. CAVs may have an impact on cost, availability, and efficiency of travel—factors that commuters and others will weigh against the quality of telepresence technology and workplace culture when making the decision to telecommute, teleshop, or physically travel. As CAV and telepresence technology develop in parallel, modelers will need to assess the cost, travel time, convenience, and other issues that will be used to compare the choice of satisfying work, shopping, and entertainment activities through mobility or telepresence.

The greater efficiency, lower cost, and improved availability of travel under CAV scenarios creates an impetus to increase trip generation.

In a future CAV scenario in which efficiency of travel is enhanced and less costly, in terms of the share of household budget spent on transportation, and telepresence technology is technically cumbersome and work culture unsupportive, trip rates per worker could increase. The increase in trip making would be from fewer persons working, shopping, or completing other activities at home.

Workers have many reasons for working at home, such as travel efficiency, reliability, and value of time. Other reasons may be less associated with transportation, such as tending to children or taking care of medical needs. Surveys and data will be needed to determine the reasons behind working from home so that modelers can create future scenarios of increased or decreased work trip generation.

For instance, if telecommuting currently accounts for 5% to 15% of work trips on a typical day, analysts may modify trip rates under future CAV scenarios between those values by using either data-supported evidence of a trend or by creating an exploratory scenario. If alternate work locations are included in a scenario, work trip rates may increase as workers who used to work at home begin to access high-quality workspaces closer to their homes. However, analysis is needed to factor in other trip making if a time window becomes available due to the alternate work location. If a scenario includes increased working from home, trip rates should be reduced.

Teleshopping is a trend that is becoming more prevalent. Studies of this trend and its impact on trip generation remain inconclusive, however. The stability of national trip rates shown in Table 4 indicates that trip making has not been in decline because of the increase in online shopping in the past decade. Nonetheless, some shopping activity is clearly being replaced by teleshopping, as indicated by increased revenues for online retailers and closing of many large retail store brick-and-mortar locations throughout the United States. Perhaps teleshopping is replacing many types of purchases, but trips are still being generated to satisfy other purchases. Trips may also be made to showrooms and then purchases made later online, effectively negating the potential reduction in trip generation from teleshopping.

Expanded Mobile Populations and CAVs

CAVs may bring about robotic vehicles that can operate without a human driver or passengers. People whose mobility options are limited today may find greater mobility independence with CAVs. The ability to independently call for a vehicle and control the schedule at a lower cost than today's demand-responsive public transportation may lead to increased trip generation by current mobility-limited populations. Modelers wishing to estimate the impact of mobility-limited populations can look to existing data from on-demand transit services. Agencies that provide these services usually collect detailed trip and user data. Analysts could create exploratory scenarios in which a portion of these mobility-limited trips moves to CAV modes and modestly increases their overall trip frequency—trips that otherwise would have been satisfied through ridesharing with another household member or through public on-demand transportation services.

Similarly, populations currently under the legal driving age could create additional CAV trips. Travel currently satisfied by household carpooling (usually called serve-passenger in travel surveys) could be a source of data for analysts to use in determining the level of increase in trip generation from younger populations. School-age children may either ride school buses or have a parent give them a ride to and from school. Parents often transport a child to school daily, and the task is often split between two parents.

Many trip-based models include a specific trip purpose for school trip generation. Most of these trips are generated as serve-passenger trips and become part of either school bus modes or are treated as household carpools. Analysts may wish to consider current travel surveys to determine the proportion of these trips to reassign to CAV modes. In robo-taxi scenarios, school-aged children may be able to call a CAV and be transported independently to and from school or other activities. These trips may add to vehicle trip generation.

Zero-Occupant Vehicle Trip Generation

CAV technology will bring about conditions in which completely autonomous vehicles (Level 5) may become prevalent as part of ridesharing fleets and owned CAVs. These vehicles can be called zero-occupant vehicles (ZOVs). Local bus transit trips could be satisfied with on-demand ZOV services that become single-occupant vehicle (SOV) or shared-ride vehicle trips. Analysts may wish to create exploratory scenarios to account for ZOV-generated VMT.

ZOV trips could be promulgated by factoring trip ends in trip tables produced by trip-based models. Analysts would need to either measure or assume the proportion of trips made by ZOVs relative to other modes, such as owned vehicles or shared vehicle services (which could also be called initial-state ZOVs). The initial state of a ZOV at the beginning of each day would need to be established in the model design by assuming a geographic distribution of ZOVs, which would probably remain in a secure storage area until called upon by the next day's travel activity. ZOVs would be connected to a centralized control system that would reposition the vehicle for optimal use for the next passenger call. This technology would learn from the previous day's trip patterns and position ZOVs as efficiently as possible at the beginning of each day.

A distribution of call wait times, possibly stratified by area type, could either be measured or assumed as part of exploratory modeling. In this way, estimates of ZOV trips could be made by area type, because denser parts of an urban region will most likely require a greater number of AVs, and market demand will require short response times for passenger pickup. Simulations of ZOVs, ridesharing, and dynamic en route ridesharing could be done as part of a research study and then summarized for aggregate trip-based models by area type.

Trip Distribution

Context

Trip distribution in trip-based travel demand models is the process of joining production and attraction trip ends to form trips from an origin to a destination. Trip-based models do not link trips together into tours; instead, individual trip purposes are maintained independently but in proportion to each other. CAVs may affect trip distribution in significant ways. Improvements in automation and connectivity of vehicles will influence the trip distribution step by influencing impedance to travel in two main areas: (*a*) improved system operational efficiency and reliability and (*b*) better convenience and trip planning. Both factors would also affect trip cost.

Automation will bring about operational improvements to vehicles and improve the efficiency and reliability of traffic flow. The result will be more reliably predicted travel times and reduced impedance to travel. Connectivity will allow route plans to be shared as travelers input their destinations into CAVs. Route plans can then be shared with traffic management centers that will be able to reliably predict demand at critical points in the network, such as traffic signals at major intersections and bridges across major geographic obstacles. V2I technology will then be able to adjust signal timings, and vehicles will be able to adjust approach speeds, creating harmonized, predictable arrival patterns.

These types of advancements in CAVs will reduce impedance to travel. Impedance to travel is used as a separation component in gravity analogy trip distribution models that are commonly used as part of trip-based models. The separation between TAZs is measured by using shortest-path algorithms and modeling networks. Travel speeds in most trip-based models are gathered from feedback loops from the traffic assignment step to reflect the effect of congestion resulting from inefficient networks. These inefficiencies could be reduced with CAVs.

Approach

Impedance to travel is usually measured in trip-based models by using travel time and, less frequently, travel distance. Some more-advanced trip-based models include composite measures of separation from mode choice modeling steps that include transit travel times, fares, and operating costs in one measure (logsums). Given that CAVs could be an additional mode, and that there could be various mixes of modal technologies (and pricing schema for various policy reasons) in shorter-term planning years, analysts may wish to consider using composite cost matrices.

Another more specific method of reflecting the gains in network performance from CAVs would be to lower the weights applied to impedance in gravity models. These weights are known as "friction factors." Friction factors are distributed generically across travel times and are stratified by trip purpose. Friction factors allow for the calibration of gravity models to observed patterns of trip distribution. The objective function for gravity calibration is trip length frequency distribution by trip purpose. If CAVs are expected to affect trip lengths—how far people are willing to travel for specific activities—then adjustment to friction factor curves to match presupposed trip length frequency distributions would be the method used to reflect the impact of CAVs on trip length.

However, trip distribution and willingness to travel specific distances for work versus food shopping or other activities are predicated on a relatively stable pattern of land use. Grocery stores are dispersed among residential areas, while work locations are often more centralized and concentrated in urban cores. If the pattern of land use is expected to remain stable into the future, even with the widespread adoption of CAVs, then friction factors should be adjusted with caution.

Mode Choice

Context

Mode choice is the process of determining the mode of travel for each person trip by trip purpose. Matrices of person trips by trip purpose are created in the previous step in the trip-based modeling process—trip distribution. Each origin-to-destination pair of TAZs is coded for connectivity to available modes; all TAZs are connected by auto, but transit service may not extend to all TAZs in a modeled region. Mode choice model parameters define three essential characteristics to compare the relative attractiveness of each mode for use: the characteristics of the user in a household, characteristics of the trip itself, and characteristics associated with the destination TAZs.

The most common mode choice modeling structure used in trip-based models is nested logit. In this design, options are nested logically into subdivisions. Each subdivided modal element has an associated disutility function that defines the probability of a user choosing that mode relative to the disutility of all other modes. Disutility is measured with many variables, and equations are estimated with multinomial regression against observed behavior. For exploratory model designs, analysts would need to presume coefficients and constants by using reasonable judgment drawn from other calibrated models.

Approach

For CAV modeling, mode choice is an important step. Figure 4 displays an example mode choice structure for CAVs. In this simple design, the primary nest of the choice model is travel

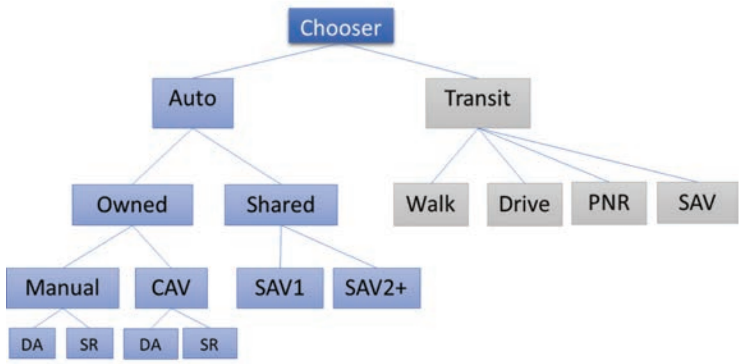


Figure 4. Example of simplified CAV mode choice structure (PNR = park and ride; DA = drive alone; SR = shared ride).

by either auto or transit. Within the transit nest, several access mode options exist, including walking, driving, park-and-ride, and drop-offs, and SAVs. On the auto side, vehicles are either owned or shared, as estimated by an auto availability modeling step. Shared vehicles could be further subdivided into rideshare vehicles or carshare club vehicles if there is a difference in the utility of those modes significant enough to warrant further nesting. The nesting structure in Figure 4 is but one example. Other structures may treat CAVs as an entirely new mode and as a third option to auto and transit. Because these are exploratory models until data become available, the design of nesting structures is experimental.

On the owned side, vehicles are divided into manually driven vehicles or CAVs (denoted as CAV in the chart). This division of owned vehicles is made because of the presumption that CAVs will have better operating characteristics and provide amenities that manually driven vehicles do not possess. Both classes of vehicles could be driven (or ridden in) or shared with other household members. Carpool formation could take place outside of the household as part of a ridesharing plan for those who choose to operate their vehicle as a rideshare vehicle, thereby lowering overall operating cost for each trip.

For estimation of the disutility of each mode, several variables could be used. First, the characteristics of the chooser could be (*a*) the income level of the household, (*b*) whether the household has any owned vehicles (manual or CAV equipped), and (*c*) whether the home location is in an area served by CAV fleet services (ridesharing through SAVs or carsharing through a CAV subscription service). The service level in an area served by CAV fleet services may indicate a variable for wait times.

Further, the disutility of each mode may include characteristics of the trip. In a mixed vehicle environment of both CAVs and manually driven vehicles, the full benefit of CAV technology may not be fully realized if manually driven vehicles in the traffic stream degrade the potential efficiency gains from CAVs. However, exclusive lanes or geographic areas dedicated to efficient CAV operation may overcome these impediments. Travel time would be a fundamental parameter in the disutility equations, and either a level-of-comfort variable or a binary variable could be estimated to indicate subjective qualities of CAV modes.

Vehicles that are owned would still require parking at the destination end of each trip. As parking becomes scarcer and less needed in an urban CAV transportation environment, the cost for parking may rise, since land owners and managers could convert space formerly dedicated to parking to other, more valuable uses. The cost of parking may become a major factor of disutility for ownership of either CAVs or manually operated vehicles for trips with destinations in downtowns and dense areas of the city.

