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Travel Demand Modeling and the Assessment of Environmental Impacts

A Literature Review

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16. Abstract
The purpose of this literature review is to assess what is currently known about the ability of travel demand forecasting models (TDMs) to provide accurate forecasts for different types of transportation plans and projects with respect to different outcome measures of interest. The role of TDMs in assessing the implications of highway expansions for vehicle miles of travel (VMT) and greenhouse gas (GHG) emissions is of particular interest given the current regulatory context. Relevant studies for this review were found using a variety of search terms in the Transport Research International Documentation (TRID) database and Google Scholar. The report reviewed the available studies with respect to the themes of limitations of the models, validity testing and sensitivity testing, and VMT forecasting.

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Travel Demand Modeling and the Assessment of Environmental Impacts: A Literature Review

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INTRODUCTION

Metropolitan Planning Organizations (MPOs) and other agencies rely on travel demand models (TDMs) to forecast the outcomes that will result from changes in the transportation system. The outcomes of proposed projects, such as highway expansions, must be evaluated in the environmental review process under the National Environmental Protection Act (NEPA) and, in California, the California Environmental Quality Act (CEQA). Under federal policy, the outcomes of long-range transportation plans required of Metropolitan Planning Organizations (MPOs) as well as state Department of Transportation (DOTs) must also be evaluated. These analyses historically focused on level of service, a measure of congestion on a roadway, but agencies are increasingly concerned with other important outcomes. In California, under Senate Bill 375 (Steinberg, Chapter 728, Statutes of 2008) and Senate Bill 743 (Steinberg, Chapter 386, Statutes of 2013), agencies must analyze the impacts of plans and projects on vehicle miles traveled (VMT) and greenhouse gas (GHG) emissions. Other outcomes of interest in California and elsewhere include safety, noise, and health and the equity implications of all these outcomes. Forecasts of these outcomes are essential inputs to planning and project selection processes to ensure that benefits outweigh environmental and societal costs.

The TDMs used today by state DOTs and MPOs to forecast the outcomes of plans and projects are an improvement over the first TDMs developed in the 1950s and 1960s, but they are not perfectly suited to their mission. One issue is that they are not capable of analyzing certain kinds of projects, for example, bicycle and pedestrian facilities, and they do not provide forecasts of many of the outcomes of interest to agencies, safety most notably. In other words, TDMs provide only a portion of the information agencies need. Another issue is the potential inaccuracy of the forecasts, whether attributable to inherent biases stemming from the construction and calibration of the model or to the influence of staff decisions about input data and parameter values. A growing body of evidence suggests that TDMs produce inaccurate forecasts. For example, a study by Volker et al. (2020) shows that TDMs typically underestimate the increase in vehicle miles of travel induced by increases in highway capacity, often quite substantially (Volker et al., 2020). Other studies have identified structural shortcomings in TDMs, with important and problematic implications (Marshall, 2018).

The purpose of this literature review is to assess what is currently known about the ability of TDMs to provide accurate forecasts for different types of plans and projects with respect to different outcome measures of interest. The role of TDMs in assessing the implications of highway expansions for VMT and GHG emissions is of particular interest given the current regulatory context (Deakin et al., 2020; Volker et al., 2020). The methodology used to identify relevant papers is first described, followed by important background on TDMs in use today. Subsequent sections review limitations of the models, explain validity testing and sensitivity testing, and discuss the specific topic of VMT forecasting.

METHODOLOGY

Relevant studies for this review were found using the Transport Research International Documentation (TRID) database and Google Scholar. The search terms, "travel demand model (or modeling)," "travel forecasting," and "regional transportation planning" were used as fixed key search terms. Terms such as "induced travel (or induced travel effect)," "vehicle miles traveled (or VMT)," "air quality," "emissions," "land use," "transportation policy (or policymaking)," "transit," and "public transportation" were combined with the fixed key search terms to specify the policies of interest to transportation agencies. The research team focused on peer-review journal articles but several items from "gray literature"—such as technical guidelines by Caltrans, professional reports (e.g., NCHRP or TCRP reports from the TRID database), book chapters, conference papers, and webpages—were also identified as relevant to the review of empirical research on the question of the ability of TDMs to forecast induced travel. Various combinations of these search terms led to the identification of 86 relevant items—68 peer-reviewed journal articles and 18 items from the gray literature—after removing redundant items and screening each item for relevance.