If an environment of MaaS comes about in the future, modelers may want to consider the composite impact of multimodal tours.

If an environment of MaaS comes about in the future, modelers may want to consider the composite impact of multimodal tours rather than individual modal options for each trip in the mode choice step. A combination of modes may lower overall trip cost, ease the disutility associated with transfers, and possibly be supplemented with incentives for use of multiple modes as public policy to reduce congestion. Modeling analysts may wish to estimate the impacts of MaaS and adjust penalties for modal transfers, parking cost, terminal time, or other parameters to reflect the ease of travel that MaaS brings to commuters and for other nonwork trip activities.

For mode choice modeling and a future with CAV and other technologies, many options can be considered. Although the focus is primarily on efficiency and reliability of roadway performance to be enabled by CAVs, it is important for modelers to consider changes that may come in parking technology, route planning, MaaS, and the ride- and vehicle-sharing environment.

Routing and Traffic Assignment

Context

Network assignment is the step in the process used to route trips by mode through networks. Network performance is then updated on the basis of the usage of each facility by comparing the loadings on each facility to its theoretical capacity. Trip-based models are usually applied by using a static user equilibrium (UE) traffic assignment model. Trips are loaded onto a network in aggregate (by TAZ) by time period or for an entire day. The initial state of the network, in terms of speed or cost or both, is updated by using the aggregate loadings of trips from and to each TAZ. The application is then run over many iterations until a predefined state of equilibrium is reached—where no user can improve his or her travel time by changing routes—within a threshold parameter.

As explained in greater detail in later sections of this report, regional dynamic traffic assignments (DTAs) are being tested for use with trip-based models to improve the limitations of static UE assignment methods. Static methods tend to overload facilities beyond available capacity, do not account for queuing and spill-back, and do not have sensitivity to intersection controls or other metering infrastructure such as ramp meters. DTA is used by taking aggregate loading from TAZs and breaking it into individual trips. The individual vehicles are then routed through a network in a simulation in which each vehicle (user) chooses an optimal path on the basis of narrow time slices of 15 seconds or less. Each link in the network is updated, and queues can be formed in response to signalized intersections and other controls.

Approach to Modeling Network System Performance and CAVs

Detailed information on system performance will be needed to model CAVs through a network accurately. Improved operational performance of CAVs is expected to be achieved from either automation or connectivity or both. Automation may result in closer headways, quicker response times, improved acceleration and deceleration profiles, and robotic controls that can use more narrow lanes. Connectivity may result in better formation of homogeneous platoons (those that have similar route plan profiles), and better coordination of signal timing in response to expected demand. Additionally, CAVs could improve network performance by optimizing departure times, speeds, and arrivals at signalized intersections or other constrained points in a network. Gains from reduced crash rates would improve reliability and trip plans. Finally, costs and pricing of portions of a network may be quickly tabulated and communicated to CAVs. Efficiency of fuel use, including electric charging rates at specific times of the day, could result in lowered operating costs. Reductions in crashes would lead to reduced insurance costs. Shared travel would spread trip cost among several users.

These details will require a detailed traffic assignment method. Current static UE models may remain in use for limited applications, but enhanced DTA models will be more functional. Current DTA models will also need enhancements to take advantage of speed harmonization, platooning, and CAV operating characteristics.

As technology advances, many options will surface to optimize the efficiency of network performance, requiring new supply model designs. Options for pricing transportation facilities or incentivizing use through discounting could become simple once vehicles are automated and connected. Users may be able to select from several options as they plan their daily activities, and pricing may incentivize efficiency in the transportation system.

As technology advances, many options will surface to optimize the efficiency of network performance, requiring new supply model design.

Controlled Intersection Facilities

CAV technology is being researched and developed to take advantage of robotic control of vehicle spacing. Tight headway combined with coordinated acceleration and deceleration has been shown in simulations to enhance throughput at intersections.

On the arterial system, intersections have the greatest impact on throughput capacity in addition to side friction and curb cuts for business access. CAVs can take advantage of traffic signal coordination by forming platoons with tight spacing and controlling speed. However, problems exist with this theory when platoons need to dissolve and intersections are tightly spaced. Research is continuing to resolve some of these issues to gain the most capacity possible at signalized intersections. Random arrivals and excess demand remain an issue.

Another aspect of CAVs that may be useful in the future is coordinated arrivals at signalized intersections. This may be accomplished from connectivity and speed control far upstream from signalized intersections along a planned route. Vehicles could arrive in expected platoons or groups, and dynamic signals could anticipate loadings. A key component of this concept is accurate route plan information retrieval into a centralized, automated management controller. Currently, traffic management centers do not have this technical capability.

For models, these technologies hold the promise to increase capacity at signalized arterial intersections. In static models, factoring arterial link capacity is all that is needed. DTA models would need to be enhanced to include simulation of route plans and speed harmonization profiles. Also, capability of simulating dynamic signalization in response to expected demand would need to be added.

Modeling CAVs on Free-Flow Facilities

CAVs are expected to improve traffic flow and total throughput capacity on freeways. Gains in capacity have been shown in experiments and in simulations that use close headway spacing and coordinated speed control to form platoons. In a mixed traffic stream of CAVs and manually operated vehicles, fewer gains in capacity are expected as platoons form and dissolve and weaving occurs. Some speculation about exclusive use of managed lanes for CAVs exists. Using a physical separation from manually operated vehicles could enable CAVs to take advantage of capacity-enhancing operation. Traffic assignment modeling of capacity improvements from CAVs in a static UE assignment procedure requires relatively simple change to link capacity. To take advantage of multiple types of per-trip SAVs, pricing analysts will need to estimate trip matrices by class, possibly categorizing SAV services into premium and nonpremium price classes.

Pricing Considerations

Tolling and pricing a network, either for financing or congestion pricing, may become much more complex in a CAV transportation environment. Managed lanes are currently set up to charge tolls for all vehicles of the same class, such as SOV or HOV 2+, the same during a predetermined time period. CAVs may enable a more dynamic and disaggregate pricing system that incentivizes the use of AVs and high-capacity vehicles. In a dynamic pricing scheme, vehicles using the lanes at the same time may be charged differently on the basis of a policy to incentivize vehicle, user, passenger, and other potential characteristics.

As connectivity becomes the norm, the potential for creating multiple user classes of vehicles is created. SAVs with higher person capacity may be favored by policy makers to discourage single-occupant CAVs and reduce VMT.

The occupancy of an SAV could be communicated to managed lane management systems, and each vehicle could be charged appropriately regardless of the time of day. Prices could be set dynamically in relation to congestion on the facility. Static modeling of these types of systems can be performed with multiple class assignment techniques already available in some software packages. Further development of software that can model dynamic pricing schema is needed.

CHAPTER 7

Adapting Disaggregate/Dynamic Models to Address CAVs

Chapter Highlights

- Provides high-level guidance on accounting for CAVs in AB travel demand models and DTA methods.
- Identifies potential model improvements.
- Discusses the contexts and approaches for modeling systems:
  - Sociodemographics,
  - Land use/built environment,
  - Auto ownership/mobility models,
  - Activity generation and scheduling,
  - Destination/location choice,
  - Mode choice,
  - Routing and traffic assignment,
  - Pricing, and
  - Truck and commercial vehicles.

Overview

The main focus of this chapter is on activity-based (AB) models. As of 2018, AB models are used by MPOs in 20 of the 25 largest metropolitan areas in the United States, and they are used by MPOs in several smaller metro areas as well. This discussion assumes some prior knowledge of the concepts and methods used in AB models. Further background can be found in the AB model primer prepared for the Transportation Research Board (TRB) by Chu et al. (2011).

The primary difference between AB methods and more traditional trip-based methods is that AB models incorporate a more disaggregated and detailed simulation of travel behavior. The travel of each individual household and person in the region is simulated across the course of a day. Trips are simulated as parts of home-based trip chains (tours), and tours are scheduled within the time available during the day. Travel decisions are simulated as discrete choices based on the model probabilities. Using disaggregate discrete choices (rather than multiplying aggregate probabilities, as is done in trip-based models) tends to make the model structure more flexible and able to incorporate several different levels and types of choice behavior. As discussed below, this flexibility is valuable in incorporating new aspects of travel behavior that may be associated with CAVs.

A secondary focus of this chapter is on dynamic traffic assignment (DTA) methods as an alternative to the more traditional static equilibrium traffic assignment methods introduced in the preceding section on trip-based models. In practice, all AB models are currently applied in combination with static equilibrium methods for network traffic assignment. Currently, the main use of dynamic traffic microsimulation is for corridor-scale, project-level analyses that typically employ fixed demand with no feedback of travel times to the travel demand model. Use of DTA methods for region-wide long-range forecasting is still in the initial implementation stages, but combining DTA with AB demand models may become more widespread in the future as the methods and software mature and network data become more plentiful and accessible. Further background can be found in the DTA primer prepared for TRB by Castiglione et al. (2015).

For DTA, the trend is toward microscopic dynamic assignment that simulates each vehicle's trajectory and each driver's behavior on the network. Rather than use fixed lane capacities and speed–flow relationships, DTA reveals traffic congestion levels and effective capacities through the simulation of how vehicles navigate the roads and intersections. Because no observed data exist on how the introduction of CAVs will affect aggregate speed–flow relationships, the use of

Dynamic models are structured to evaluate individual behavioral responses to changes in the transportation system and thus are well suited to evaluate CAV impacts.

a simulation method that can represent detailed differences in the ways that human drivers and AVs will navigate road networks may be the most promising approach for learning how CAVs will influence traffic capacity and congestion levels.

Modeling System

Disaggregate modeling systems—and AB and DTA models in particular—are well suited to evaluating CAVs, with some modifications. The structure of the disaggregate system (as shown in Figure 5) focuses on individual characteristics of the people and vehicles in the system.

Much of the recommended guidance requires adding some complexity to the models, so considering the most useful modifications is important. Guidance that will add complexity should only be considered if the features and sensitivities resulting from the model improvement are a high priority for the planning context. Table 7 summarizes model improvements for AB and DTA methods.

Sociodemographics

Context

An attractive feature of AB models is the feasibility of using a large number of household and person characteristics in the models. Because each household and person is simulated separately, each can have its own set of sociodemographic characteristics. The distribution of those characteristics

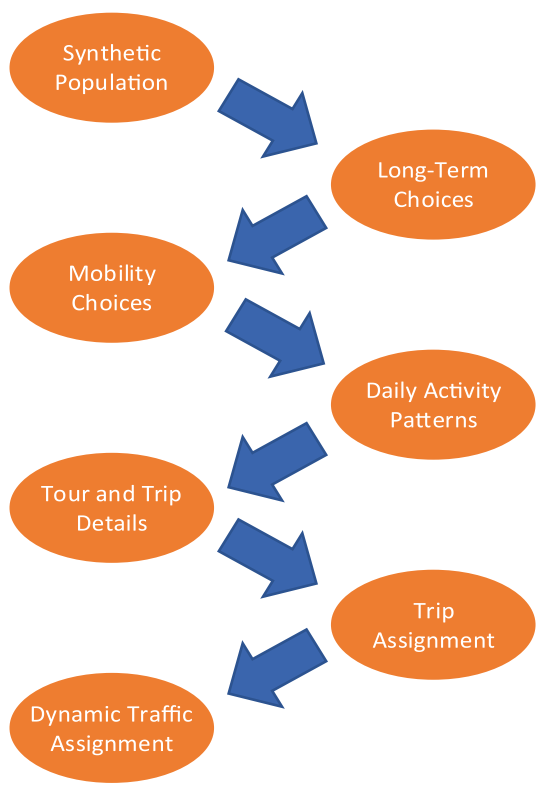


Figure 5. Typical Disaggregate AB and DTA Model Components.

Table 7. Summary of model improvements for AB and DTA models.

Model Component	Disaggregate AB/DTA Model Improvements
Sociodemographics	
Population synthesizer	Control for age and income
Population synthesizer	Add smartphone ownership and education level
Built Environment	
Urban form	Set place type by area type and development type
Mobility	
Vehicle ownership	Add CAVs as an option for households to own
Vehicle ownership	Add purchase cost, incentive policies, parking cost, or accessibility variables to distinguish vehicle type
MaaS	Add carsharing, ride-hailing, bikesharing memberships
Activity Generation and Scheduling	
Activity generation	Lift age restrictions for CAVs, add constraints for persons with disabilities and seniors using conventional vehicles
Activity generation	Adjust value of travel time (VOT) and review induced demand
Activity generation	Add representation of empty car trips
Destination/Location Choice	
Work/school locations	Integrate with land use model to provide sensitivity
Mode Choice	
Mode choice	Add new modes (CAVs, TNCs, shared modes, microtransit)
Mode choice	Adjust VOT for CAVs
Access/egress	Add access and egress modes (TNCs, shared modes, microtransit)
Mode choice	Add dynamic pricing for new modes, adjust parking costs for CAVs
Mode choice	Adjust age and disability restrictions for CAVs
Parking choice	Add parking choice model to include off-site parking
Routing and Traffic Assignment	
Dynamic assignment	Add vehicle-following and speed characteristics for CAVs
Vehicle operations	Parameterize vehicle operating characteristics
Vehicle operations	Track empty vehicles and their travel characteristics
Dynamic assignment	Simulate different levels of CVs in mixed traffic
Dynamic assignment	Simulate nonrecurring congestion with/without CAVs
Pricing	
Cost models	Determine cost per mile for each new mode by time period
Parking costs	Adjust parking cost as demand shifts away from high-cost areas
Truck and Commercial Vehicles	
Supply chain	Adjust cost and time for CAVs
Truck touring	Adjust driver hours of service for CAVs
Truck touring	Add pick-up and delivery services by TNC

across the population is controlled through population synthesis. In the synthesis process, distributions of key variables such as income, household size, number of workers, and age group are controlled at a detailed geographic level such as Census tract, Census block group, or TAZ.

Approach

Age group is currently an important determinant of the likelihood of using new transportation options such as Uber, Lyft, car2go, and other TNCs. Younger households and persons are more likely to use these new options, particularly for utilitarian purposes. After age is taken into account, people with higher incomes are also more likely to use TNCs. Age and income will also be important variables for modeling CAV use. As discussed in more detail below, age- and income-related preferences may be quite different for owning a private CAV as opposed to using CAV-based TNCs. As a result, it is useful to set age and income as controlled variables to ensure that the synthesized population is more accurate.

An advantage of population synthesis is that additional characteristics of the population can be added when data become available to control for these characteristics. One example is the strong relationship between smartphone ownership and other new technologies, such as AVs. The population synthesizer could be adapted to identify smartphone ownership for households that will have access to MaaS. Another personal characteristic that influences smartphone ownership (and possibly adoption of new technologies) is education level, so this could also be added to the population synthesizer.

Land Use/Built Environment

Context

AB models use a wide variety of built environment variables as inputs. Some of these, such as intersection density and mixed-use indices, are important in modeling the use of walk and bike modes and trip-chaining behavior. Destination choice and location choice models use several categories of employment and student enrollment as attraction variables, as well as other variables such as parks and open space and single- and multifamily housing units.

Place type is another means of identifying the characteristics of the built environment for use in travel models. Place types can be set as a combination of area type (central business district, urban, suburban, rural) and development type (residential, employment, mixed use, transit oriented, greenfield) (Outwater et al. 2014). Place types are an important indicator for mobility services, which tend to be deployed in business districts and urban areas.

Approach

If the AB travel model is integrated with a land use model, the same type of accessibility measures should be fed back to the land use model, typically in the form of mode/destination logsums across all available modes and destinations from a given residential location.

Depending on the scenario, these factors could act in opposite directions or in the same direction. Thus, the net effects on accessibility, commuting distances, and residential patterns are not obvious, but it is important to include as many of these factors as possible to avoid obtaining a one-sided result.

Auto Ownership/Mobility Models

Context

Like many advanced trip-based models, AB models predict auto ownership as a longer-term decision that conditions day-level travel choices. Some AB models also include simple models of other possible longer-term mobility factors, such as transit pass ownership, availability of free or subsidized parking at the workplace, toll transponder ownership, or bicycle ownership.

Approach

To represent private CAV ownership, the auto ownership model can be enhanced to predict both the number and type of vehicles—CAV or conventional. The simplest approach is to make it an all-or-nothing choice between owning CAVs or conventional vehicles. The left side of Figure 6 shows this structure in which a household first chooses what type of vehicles to buy and then how many. A more complex approach would be to also allow mixed ownership, as demonstrated in the right side of Figure 6, in which a household first chooses how many vehicles to purchase and then what type. Most current AB models used in practice enforce travel schedule consistency for persons but not for vehicles. As a result, these new data on vehicle type could be used initially to influence travel behavior rather than constrain individual travelers to specific vehicles.

The types of variables that can be used to model the choice between owning CAVs and conventional vehicles include

- Sociodemographics such as age and income, as mentioned above;
- Relative purchase costs of CAVs and conventional vehicles;
- Incentive policies to encourage CAV ownership and conventional vehicle trade-in;
- Relative operating costs of CAVs and conventional vehicles, if any substantial differences are assumed;
- Accessibility/utility difference of using a CAV for home–work commutes and perhaps other types of destinations (e.g., a reduced disutility of in-vehicle time for CAVs would make purchase more likely for those with long commute times); and
- Parking costs paid at the residence or workplace(s) that might be avoided with a self-parking CAV.

Transportation planners might also consider including an interaction between the number and type of vehicles owned. For example, planners could assume that households choosing to purchase a CAV would be more likely to own one vehicle rather than two vehicles, because the CAV could serve as a private taxi to take both would-be drivers to their destinations. This assumption, along with most of the assumptions used to represent CAVs in the models, is clearly speculation and not based on any data from actual purchase decisions. Thus, it is important to use the models initially in an exploratory way to investigate the implications of different

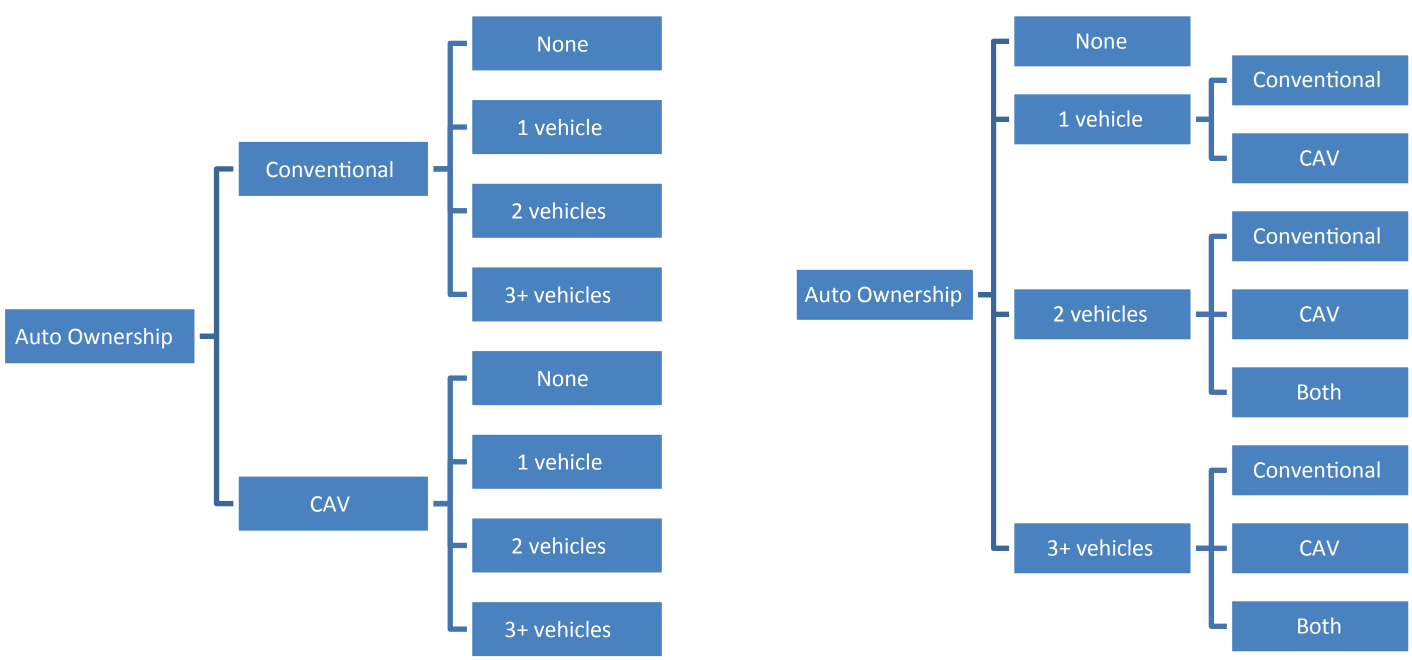


Figure 6. Potential nesting structures for auto ownership models with CAVs.

assumptions. It is also important to refine the assumptions over time as new data become available from stated preference surveys and (eventually) actual purchase decisions.

For the other types of mobility models, planners could consider modeling membership in a CAV sharing club or group. The high purchase cost and taxi-like usage characteristics of CAVs may encourage shared ownership across households that uses some type of shared scheduling app similar to TNCs but is limited to a small set of owners. This would presumably offer a shared purchase and maintenance cost, but with the possible inconvenience of not having the vehicle available when needed and having to use a TNC or other mode instead.

Once the number of possible users of a shared CAV service becomes large enough (i.e., approaching today's Zipcar and car2go systems), the differences between CAVs and other TNCs such as Uber and Lyft will largely disappear. In either case, the vehicle will come and pick up the user, and it will be possible to schedule use in advance. The main remaining difference may be in the cost structure, with some operators requiring a membership price in return for lower per-trip cost (and perhaps greater availability). If the only difference is in price structure, it is not obvious that it will be worth the effort to model membership-based CAV sharing and Uber- and Lyft-type CAV sharing as separate options. Instead, they could be modeled as a single mode with an average price.

Activity Generation and Scheduling

Context

Current activity scheduling models predict activities and trips for each person in a household, subject to time constraints and vehicles available. Some AB models also jointly schedule travel across household members constrained by the same time and vehicle availability. Vehicles are not typically tracked in AB models, so there is no constraint on the use of a specific vehicle, just constraints on the total vehicles available for the household.

AB models allow household members to choose between multistop tours to complete several activities and several individual tours to complete the same activities. These trade-offs will become more complex as travelers choose whether to continue to trip-chain or send the vehicle to complete some activities. Activity-scheduling models are sensitive to accessibility, so more congested time periods and higher tolls or parking would tend to push peak period travel into off-peak periods. Improved accessibilities and reduced travel cost will also induce overall demand for travel, something that AB models measure directly.

Approach

Some aspects of current activity-generation and -scheduling models may need to be reconsidered in light of the increased availability of travel without a driver. Age restrictions or references to persons with driver licenses will only be relevant for conventional vehicles. Lifting these constraints will induce travel from these populations. Some AB models may not currently limit driving for these populations but are calibrated to data that do. Adding these constraints to the models and then recalibrating could provide a means to support the estimation of induced demand.

Another aspect of autonomous and connected travel is that travel is less onerous overall. This stems from travelers being able to multitask, vehicles traveling closer together, and the ability for travel in a vehicle to begin and end at places other than where the vehicle is parked. Reductions in travel time and cost will tend to increase the amount of travel that people engage in, given latent demand for travel. This type of induced demand is represented by the accessibility measures included in activity generation models.

The current time-scheduling component focuses on schedule constraints for persons rather than vehicles. Adding new components that track vehicles would allow the models to constrain travel on the basis of which household vehicle is available—a CAV or a conventional vehicle. This change would add considerable complexity to the modeling system but would provide a more direct estimation of ZOVs. This is likely an AB model improvement that would occur in the future, rather than in initial versions of CAV modeling.