The relevant items were reviewed with respect to the following questions:

- What are the roles of TDMs in transportation planning and environmental review processes?
- What characteristics of TDMs limit their usefulness in these processes?
- What are current practices with respect to validity testing and sensitivity testing of the forecasts that TDMs produce?
- How are TDMs being used to assess the impact of highway capacity on VMT?

TRAVEL DEMAND MODELS

Travel demand models (TDMs) are calibrated using data about current travel patterns and are used to forecast future travel patterns (Miller, 2020). They can be used to create and compare different transportation policy scenarios by adjusting model inputs as well as model parameters (Franklin et al., 2002; Malayath & Verma, 2013). These models generate forecasts of travel demand choices and transportation system performance (Davidson et al., 2007). Such forecasts are indispensable for policymakers in evaluating proposed road network improvements and other targeted infrastructure investments (Michael, 2016; Transportation Research Board, 2007). They are an important tool for assessing the degree to which such investments will help an agency achieve its goals, including congestion reduction and air quality improvements (Handy, 2008).

The original TDMs were developed for the purpose of determining the need for additional highway capacity given expected population and economic growth, with the goal of maintaining acceptable levels of congestion. This remains a primary purpose for today's models, though they are also used for broader array of purposes (Handy, 2008). Regardless of the type of model (as described below), key inputs to the model include representations of the future transportation network and future land use patterns. Traditionally, future land use patterns were taken as a given, and the model was used to forecast congestion levels for two scenarios: the "no-build" scenario, with no improvements to the current transportation network, and the "build" scenario, reflecting improvements to the network. When used in the long-range planning process, the model is used to forecast the performance of the proposed future network. When used in the environmental review process, it is used to forecast the impacts of specific projects. The model outputs include vehicle counts on individual road segments as well as estimated speeds, which together can be used to estimate not just congestion levels but also emissions of various air pollutants as required by federal and state policy. Models are now being used in California and some other states to estimate GHG emissions under different scenarios as well as increases in VMT stemming from increases in highway capacity.

Many of the TDMs in use today are largely similar to those first used in the 1960s. These four-step travel demand models consist of submodels for trip generation, trip distribution, mode split, and route assignment (Ferdous et al., 2012; McNally, 2007). Although these models have become more sophisticated over time, their basic structure and inherent assumptions remain the same. The primary inputs to the model are land use data in the form of population and employment data for each "traffic analysis zone" and the roadway network (excluding local streets) represented as links (with characteristics such as capacity and speed limits) and nodes. Some models also incorporate a transit network depicting rail and bus routes with schedules and fares. Trip generation models estimate "trip ends" – the number of trips originating in or ending in each zone by trip purpose. Trip distribution models link the trip ends to estimate the flows of trips between zones based on travel times between zones. Mode split (or more sophisticated "mode choice") models estimate the split of those trip flows across modes. Finally, the route assignment model assigns trips to the network based on estimated travel times to determine the number of vehicle trips on each roadway segment. Over the decades, mode split and route assignment models have advanced to a greater degree than trip generation and trip distribution models. Another notable innovation is the move to tour-based models, which account for the fact that individual trips are often linked together in "tours," for example, when an individual stops at a coffee shop on the way to work and at a grocery store or the gym on the way home (Hasnine & Nurul Habib, 2021).