AVs offer opportunities for household members to optimize travel more directly, as vehicles can reposition themselves to serve multiple household members. This practice may reduce trips if household members carpool to multiple destinations. This practice may also increase trips if household members return the vehicle home after each trip. Activity-generation models will need to recognize that some movements will be this actual repositioning and keep track of these zero-occupant movements to assess impacts on the transportation system.

Destination/Location Choice

Context

Destination choice is deployed in AB models in two ways: first, to identify usual work and school locations, and second, to identify destinations for each activity for each household member over the course of the day. Most work and school trips go to the usual location each day, but sometimes travelers attend a business meeting or work at a different location.

AB models generally treat residential location as fixed on the basis of population synthesis in the base year, and perhaps modified by a land use model for future years. In contrast to trip-based models, AB models predict the usual work location for each worker and the usual school location for each student as longer-term decisions, and then predict the travel behavior for a specific day conditional on those usual work and school locations.

Destination choice models rely primarily on level-of-service characteristics (e.g., time, cost, distance) to identify preferred destinations, but these models are also sensitive to demographic and built environment factors. Travel time and cost variables are typically represented as mode choice logsums, so changes in accessibility for any mode will affect the attractiveness of a destination.

Approach

Although CAVs are expected to have several impacts on destination choice, no adjustments have been made to the current implementation of destination choice models. The expected impacts on destination choice models include the following:

- In most places in the United States where the auto is already the dominant mode, the main effect of reduced in-vehicle VOT for CAVs will be longer trips, nonmandatory trips in the short term, and commute trips in the longer term. This is the primary way that VOT affects VMT in the models.
- CAVs could make it more attractive for people to choose a job farther from their home or choose a residence farther from their workplace or both. Some other effects, however, might work in the opposite direction. The choice of usual work location is part of the AB model, and it is important that the model include accessibility measures such as mode choice logsums (the expected utility across all available modes) between home and alternative work locations.
- If the dominant mode of CAV use is TNC-based, then a higher price per mile than for private AVs may mitigate longer trip lengths. If customers begin to trade off the purchase of an automobile with the prospect of using on-demand mobility services, then the price per mile for the private AV will be higher than that for the on-demand service.

- CAVs will increase the convenience and attractiveness of destinations in parking-constrained areas. Parking cost is currently an impediment to driving to these areas, and both AVs and TNCs will avoid parking charges.

Some AB models currently assign joint travel among household members, and this behavior is likely to change as AVs offer opportunities to travel between destinations to serve additional household members. Current restrictions on joint travel and mode switching should be reconsidered in light of the flexibility that CAVs offer.

Mode Choice

Context

Current AB models contain a tour-based and a trip-based mode choice. New modes for on-demand services—TNCs (solo), TNCs (shared), carshare, bikeshare, microtransit—are not well represented, although a few AB models are adding TNCs as a new mode. The current model structure and mathematical formulations are sufficient to consider these new modes.

Current AB models do not distinguish vehicle types (e.g., hybrid, electric, autonomous, connected). Vehicle choice models would be needed to assign a specific vehicle to a specific person in the simulation, but vehicle type could also be added as a nest within the mode choice model. Current mode choice models may restrict driving to persons over 16 years of age, but the majority do not segment the population by persons with disabilities or seniors who cannot drive. These populations will have new access to auto modes that are not available today.

Approach

New mode choice models will need to incorporate relevant new modes such as TNCs, carshare, bikeshare, and microtransit. Auto modes can expand to include taxi, TNC, carshare, and CAV. Transit modes can expand to include on-demand microtransit and taxi, TNC, carshare, and bikeshare as new access and egress modes. The bike mode can expand to include bikeshare. Most of these options will require new assumptions about the use of these new modes; for example, people can pick up a car in the middle of a tour to complete one or more trips. At this point, it is unclear how to represent these new modes in a nested logit model structure, as the data with which to estimate nested mode choice models are limited for these new modes. Thus, care should be taken to test the impacts of different nesting structures.

Today, it is unclear how to represent new modes such as TNC, carshare, bikeshare, and microtransit in a nested logit model structure, as limited data are available for these modes.

Not having to drive the vehicle may make in-vehicle time in a CAV less onerous than time spent in a conventional vehicle and thus reduce the value (disutility) of travel time (i.e., VOT). Values of time spent waiting, walking, driving, or riding are all separately evaluated to ensure that the model simulates behavioral choices correctly. The expected reduction in VOT for in-vehicle time spent in a CAV can significantly affect the choice of CAV over another mode.

Current mode choice models represent access modes as walk and drive (and sometimes transit), and egress modes are typically limited to walking. Some models represent park-and-ride and kiss-and-ride as separate drive access modes. New modes will offer multiple new access and egress modes, such as TNCs and bikeshare. Expanding the egress mode options beyond walking and transit may improve the convenience of transit.

Dynamic pricing of new modes should be represented in AB models, which currently rely on 5–10 different time periods for estimation of travel times and costs. As a result, calculating aggregate prices by time periods will be more effective than trying to expand the number of time periods, owing primarily to the added complexity and processing time required. Current pricing models for TNCs offer a carpool mode at a lower price; this is another complexity that may be difficult to implement as a separate mode. The trade-offs in pricing for buying a new vehicle compared with using an on-demand service may also change over time as customers begin to understand the per-mile costs of owning versus subscribing to a service. The per-mile travel cost for privately owned CAVs may differ substantially from the per-mile cost of CAV-based TNCs.

The introduction of CAVs will affect all the auto modes (conventional vehicle and CAV for privately owned and on-demand services) in different ways. The use of privately owned CAVs will be quite different from the use of conventional vehicles, since the vehicles can be repositioned for multiple travelers. In addition, travelers can engage in multiple activities in the vehicle because there is no need to drive. Travelers can also expect no parking cost and higher convenience in congested areas, but they may see a higher operating cost if the vehicle is sent home or to pick up another traveler. Moreover, planners must remember that on-demand services will be available in some areas but not others. The added complexity of identifying each new mode in the mode choice model will depend on the importance of each new mode to the region of interest.

New modes offer tremendous choice for mobility-challenged populations (children, seniors, and persons with disabilities), because owning a private CAV can serve their travel needs better than conventional vehicles that require a driver. Many of the new AB models incorporate age as an input, so the models can be adjusted to allow younger and older travelers to travel in a private CAV or on-demand CAV. Since current models tend not to identify the population of persons with disabilities, this change could be made to the underlying demographics so that these travelers could have more options in mode choice. Again, the complexities of adding these constraints should be weighed against the additional detail provided.

Routing and Traffic Assignment

Context

Several agencies have been developing DTA methods applied at a regional or corridor scale to improve the commonly deployed static traffic assignments. DTA methods are disaggregate, simulating each vehicle's movement on the road network. Integrating DTA methods with AB models to complete the disaggregate modeling system has been researched for many years. Currently, several test beds are under development but have not yet been used in planning applications.

DTA methods are disaggregate, simulating each vehicle's movement on the road network. DTA is advantageous for evaluating CAVs because simulation can be used to better understand mixed-flow versus CAV-only operations.

DTA is advantageous for evaluating CAVs because the operational characteristics of CAVs are different from those of conventional vehicles. The differences can be simulated to better understand the operational characteristics of mixed-flow and CAV-only operations.

DTA simulations assign vehicles by user class, which can be defined by type of vehicle (e.g., car, truck, CAV), number of occupants, or type of trip (e.g., commute versus discretionary travel). The number of user classes adds complexity and processing time and should be selected to identify the most important characteristics of the infrastructure and policy improvements under consideration. At least two classes are important to understanding new technologies: conventional vehicles and CAVs. If zero-occupant CAVs need to be tracked separately, then another user class for these vehicles can be included.

Approach

DTA can identify different vehicle-following distance and speed characteristics, depending on the level of automation. If these vehicles are traveling in mixed traffic, then overall travel times (i.e., skims) are generated for all vehicles. If separate facilities are considered for CAVs, then it is important to separately track the travel times for CAVs and conventional vehicles.

Given the complexity of DTA models, especially DTA models that are integrated with AB models, there is a benefit to applying the DTA model to simulate operating characteristics for use in regional travel demand models in place of an integrated AB–DTA model. The operating characteristics can then be regressed to estimate functions that do not require simulations (e.g., simulating wait times for a TNC trip as a function of land use density or simulating the freeway speed of a CAV on a congested facility as a function of the speed of a conventional vehicle in a separate lane). This process can be effective in specifying changes in capacity that result from CAV operations and ultimately for redefining volume-delay functions for CAVs that can then be applied in static assignment.

Another area in which DTA models can provide insight is the repositioning of CAVs when not in use. This is also referred to as ZOVs when traveling without a passenger. This repositioning will occur for both privately owned and fleet-operated CAVs. Repositioning to pick up another passenger can be directly simulated from the drop-off and pick-up locations of each passenger. Repositioning that is used to avoid parking costs can be more difficult, as the parking locations for these trips may not be predetermined. Nonetheless, the inclusion of these ZOV trips is critical to understanding congestion in the system. These DTA simulations can offer insight into the performance impact on the transportation system and, in turn, the impact on traveler behavior.

Connected infrastructure, such as V2V or V2I, provides a significantly different set of operating characteristics than conventional vehicles as the percentage of connectivity increases. These operational characteristics can be better understood by simulating different levels of CAV adoption for vehicles and infrastructure. Optimized signal timings or route switching can be simulated to produce functions that describe these operations.

Another area in which DTA models provide additional detail is operations during an accident or other nonrecurring event. Delays associated with nonrecurring events are significant, and CAVs are expected to significantly reduce accidents once human drivers are no longer part of the traffic flow. DTA models can produce the operational improvements that lead to time and cost savings for all travelers as a result of fewer accidents.

Pricing

Context

Pricing has been identified as an important policy approach to encouraging shared AV use (Zmud et al. 2017). Current AB models incorporate pricing as an input for determining whether to travel, where to travel, and how to travel (which mode). These models are iterated to address congestion effects but are typically too time consuming to iterate for dynamic pricing effects.

Current vehicle ownership models do not incorporate pricing as an input since the vehicle type is not critical to the performance outcomes. When households are faced with new mobility choices, it may become more important to recognize purchase cost for vehicles as a trade-off for the cost of using a mobility service.

Approach

As new data on TNC operations and costs become available and new research on traveler choice for these new services is conducted, planners can develop pricing inputs for new modes.

These pricing inputs can approximate dynamic pricing by time period. Since costs for new services are changing rapidly and the cost for CAVs is not yet set, planners should test many different pricing options to evaluate the range of expected outcomes. Modeling of current vehicle purchasing decisions should incorporate cost and demographics to directly represent the importance of cost in determining whether to purchase a CAV or a conventional vehicle and the tradeoff with mobility services as a subscription.

Truck and Commercial Vehicles

Context

Disaggregate microsimulation models for goods movement and commercial vehicles represent the supply chain for products from producer to consumer and pick-up and delivery services to deliver products to their final destination. These freight forecasting models follow a series of sequential steps to simulate commercial vehicle movement:

- Supply chain:
  - Firm synthesis,
  - Procurement markets,
  - Distribution channels,
  - Shipment size and frequency, and
  - Modes and transfers.
- Truck touring:
  - Vehicle and tour pattern choice,
  - Number of tours and stops,
  - Stop sequence and duration,
  - Delivery time of day, and
  - Truck assignment.

Most current models focus on truck assignments. Rail simulation models address operations for carloads, but they are not typically applied in a planning context.

Given the continued driver shortage in the trucking industry and the potential to lift restrictions on driver hours of service, CAVs could dramatically affect the shipment of goods by truck. Current disaggregate models are well positioned to adapt to these changes.

Approach

Current supply chain models do not require any structural changes to represent CAVs. The primary impact will be to adjust the time and cost for trucks, which could in turn increase market share for trucks. Early pilot tests have shown significant cost savings for connected trucks, which can be incorporated as a new input.

Current truck touring models restrict drivers to regulated hours of service, and if regulations change with CAV technology, then the models can adapt to recognize this flexibility. If current models do not recognize this restriction, they should first be adapted to restrict drivers, and then the restriction can be lifted to represent the new rules.

Current truck touring models identify pick-up and delivery services operated by shippers or carriers rather than TNC-style delivery services using noncommercial service vehicles. The use of CAVs and/or drones for pick-up and delivery could shift the vehicle and tour pattern choice models, along with the number of tour and stop models. Truck touring models should be adapted to incorporate this additional source of pick-up and delivery services.

CHAPTER 8

Adapting Strategic Models to Address CAVs

Chapter Highlights

- Provides high-level guidance on accounting for CAVs in the strategic models developed to supplement more sophisticated modeling efforts as screening tools for evaluating policies.
- Depicts the typical strategic model components.
- Identifies potential modeling changes.
- Discusses the contexts and approaches for modeling
  - Sociodemographics,
  - Built environment,
  - Mobility,
  - Accessibility,
  - Pricing,
  - Travel demand,
  - Mode choice, and
  - Truck and commercial vehicles.

Overview

Strategic models for planning have existed in various forms for a long time. Several forms of strategic models for transportation planning have been developed in recent years to address a gap in the technical understanding of an uncertain future. Scenario planning has received additional attention among transportation planners as an appropriate means of evaluating these uncertain futures. Strategic planning models for transportation have been developed to provide more robust statistical evaluation of impacts for transportation scenarios. These models are intended for use as visioning tools, specifically to help guide transportation policies and investments, so planners have adopted a revised name, "strategic visioning frameworks," to emphasize this purpose.

Current strategic visioning frameworks have been developed to address specific transportation policies, such as greenhouse gas reduction strategies or smart growth policies. These resources bridge the gap between regional planning visioning exercises and transportation plans. FHWA, along with several state DOTs, is sponsoring a new pooled fund effort to develop an open-source framework to consolidate these tools and evaluate a broader range of strategies in a consistent modeling system (NCHRP n.d.) TRB also sponsored development of a sociodemographic strategic planning tool (Zmud et al. 2014).

The current strategic visioning frameworks were designed to be faster, allowing for extensive scenario testing. The processing speed is accelerated by not including detailed multimodal transport networks and instead describing the built environment and transportation supply by using aggregate measures. These models are developed and applied as disaggregate models maintaining detailed personal, household, and firm characteristics that influence travel demand, combined with aggregate land use and transport supply measures. The models allow for many (even hundreds of) scenarios to be processed quickly, after which visualizers can help interpret the scenarios interactively to provide a thorough understanding of the impacts derived from various combinations of policies and investments.

Another important feature of strategic visioning frameworks is ensuring that the interaction between different policies or future scenarios is integrated so that population, land use, employment, transport supply, and travel behavior are linked. These linkages are important to understanding how the combination of policies or transport supply or demographics on travel demand can influence each other (and not be double-counted). Sometimes transport policies target similar demographic populations and are more or less effective in combination with other policies. The land use and transport interactions are used to quantify induced demand for travel, which is a critical aspect of uncertain futures.

Strategic visioning frameworks include more complex behavioral representations of travel behavior than do sketch planning tools but are less complicated than integrated land use and travel demand forecasting models.

Model System

Like AB models, strategic models are structured to be able to represent AV policy analysis as well but also require some modifications depending on the questions being asked of the model. Strategic models are currently sensitive to many of the behavioral impacts required and can be adapted to represent changing behaviors. Figure 7 illustrates a typical set of strategic model components.

VisionEval (http://visioneval.org) is an example of a strategic modeling framework that has been used to represent emerging travel modes. Table 8 summarizes the model improvements for various components within strategic models. Strategic models have several components that are relevant to vehicle ownership and availability, including representing vehicle ownership costs (purchase, insurance, operating), bike ownership, vehicle age, and fuel efficiency. In addition, these components can be easily adapted to include carshare and bikeshare membership. Strategic models also incorporate household budgeting, allowing the introduction of AVs into the household budget.

Urban form is currently represented in strategic models as a combination of development and area type (e.g., transit-oriented development in a residential area). These models can be adjusted to incorporate place types that are important for AVs (e.g., parking-constrained areas). Life-cycle variables that define modality choice (e.g., young single adults, families, retirees) can also be incorporated into the urban form and VMT models.

Most strategic models estimate VMT directly, and adjustments for different policies are provided through empirical research. These adjustments can be included for households that optimize their travel with AVs or adjust their trip chaining because the AV can be used to pick up and deliver multiple household members. A new model component for estimating the VMT associated with deadheading (i.e., cars with no occupants that are repositioned or sent to pick up another passenger) could be developed for both privately owned AVs and for-hire AVs. Strategic models also currently evaluate induced demand, but this impact may need to be evaluated once empirical evidence on AV use is documented.

Strategic models do not typically include a traditional mode choice model. Instead, modal shares of interest are directly modeled on the basis of characteristics of supply and demographics. Models can be constructed to directly estimate VMT from for-hire services (e.g., carshare, bikeshare, or TNCs) or other modes that may emerge.

Sociodemographics

Context

Strategic visioning frameworks often begin the process with a population synthesizer such as those developed for AB models and a firm synthesizer similar to those developed for supply chain or tour-based freight models. Characteristics of households, persons, firms, or establishments can vary depending on the model but typically include number of persons and workers by age, life cycle, income for households, and number of employees and industry for firms or establishments. For regional analysis, population synthesis is often controlled by county and

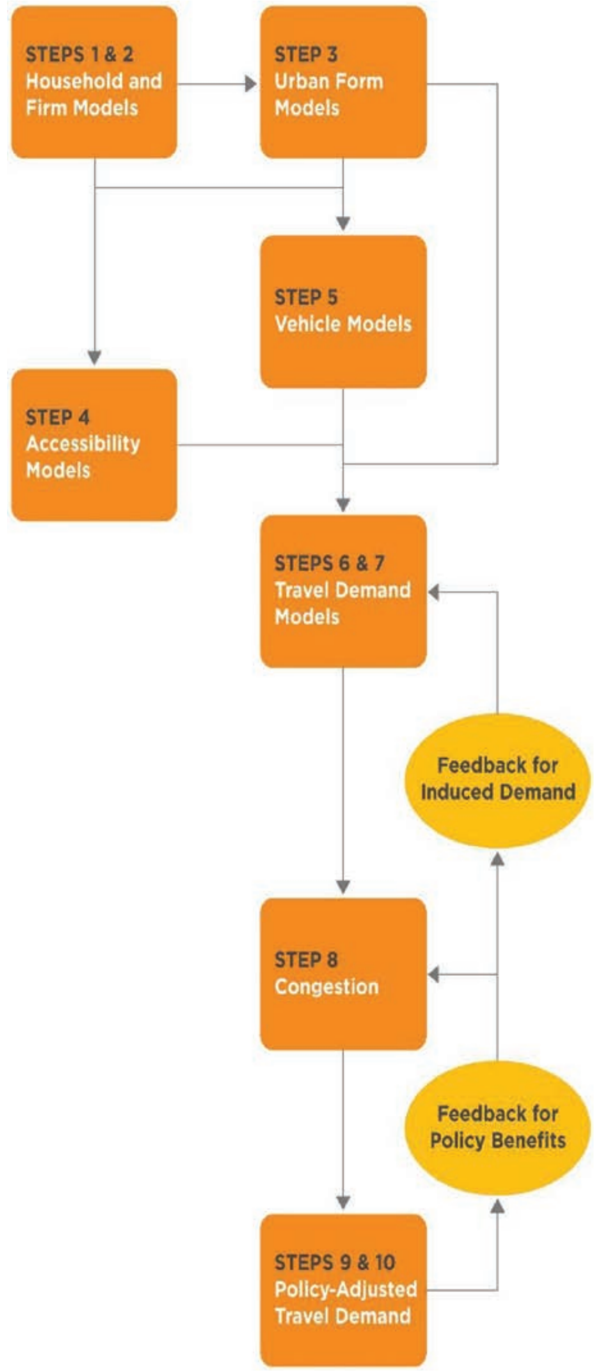


Figure 7. Typical strategic model components.

state control totals. The population is controlled for by household income and age of persons in the household. Per-capita and household income are calculated for each forecast year. A household age model is used to identify persons by age in each household.

Firm synthesis is controlled by regional, county, and state control totals. The County Business Patterns data collected by the U.S. Census Bureau are used to allocate firms to counties by size and type. Other data sources, including Woods & Poole, InfoGroup, and state-produced

Table 8. Summary of model improvements for strategic visioning models.

Model Component	Strategic Model Improvements
Sociodemographics	
Population synthesizer	Add smartphone ownership and education level
Built Environment	
Urban form	Adjust urban form
Urban form	Estimate area type, development type
Mobility	
Vehicle ownership	Add household vehicle ownership costs for CAVs
Vehicle age model	Represent higher turnover for buying CAVs
Vehicle choice	Add household AV choice model for vehicle use
MaaS	Add carsharing, ride-hailing, bikesharing memberships
Accessibility	
Parking supply	Add parking supply
Modal accessibility	Add walking and biking accessibility
Pricing	
Household budgets	Incorporate all aspects of cost for CAVs and MaaS
Parking costs	Segment parking cost
Fuel cost savings	Increase fuel efficiency for CVs and AVs
Car service cost	Model SAV cost
Travel Demand	
VMT model by vehicle type	Adjust VMT for households owning CAVs
VMT model by vehicle type	Add VMT for fleet-owned CAVs
Feedback for congestion	Separate VMT models for AVs and SAVs
Feedback for congestion	Separate VMT models for CAVs
Feedback for induced demand	Add VMT adjustment for induced demand
Household VMT model	Adjust VMT for mobility-limited populations
Mode Choice	
VMT by mode	Add CAVs and TNCs on basis of cost per mile
Truck and Commercial Vehicles	
Mode choice–long haul	Add choice models for current modes and CAVs
Vehicle type–long haul	Add choice model for medium/heavy trucks and CAVs
Vehicle type–short haul	Add choice model for light/medium/heavy trucks and AVs/drones
CV VMT model	Add feedback for congestion

economic forecasts can be used to supplement the data, support forecasts, or provide control totals. Input–output data from the Bureau of Economic Analysis are used to describe what each industry produces and consumes. These relationships are known as make-and-use tables. When multiple commodities are made or used, then the data represent a proportional value. These data tables are used to assign production and consumption categories to the firms synthesized with the County Business Patterns data.

An advantage of the population and firm synthesizers is that additional characteristics can be added when data become available.

Approach

One distinct advantage of the population and firm synthesizers is that additional characteristics of the population or employment base can be added when data become available to control for these characteristics.

One example is the strong relationship between smartphone ownership and other new technologies, such as AVs. The population synthesizer could be adapted to identify smartphone ownership for households, and then that information could be used as an indicator of household adoption of AV technology. Another personal characteristic that influences smartphone ownership (and, possibly, adoption of new technologies) is education level, so this characteristic could also be added to the population synthesizer.

Built Environment

Context

Currently, strategic visioning frameworks include an urban form model that allocates future households and employment to different types of built environment. These data are not located geographically but are based on different area types (urban core, close-in community, suburban, and rural) and different development types (residential, commercial, mixed use, transit oriented, greenfield), as noted in Table 9. These projections can be estimated from available data sets such as the Environmental Protection Agency's Smart Location Database.

Approach

The current urban form models do not include accessibility, so these models are not sensitive to travel time or cost. The household models are based on several demographic characteristics, and the employment models allocate randomly because no data were available to estimate model coefficients. The value of these models for evaluating the impacts of CAVs lies in their ability to provide input on the assessment of on-demand service (e.g., TNCs), in which level of service depends on the area type or the density of an area. This information may also influence adoption rates for CAVs and thus could be used as input to vehicle ownership models. In the long term, there may be evidence that CAV adoption or MaaS could influence residential or employment locations. If data exist to support this assumption, then new urban form models that include CAV adoption or MaaS can be estimated. These models would then be sensitive to changes in CAV adoption or MaaS, and residential and employment locations would vary depending on these assumptions.

Strategic visioning frameworks currently address the influence that changes in parking cost have on travel demand but not on urban form. Parking capacity or access and egress time do not currently influence urban form or travel demand. CAVs are expected to reduce demand for parking in high-density areas, but the cost may increase as parking capacity is repurposed for other land uses. The relationship between parking cost and travel demand will need to be reestimated for CAVs to account for the trade-off between parking cost and operating cost related to repositioning the CAV outside parking charge areas.

Table 9. Place types, by area type and development type.

	Area Type			
Development Type	Urban Core	Close-in Community	Suburban	Rural
Residential	✓	✓	✓	✓
Employment	✓	✓	✓	✓
Mixed use	✓	✓	✓	✓
Transit oriented	✓	✓	✓	✓
Rural/greenfield				✓

Mobility

Context

Mobility models simulate household-level choices to provide mobility options for all persons in the household. These models are primarily focused on household vehicles but also identify AVs, car service subscriptions, and bicycle ownership. These characteristics could be expanded to include transit pass ownership, ride-hailing service participation, or bikeshare subscriptions.

Like trip-based and AB models, the mobility models currently built for strategic visioning frameworks identify the number of household vehicles. Then the household vehicle models assign vehicle type, vehicle age, and powertrain to each vehicle in the household (going beyond what current AB models predict). Powertrains are currently categorized as internal combustion engine, hybrid electric vehicle, plug-in hybrid electric vehicle, and electric vehicle. The model addresses autonomous and conventional carsharing by comparing the cost of using these services with the marginal cost of vehicle ownership to determine which households would use the services and, consequently, how many fewer cars they would own. The marginal cost approach is used because households make choices at the margin (to own one more car or one less car) and because vehicle travel and ownership costs do not scale uniformly (i.e., the second car owned does not double the miles traveled).

Current vehicle ownership models estimate the ratio of household vehicles per driving-age person according to categories of no vehicles, less than one vehicle per driving-age person, one vehicle per driving-age person, and more than one vehicle per driving-age person. The vehicle models are further affected by elderly populations.

Approach

Current vehicle ownership models estimate AV adoption on the basis of the assumed costs of owning or using an AV as compared with a conventional vehicle and a household budget. Adoption rates can then be estimated following application of the vehicle ownership model or can be adjusted by revising the input cost and discount parameters. Another option would be to incorporate an adoption parameter representing a household's preferences for buying an AV.

The cost approach to identifying households who will buy or use AVs is sensitive to the assumed cost of purchasing an AV, the depreciation and interest rates for financing the vehicle, the insurance cost (including a discount for AVs), the registration cost, and a reduced parking cost. These costs are used to estimate a per-mile cost for owning a vehicle and are compared with the same costs for using a car service (both conventional and AV) plus the overhead and cleaning costs and the service life of the vehicle. Again, these costs are translated to a per-mile cost for using these services.

One additional feature of current strategic positioning models is the assessment of greenhouse gases and other particulates on the basis of the vehicle powertrain, age, and type. AVs will likely be more fuel efficient on average, as they will likely constitute a greener vehicle fleet and be more fuel efficient, owing to the built-in optimal driving behavior. CVs will likely be even more fuel efficient under sufficiently saturated conditions, owing to the improved driving behavior afforded by vehicles that communicate with one another. These fuel efficiencies can be directly attributed to the CAVs owned by households and those operated as fleets for carsharing or ride-hailing.

MaaS can be separately represented in strategic visioning frameworks as an additional service to the household. Some TNCs have tried certain types of subscription services, but typically there is no charge to sign up. Nonetheless, typical demographics exist for households that use

TNCs, and with new data on these types of households, mobility models can represent households signing up to use MaaS.

Bikeshare is another option to consider as a mobility model, parallel to the bike ownership model. In general, this new mode may not have enough of an impact to warrant the extra effort to track it separately, but in cities with significant bikesharing, this may be worthwhile.

Accessibility

Context

In strategic visioning frameworks, accessibility is measured on the basis of transport supply and demographics. Transport supply is currently freeway lane miles and transit revenue miles for the base and future years. These measures allow for calculating freeway and transit miles per capita as well as calculating the interaction of freeway and transit miles with household income, population density, elderly populations, and urban form (area type and development type). Accessibility measures are then used to inform the travel demand models.

Approach

The calculation of accessibility should be updated as new modes come online so that these measures can reflect observed behavior for new mobility options and add detail on existing mobility options. Current accessibility measures are based on an individual's perception of the value of time spent traveling, which is likely to change significantly if drivers are no longer required to drive and can use this time to do other things (e.g., working, reading, watching a show). Passengers will likely also adjust their perception of travel time if the driver is now available to engage in other things with the passenger (e.g., playing a game, sharing photos, making travel plans). The parameter estimate for these accessibility measures will reflect these changes in perception.

Accessibility measures should be updated as new modes come online so that these measures can reflect observed behavior for new mobility options.

Parking cost and inventory are aspects of accessibility that have not been incorporated in the current strategic visioning frameworks. These aspects could be included directly or indirectly as additional accessibility measures for specific place types. Parking will potentially change as CAVs allow for parking remotely, and this may result in higher costs for parking in dense urban areas as a result of lower demand.

Accessibility for nonmotorized travel (walking and biking) could be incorporated by providing the supply of nonmotorized facilities (base and future years) and then calculating accessibility for nonmotorized travel. These accessibility measures could be used to influence biking or walking miles, bike ownership, or bikeshare subscriptions, or to reduce or increase household VMT on the basis of changes to nonmotorized supply.

Pricing

Context

One of the benefits of strategic visioning frameworks is the use of a household budgeting model, which can account for the mix of long- and short-term decisions that intersect. The cost of owning a conventional vehicle or AV is typically not considered in travel demand models, but the trade-off between owning (and using) a household vehicle versus using alternative modes, TNCs, or carshare for mobility is becoming more important. Current household budgeting components estimate a household's budget for transport and then, on the basis of this budget, limit choices for owning. In addition, the full cost of driving a household vehicle can be directly incorporated into the mode choice component.

Approach

The elements of the cost function developed for the household budgeting model should be refined to accommodate all aspects of cost that travelers consider. The current household budgeting model can be reestimated for each location and thereby provide locally specific parameters. Research on the elements of the cost function and how to represent new modes like TNCs and carshares with autonomous technology is needed to understand sensitivities. Household budgets limit the amount each household can spend on transportation. Each mode has a cost associated with its use. Ownership costs include depreciation, financing, insurance, vehicle licensing or registration, and parking cost. Operating costs include fuel, tire, and maintenance costs.

Travel Demand

Context

Strategic visioning frameworks predict travel demand on the basis of a variety of factors, directly from the household and firm characteristics as well as from the transport supply and policies specified. Current models identify household VMT and commercial VMT as a starting point and then adjust these measures on the basis of the influence of various transport policies (i.e., travel demand management programs, nonmotorized travel, ecodriving). The nonauto modes are addressed in this chapter under the topic of mode choice, and commercial vehicle travel is addressed under the topic of trucks and commercial vehicles. The remainder of this section focuses on auto VMT.

Average daily VMT is predicted in strategic visioning frameworks by estimating total daily VMT and then allocating it to freeways and arterials. These allocations are then used to determine congestion levels for freeways and arterials as well as average speeds for these facility types. Congestion levels are then fed back to travel demand models to allow for equilibration of daily VMT. Congestion that arises from local street grids owing to different types of development, is also accounted for. Currently, street grids are identified according to design: either a neotraditional (grid) street design or a conventional (public utility district) network design.

Induced demand for auto travel is determined as a function of future changes in the transportation system, and adjustments to estimates of travel demand are made to reflect the effects of changes in the urban form of the region in the future. The sensitivity of the model to induced demand and urban form effects is based on work completed by Cervero (2003) for the Path Model. Induced demand is currently a result of changes to the transportation system supply.

Approach

The flexibility of strategic visioning frameworks offers advantages for modeling travel demand for different segments of the population or for different facilities (freeways, arterials, other). VMT is currently predicted for different vehicle powertrains and for households owning AVs. This VMT is then allocated to different vehicle types according to household vehicle ownership. Current research simulating VMT for household-owned AVs can inform these models and account for deadheading (e.g., empty vehicle trips) to reposition the vehicle for the next passenger (or household member).

VMT will also likely change when enough CAVs are on the road to make better use of existing capacity and, as a result, increase speeds. Intersection delay may also be significantly reduced with sufficient CV market share. These changes may ultimately increase VMT, so changes to VMT by mode, vehicle type, and other relevant dimensions can be added to strategic visioning frameworks to account for these impacts. Another advantage of the direct demand approach is that AVs will improve mobility options for those who currently cannot drive because of age, physical disability, or income (Levinson 2015). VMT that results from these new populations choosing auto modes can be estimated and included.

New research offers insight into how AVs will induce demand, showing that VMT could increase more than 80% from additional trip making, traveling farther, and zero-occupant trips.

The question of how AVs will induce demand is a concern for many planners. Significant speculation about how AVs will both reduce and increase VMT exists. Current escorting travel (i.e., driving a child to school) could be reduced because these trips may be chained together to serve multiple passengers or purposes. New research from the University of California, Berkeley (Harb et al. 2017) shows that VMT could increase more than 80% from travelers making additional trips, traveling farther, or sending the car to pick up deliveries. The calculation of induced demand in strategic models is estimated as an elasticity and applied within the feedback for congestion and transportation policy influences. The household budgeting model also constrains VMT, since there is a cost to each mile traveled.

Mode Choice

Context

Strategic visioning frameworks typically predict miles traveled for each mode separately, rather than as a probability of choosing a certain mode for each trip. These are aggregate predictions of miles traveled for each mode and household. Currently, these models estimate walking trips and miles traveled for bikes/lightweight vehicles and autos. Bike and auto travel sum to total daily miles traveled. Walking trips are separated to evaluate the impacts of transportation and land use policies on walking travel. Bus and rail VMT is also calculated. Auto VMT is assigned to each household vehicle (manual and autonomous), and carsharing is an option for a portion of household miles traveled.

Mode choice is handled in several different ways in strategic visioning frameworks. VMT is estimated directly for SOV travel and for total household vehicle travel. Levers for estimating VMT reduction from travel demand management policies or bicycles exist. VMT is further assigned to each household vehicle. Bus and rail miles traveled are estimated separately.

Approach

Recent changes were made to one of the strategic visioning frameworks to incorporate CAVs and ride-hailing services that TNCs provide. This model calculates a per-mile cost for each household vehicle that incorporates purchase price and operating cost. The car service option also has a per-mile cost to use the car service, and this cost is segmented for autonomous and conventional vehicles. Additionally, the model calculates a per-mile cost for CAVs that incorporates purchase price and operating cost. Ride-hailing services (e.g., TNCs) can also be included with a per-mile cost, which can be adapted to represent two options: ride-hailing in a conventional household vehicle and ride-hailing in a shared conventional household vehicle. While it is possible to expand ride-hailing services according to whether they are shared, this expansion is likely too complex for current strategic visioning frameworks, given the uncertainty involved in these new services.

Strategic visioning frameworks rely on elasticities to estimate impacts for a model component, and these impacts are integrated so that other parts of the modeling system are influenced. Elasticities are typically derived from observed data but can also be derived from a range of assumptions. Strategic visioning frameworks are intended for use as scenario planning tools, and applying a range of assumptions to determine the range of impacts they produce is encouraged.

Trucks and Commercial Vehicles

Context

The three primary elements to the truck and commercial vehicle models in current strategic visioning frameworks are

- Commodity flows,
- Mode choice for long distance, and
- Vehicle type for short distance.

Commodity flows are developed by identifying firms that buy or sell goods in each industry and matching firms that will trade goods on the basis of their distance apart and the size of each firm. Input–output tables provide direction for allocating goods demand to each buyer–supplier pair on the basis of the employment of the buyer firm. An estimate of consumption (of the commodity being consumed) by a buyer firm is calculated on the basis of the value (in dollars) consumed per employee, which is obtained with input–output economic tables.

Commodity flows are then segmented by long-distance or interstate movements and short-distance or intrastate movements. Interstate trips are assigned to modes (air, rail, and truck). Mode choice is completed with a fixed allocation model with historical average mode proportions by commodity type found in the Freight Analysis Framework data for the Freight Analysis Framework zone pair and commodity in question. Intrastate trips are assigned to one of two truck types: heavy or medium. This assignment is based on commodity type and volume according to Vehicle Inventory and Use Survey data. Any unobserved heavy truck VMT in the model as compared with Highway Performance Management System data is presumed to reflect unmodeled through trips (e.g., empty truck movements or backhauls). Any unobserved medium truck VMT in the model as compared with Highway Performance Management System data is assigned to pick-up and delivery trips.

Approach

Current vehicle type models in strategic visioning frameworks apply fixed factors to predict medium and heavy trucks. A choice model would add sensitivity to new technologies. Drones could change the pick-up and delivery systems for medium trucks. Connected heavy trucks could reduce time and cost for long-distance movement of goods. AVs may avoid the problem of driver shortages, which have constrained growth in the trucking industry, and hours-of-service regulations may change if drivers are no longer needed as much or are not required to drive (but remain in the vehicle for pick-up and delivery purposes). New technologies will undoubtedly affect the choice that suppliers make about which vehicle type should be used to deliver goods.

Current freight mode choice models represented in strategic visioning frameworks apply fixed factors. A choice model would add sensitivity to expected reductions in trucking costs with the CAV technology so that modal shares could reflect the resulting modal shifts. Data from the Commodity Flow Survey, in combination with national multimodal networks and assumptions about CAV mode shares, could be used to estimate a freight mode choice model.

CHAPTER 9

Communicating in an Uncertain Environment

Chapter Highlights

- Provides guidance for how transportation planners and modelers can communicate about the uncertain future.
- Distinguishes certainties from uncertainties in a CAV future and presents tips for talking about both.

As the transportation planning industry strives to find ways to anticipate impacts under highly unstable conditions, planners and modelers are also challenged to communicate this uncertainty to senior decision makers and elected officials without the information appearing useless and without providing projections that appear more solid than they are. Billions of dollars of investments are at stake.

How does a responsible planning or modeling professional present forecasts that are steeped in uncertainty without leaving decision makers in high-risk situations and leaving stakeholders suspicious? Conversely, when decision makers, businesses, or citizens are certain that they know the best options for future investment, how do planning professionals constructively educate them so that they internalize that their certainty is unfounded? Saying "I just don't know, but this is the best I can come up with" is not useful. Likewise, saying "I do know" is highly suspect and potentially unethical. How can transportation professionals effectively communicate in these difficult and changing times? This section explores ways to leverage advances in neuroscience to provide enhanced communication that benefits decisions makers and planners.

Decision-Making Continuum

In making decisions, executives and leaders have a continuum of options:

- **No-brainer decisions:** These are decisions that have been made many times before. They have a been-there-done-that quality. Because the future is like the past, there is little risk and little new thought is required.
- **Calculated decisions:** These are complicated decisions that can be calculated. Again, the future is like the past, so historical experiences assist in calculating a future state with reasonable certainty. Calibrated models support these kinds of decisions in transportation planning.
- **Nuanced decisions:** These are the decisions for which data alone are not enough. Data and analysis are only two of the inputs into a nuanced decision. Nonquantitative factors must also be considered. Politicians and executives inhabit this world and routinely make decisions with this level of uncertainty and risk.
- **Decisions in uncertainty:** These are decisions made during periods of deep change. Hindsight does not lead to foresight. Data provide minimal assistance. It is an uncertain and unnerving time. This is the world in which transportation professionals live when it comes to AVs and their impacts. Modeling is of limited value, past experience is of little use, and the future is not yet clear.

Planners, modelers, and leaders work inside this framework. Due to confirmation bias (a shortcut in the brain in which new information tends to be interpreted as confirmation of existing beliefs and habits), they will try to force the changing world into their old framework. For example, planners and modelers historically work with calculated decisions. For years, models have used reasonably accurate data to provide realistic predictions of a future state. Past was indeed prologue.

Transportation planners and modelers are challenged not only to finds ways to anticipate impacts under highly unstable conditions but also to communicate the uncertainty to decision makers and policy makers.

During uncertainty, planners and modelers naturally seek more data because doing so fits their mental model. Given their habits, they expect decisions to be calculated and will attempt to use models even when data do not exist to support them. Otherwise, they are likely to feel uncomfortable, which leads to reluctance to communicate with leaders.

Leaders—particularly those with a political background—live with nuanced decisions. Each day they face decisions in which data are an input but not necessarily the basis for the decision. They understand the role of appearance, positioning, and juggling political risks. Trust is their currency. They must maintain the trust of their constituents and colleagues, whose support they need. They are likely to be comfortable in an uncertain environment because, for them, uncertainty is normal. Their confirmation bias will cause them to view the implications of AV impacts from the perspective of risk, perception, and messaging.

Today, however, planners, modelers, and leaders are being thrust into decision making in deep uncertainty. Research in the field of neuroscience holds tips that provide a framework for communicating during times of deep uncertainty.

Talking About Uncertainty

Simply put, the brain can be understood as having two electrical circuits: reward and threat. The threat circuitry (via the amygdala) is more easily activated, is faster, and influences behavior and reactivity quickly. With the slightest provocation, the threat circuit is set into motion. There are five ways to activate either the threat or the reward circuits (Rock 2008), two of which are most relevant here: certainty–uncertainty and control–lost control. The intent is to present information to leaders in such a way that the reward circuitry is maximized and the threat circuitry is minimized. The goal is to intentionally communicate what is certain while being clear about uncertainty and to emphasize where there is control while being honest about where there is no control.

Certainty: What We Know

When communicating with leaders, a planner or modeler can discuss that for which there is reasonable certainty. For example, the planner or modeler knows transportation trends, observes investment patterns for AV technology, and can make reasonable estimates of high- and low-risk transportation investments. While being careful not to overstate the surety of transportation trends, planners and modelers generally know there is

- Growth of the sharing economy,
- Decline of auto ownership among younger adults, and
- Preference for mixed-use communities in many urban areas.

They can observe that the AV industry

- Is motivated by the private sector,
- Receives heavy private investment in AV technology from large companies, and

- Has automotive companies positioning for a shifting auto ownership model and the growth of transportation network providers.

Additionally, not all transportation investments carry equal risk. Low-risk investments are those that are unlikely to be heavily affected by AV technology over the investment's life span. They may include

- Resurfacing and rehabilitation of existing roadways and bridges,
- Projects within existing right of way,
- Updating of traffic signal systems, and
- Projects that can be completed quickly and have a short life span.

In short, reasonable certainty that AVs are on their way exists, and the planning and modeling communities can provide guidance on the features and project types that are low risk and that can proceed without undue concern.

Uncertainty: What We Do Not Know

Today, many unknowns about AVs and their impacts exist. To maintain trust with decision makers and policy makers, it is essential to be honest and straightforward about uncertainties. For example, for AVs, there is uncertainty about

- The specific time horizon for AV entrance into the market,
- The split between fleet and private ownership,
- Market acceptance,
- The speed of market penetration, and
- The impact on travel (more or less VMT).

These unknowns create high-risk investments that may be significantly affected by AVs and have high costs and long life cycles. These projects require more deliberation and may lend themselves to an incremental decision-making approach.

High-risk investments may include

- Extensive right-of-way purchase in an urban area;
- Long-term agreements for operation of roadways or parking structures;
- Large-scale widening projects, particularly in urban areas;
- Large-scale transit projects in urban areas;
- Projects that have a project development period; and
- Projects that have a long life span.

Control: What We Have Control Over

Decision makers and policy makers have more control than they may think, and planners and modelers can assist by highlighting these areas when communicating with them. Decision makers control

- Which projects to support and when;
- The way they move forward, such as
  - Proceeding with low-risk projects,
  - Implementing exploratory projects, and
  - Increasing their options by inserting incremental decision points into high-risk projects;
- Which policies to implement and when; and
- Development of messaging plans for high-risk investments.

Control: Where to Take Control

Decision makers and policy makers can create control by adding flexibility to high-risk projects in the form of incremental decision points, thereby reducing the risk. At each decision point in the project development process [programming; start of the environmental process; and start of plan, specification, and estimate (PS&E) development immediately prior to letting], the project can be reassessed to determine whether revisions are needed on the basis of the evolution of the AV environment.

Choose Words Carefully

Fundamental to responsible communication during deep uncertainty is planners' choice of language. Prior to communicating information on AVs and other related advances, planners must be prudent in considering word choice. Planners and modelers should be cognizant of the differences between fact and conjecture and between certain and probable, so that they avoid predictions and bias toward assuredness.

Examples include the following wording:

1. **Overly assured:** "The results of the modeling show that AVs will impact. . . ."
   More accurate: "We were simply exploring what might be possible, given how the models are calibrated with today's data."
2. **Overly assured:** "The information from the survey says that the outcome will be. . . ."
   More accurate: "As with all human behavior, choices could change when people actually get accustomed to the technology."
3. **Overly assured:** "The media report that company X's AVs will be on the road very soon."
   More accurate: "Please note that, although what is trending in the media is encouraging, there remain many issues to be resolved."
4. **Overly assured:** "As a planner, I am excited about the potential positive changes we can make with this new technology."
   More accurate: "Given what I just presented, we must be aware that the technology is possible, and it is probable that it will develop to maturity, but our expectations of impacts will take much more time to be proven."

Planners and modelers can (and must) be effective communicators to executives and leaders during this time of deep uncertainty. They do so by (*a*) being aware of the differences in decision-making approaches, (*b*) consciously framing their comments to leverage certainty versus uncertainty and control versus no control in their discussions, and (*c*) choosing words responsibly and carefully.

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List of Acronyms

AB	activity based
ADS	automated driving system
AV	automated vehicle
CAV	connected and automated vehicle
CV	connected vehicle
DAPP	Dynamic Adaptive Pathways Planning
DOE	Department of Energy
DOT	department of transportation
DSRC	dedicated short-range communications
DTA	dynamic traffic assignment
FHWA	Federal Highway Administration
FMVSS	Federal Motor Vehicle Safety Standards
GHG	greenhouse gas
GPS	global positioning system
IEEE	Institute of Electrical and Electronics Engineers
lidar	light detection and ranging
MaaS	mobility as a service
MPO	metropolitan planning organization
NCSL	National Conference of State Legislatures
NHTSA	National Highway Traffic Safety Administration
OEM	original equipment manufacturer
PMT	passenger mile traveled
RDM	robust decision making
SAV	shared autonomous vehicle
SOV	single-occupant vehicle
TAZ	traffic analysis zone
TNC	transportation network company
UE	user equilibrium
U.S. DOT	U.S. Department of Transportation
V2I	vehicle-to-infrastructure
V2V	vehicle-to-vehicle
V2X	vehicle-to-everything
VMT	vehicle mile traveled
VOT	value of travel time
ZOV	zero-occupant vehicle

APPENDIX

Regulatory Context for CAVs

The regulatory context for CAVs is addressed at the federal level by NHTSA through guidance and by Congress through legislation, and at the state level through legislation. Recent activities at both levels are presented below.

NHTSA Guidance on AVs

In September 2016, the U.S. DOT published a federal automated vehicle policy via NHTSA that took initial steps toward a unified, national regulatory framework for AVs. Then, in September 2017, NHTSA issued *Automated Driving Systems 2.0: A Vision for Safety* (NHTSA 2017), which replaced the earlier policy framework. The 2017 framework was divided into two sections. The first offered voluntary guidelines for the AV industry in designing best practices for testing and deployment of AVs. It covered vehicles that incorporate SAE Levels 3–5, or highly automated vehicles. The policy framework did not carry a compliance requirement or enforcement mechanism. Instead, it offered suggestions on 12 priority safety design elements and encouraged industry participants to perform voluntary safety self-assessments that demonstrate their approach to testing and deployment. The voluntary safety self-assessments were intended to build public trust in AVs and encourage the establishment of industry safety norms.

The second part of NHTSA guidance clarified NHTSA versus state responsibilities vis-à-vis automated driving systems (ADSs) (see Table A-1). NHTSA regulates motor vehicles and motor vehicle equipment, while states are responsible for regulating the human driver and most other aspects of motor vehicle operation. NHTSA also recommended that states adopt four safety-related types of legislation:

- A technology-neutral environment—all organizations meeting federal and state law prerequisites should be able to test vehicles in a state;
- Licensing and registration procedures;
- Reporting and communications methods for public safety officials; and
- Reviews of traffic laws and regulations that could be barriers to ADS testing and deployment.

In 2018, the U.S. DOT plans to release a third iteration of the guidance, AV 3.0. While the 2017 policy framework was focused on passenger vehicles, the 2018 policy guidance is expected to cover all modes of transportation, including public transit, rail, commercial trucks, and aviation.

NHTSA Action on CVs

Federal regulatory action for CVs has focused on V2V technology. In August 2014, NHTSA issued an advance notice of proposed rulemaking to begin implementation of V2V communications technology. Then in January 2017, NHTSA issued a proposed rule to establish new FMVSS

Table A-1. Federal and state regulatory roles.

NHTSA's Responsibilities	States' Responsibilities
Setting FMVSS for new motor vehicles and motor vehicle equipment	Licensing human drivers and registering motor vehicles in their jurisdictions
Enforcing compliance with FMVSS	Enacting and enforcing traffic laws and regulations
Investigating and managing the recall and remedy of noncompliance and safety-related motor vehicle defects nationwide	Conducting safety inspections, where states choose to do so
Communicating with and educating the public about motor vehicle safety issues	Regulating motor vehicle insurance and liability

Note: FMVSS = Federal Motor Vehicle Safety Standards.

to mandate V2V communications for new light vehicles and to standardize the message and format of V2V transmissions. FMVSS are federal regulations specifying design, construction, performance, and durability requirements for motor vehicles and regulated automobile safety-related components, systems, and design features. As a purported rationale for the rulemaking itself, NHTSA's 2017 proposed rule stated that "without a mandate, manufacturers would not be able to move forward in an efficient way and that a critical mass of equipped vehicles would take many years to develop." However, as of 2018, such rulemaking has not advanced. In November 2017, NHTSA issued a statement that it had not made any final decision on the proposed rulemaking concerning a V2V mandate. The CAV industry is moving forward regardless of the rulemaking.

Congressional Action

In September 2017, the House of Representatives passed the SELF DRIVE Act, and the Senate followed by passing the AV START Act in October 2017. These acts respond to calls for regulatory changes at the federal level to promote the development of AV technology. Both seek to preserve the existing regulatory approach to vehicle safety while making modest changes to accommodate self-driving technologies. Both expand federal preemption of state authority over AVs by prohibiting state and local governments from legislating in the areas of vehicle design, construction, or performance, thus suggesting that state and local regulations should be focused on traditional state-regulated areas like registration, licensing, insurance, and traffic laws.

The two acts take different approaches to privacy and cybersecurity. The SELF DRIVE Act stipulates that a manufacturer may not market a highly automated AV unless that manufacturer has developed a privacy plan and a cybersecurity plan that identifies, mitigates, and prevents privacy and cybersecurity vulnerabilities. The AV START Act establishes a Data Access Advisory Committee to produce a report to Congress with policy recommendations on ownership and control of data generated or stored by AVs. The AV START Act does require that manufacturers have a detailed plan for identifying and reducing cybersecurity risks.

State Legislature Action

State legislatures are becoming increasingly engaged with the topic of AVs and are considering how best to regulate on the topic, spurred in part by NHTSA's *Automated Driving Systems 2.0: A Vision for Safety*. The National Conference of State Legislatures' (NCSL) Autonomous Vehicles Legislative Database provides current information on state legislative efforts targeting AVs (http://www.ncsl.org/research/transportation/autonomous-vehicles.aspx). According to NCSL, 41 states and the District of Columbia have considered legislation related to AVs since 2012, and of those, 22 states (Alabama, Arkansas, California, Colorado, Connecticut, Florida, Georgia, Illinois, Indiana, Louisiana, Michigan, Nevada, New York, North Carolina, North Dakota, Pennsylvania, South Carolina, Tennessee, Texas, Utah, Virginia, and Vermont) and the District of Columbia have passed legislation. Also, governors in Arizona, Delaware, Massachusetts, Washington, and Wisconsin have issued executive orders related to AVs. In general, the executive orders support study, assessment, and preparation for the widespread adoption of CAVs.

The regulatory context for AVs in the states is as dynamic as it is varied. Legislation and executive actions have been state specific, with no attempt at coordination across states, thus prompting the congressional action discussed previously that attempts to provide a national policy framework. A brief summary of state regulation based on information from NCSL and the Council of State Governments follows.

- A few states have only addressed truck platooning in legislation.
  - Alabama: 2018 legislation establishes a legal definition of a truck platoon and exempts the trailing trucks in a truck platoon from the state's "following too closely" provisions if the truck platoon is engaged in electronic brake coordination.
  - Arizona: More than 600 self-driving cars are reportedly being operated on public roads in Arizona. Waymo has received permits to operate a ride-hailing service without human drivers. Arizona suspended Uber's self-driving vehicle tests after a fatal accident in that state in March 2018.
  - Arkansas: 2017 legislation regulates the testing of vehicles equipped with driver-assistive truck platooning systems.
  - South Carolina: 2017 legislation specifies that laws on minimum following distance for vehicles traveling along a highway do not apply to the operator of any nonleading vehicle traveling in a platoon.
- In many states, legislation only enables testing on public roads or studies to examine the enabling of testing or use of AVs.
  - Connecticut: 2017 legislation requires the development of a pilot program for up to four municipalities for the testing of fully automated vehicles on public roads. It specifies the requirements for testing, including having an operator seated in the driver's seat and providing proof of insurance of at least $5 million.
  - Indiana: Lawmakers have been working on legislation to establish a certification system (i.e., set safety and other standards) for driverless cars.
  - Maryland: The Hogan administration is making available permits for the testing of CAV technology. The first permits were issued to a Howard County company to allow testing at parking lots owned by the Maryland DOT.
  - Minnesota: An executive order issued in March 2018 establishes an Advisory Council on Connected and Automated Vehicles to study, assess, and prepare for the opportunities associated with the widespread adoption of CAVs.
  - Nebraska: Lawmakers are considering two AV-related bills. One allows AVs on state roads and highways but still requires testers to be able to continuously monitor them and take control of the vehicle if necessary. The second allows researchers to test AVs only in Lincoln.
  - New York: 2017 legislation allows the commissioner of motor vehicles to approve AV tests and demonstrations.
  - North Dakota: 2017 legislation requires the DOT to study the use of vehicles equipped with ADSs on highways and the data or information stored or gathered by the use of those vehicles.
  - Ohio: An executive order signed in January 2018 creates a statewide center for AV research and smart road technology called DriveOhio.
- In other states, legislation enables the use of an ADS on public roads and requires a human driver to be in the vehicle.
  - Colorado: 2017 legislation allows a person to use an ADS to drive or control a function of a motor vehicle if the system is capable of complying with every state and federal law. The

Colorado DOT is considering a congestion-relief plan for Denver's western suburbs that could include a dedicated lane for AVs.
  - Georgia: 2017 legislation exempts a person operating an automated motor vehicle with the ADS engaged from the requirement to hold a driver's license.
  - District of Columbia: 2012 legislation requires a human driver to be in the vehicle and be prepared to take control of the vehicle at any moment. DC is currently inviting companies to test AV technology on one street that connects the new Wharf waterfront plaza development to the National Mall.
  - Illinois: 2017 legislation preempts local authorities from enacting or enforcing ordinances that prohibit the use of vehicles equipped with an ADS.
- Some states have recently removed requirements that a human driver should be behind the wheel at all times.
  - Arizona: A 2018 executive order removes a requirement that a human driver be behind the wheel of an AV at all.
  - California: In March 2018, state officials announced that fully driverless cars (i.e., no human driver inside) will be allowed on public roads; however, a remote operator is required to monitor the vehicle as it is being tested on public roads. Companies wishing to test must seek permission from law enforcement and provide them with the routes the cars will take.
  - Florida: 2016 legislation expands on that of 2012, allowing the operation of AVs on public roads and eliminating requirements for the testing of AVs and the presence of a driver in the vehicle.
  - Michigan: The state enacted a series of laws in 2016 that authorize further testing and use of AVs on all public roads. The laws were some of the first to permit the operation of AVs without a human driver.
  - Nevada: 2017 legislation allows the use of driver-assistive platooning technology on highways in the state. It also permits the operation of fully automated vehicles in the state without a human operator in the vehicle and specifies that the original manufacturer is not liable for damages if a vehicle has been modified by an unauthorized third party.
  - North Carolina: 2017 legislation establishes regulations for the operation of fully automated vehicles on public highways and specifies that a driver's license is not required for an AV operator. It requires that an adult be in the vehicle if a person under 12 is also in the vehicle.
  - Tennessee: 2017 legislation permits ADS-operated vehicles on streets and highways without a driver in the vehicle if it meets certain conditions. ADS-operated vehicles are exempt from licensing requirements. The ADS is considered a driver for liability purposes when it is fully engaged and operated properly.
  - Texas: 2017 legislation allows an automated motor vehicle to operate in the state regardless of whether a human is present in the vehicle as long as certain requirements are met, and it specifies that the owner of an ADS is the operator of the vehicle when the system is engaged. The system is considered licensed to operate the vehicle.
  - Utah: A 2018 bill passed by the House Transportation Committee and sent to the full House in March allows AVs on all roads and creates somewhat different rules, liability, and insurance requirements for different levels of autonomy.

As the technology for AVs continues to develop, state legislation will continue to evolve to address the potential impacts of these vehicles on the road.

Abbreviations and acronyms used without definitions in TRB publications:

A4A	Airlines for America
AAAE	American Association of Airport Executives
AASHO	American Association of State Highway Officials
AASHTO	American Association of State Highway and Transportation Officials
ACI–NA	Airports Council International–North America
ACRP	Airport Cooperative Research Program
ADA	Americans with Disabilities Act
APTA	American Public Transportation Association
ASCE	American Society of Civil Engineers
ASME	American Society of Mechanical Engineers
ASTM	American Society for Testing and Materials
ATA	American Trucking Associations
CTAA	Community Transportation Association of America
CTBSSP	Commercial Truck and Bus Safety Synthesis Program
DHS	Department of Homeland Security
DOE	Department of Energy
EPA	Environmental Protection Agency
FAA	Federal Aviation Administration
FAST	Fixing America's Surface Transportation Act (2015)
FHWA	Federal Highway Administration
FMCSA	Federal Motor Carrier Safety Administration
FRA	Federal Railroad Administration
FTA	Federal Transit Administration
HMCRP	Hazardous Materials Cooperative Research Program
IEEE	Institute of Electrical and Electronics Engineers
ISTEA	Intermodal Surface Transportation Efficiency Act of 1991
ITE	Institute of Transportation Engineers
MAP-21	Moving Ahead for Progress in the 21st Century Act (2012)
NASA	National Aeronautics and Space Administration
NASAO	National Association of State Aviation Officials
NCFRP	National Cooperative Freight Research Program
NCHRP	National Cooperative Highway Research Program
NHTSA	National Highway Traffic Safety Administration
NTSB	National Transportation Safety Board
PHMSA	Pipeline and Hazardous Materials Safety Administration
RITA	Research and Innovative Technology Administration
SAE	Society of Automotive Engineers
SAFETEA-LU	Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (2005)
TCRP	Transit Cooperative Research Program
TDC	Transit Development Corporation
TEA-21	Transportation Equity Act for the 21st Century (1998)
TRB	Transportation Research Board
TSA	Transportation Security Administration
U.S.DOT	United States Department of Transportation

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