Activity-based models discard the zone-based approach and instead simulate the behavior of individual households and their individual members at a fine level of spatial detail. They explicitly model travel demand as deriving from an individuals' involvement in different activities. They start by predicting which activities are conducted when, where, for how long, and with whom, and then predict the travel choices that individuals will make to complete the predicted activities. Activity-based models include an explicit representation of the timing and sequencing of travel, using tours and trips as fundamental units of travel demand, and incorporating interrelationships among many long-term and short-term dimensions of travel (Castiglione et al., 2014; Vovsha & Bradley, 2006). They enable the incorporation of psychological as well as socio-demographic factors as predictors of travel choices (Shiftan & Ben-Akiva, 2011). Activity-based models enable agencies to evaluate the effect of alternative policies on individuals' travel behavior at a high level of temporal and spatial resolution and select the best policy alternative considering a potential wide range of performance indicators (Givoni et al., 2016a; Shiftan & Ben-Akiva, 2011; Vovsha & Bradley, 2006; Malayath & Verma, 2013).

Activity-based models and some four-step models employ discrete choice models to predict the probability that an individual makes a given choice from a set of available choices. These models assume that this probability depends on the ratio of the utility of the given choice relative to the sum of the utility across all available choices. Because these models take a logit form, the sum of the utilities across all choices is referred to as the "logsum." For mode choice models, the utility of choosing a particular mode is assumed to depend on travel times (in-vehicle and out-of-vehicle), monetary costs, and other factors such as land use characteristics or the number of transfers for transit trips. Income and/or auto ownership are sometimes incorporated into the model.

Other variations of TDMs have been developed, sometimes for specific purposes, but are not widely used in transportation planning practice. Moekel et al. (2020) propose a hybrid model that overcomes some of the limitations of four-step models but is easier to implement than activity-based models. A systematic literature review by Alipour and Dia (2023) provides insights into the recent development of land use, transport, and energy-environment (LUTEI) modeling frameworks focusing on policy integration by forecasting changes in travel behavioral patterns toward ride-hailing services, walking, biking, and shared mobility services to achieve goals of more sustainable transportation modes (Alipour & Dia, 2023). Another study by Croce et al. (2019) suggests a framework for “transport system models” that integrates transport supply and transport demand models with the optimization of the operation of electric vehicles for a better sustainable transportation decision-making process (Croce et al., 2019).

LIMITATIONS OF TRAVEL DEMAND MODELS

Although TDMs play an important role in transportation planning and environmental review processes, notable limitations moderate their effectiveness as decision support tools. Forecasting is an inherently uncertain exercise, and the longer the time period of the forecast, the more uncertain it is. Although TDMs are frequently used for long-term forecasts (i.e. more than 20 years into the future), short-term forecasts come with less uncertainty (Karner, 2022).

Sources of Uncertainty

Once source of uncertainty is the nature of current travel behavior. TDMs have traditionally been calibrated based on data collected through travel diary surveys with supplemental data from other sources. Travel diary surveys collect data from a sample of individuals and households about each of the trips they make on the day of the survey, including the origin, destination, mode, and timing of the trip. Modelers apply statistical methods to these data to estimate the equations that make up the model, meaning that the model is only as good as the data on which it is based. Especially in recent years, serious questions have been raised about the quality of data collected through travel diaries. Concerns include biases in the sample of households participating in the survey as well the possibility that survey participants misreport their travel or even omit trips altogether. Outdated, insufficient, or aggregated data on travel patterns, population demographics, and infrastructure conditions can undermine the precision of travel demand models (Pulugurtha et al., 2019; Zhang et al., 2012).

A second source of uncertainty in the use of TDMs for forecasting is that agencies must also forecast the inputs to the model with some level of uncertainty. This is not so much an issue for the transportation network, as the network is with the control of the MPO and state DOT: the agency assumes or proposes rather than forecasts the network in most situations. Future land use patterns, on the other hand, must be forecast. These forecasts include not only total population and employment in the region over time but also its spatial distribution across the region. Land development is notoriously difficult to forecast, however, and depends to some extent on changes in the transportation network (Handy, 2005). Most models do not directly account for the reciprocal relationship between land development and transportation investments, a failure that limits their ability to accurately forecast future travel patterns (Acheampong & Silva, 2015; Waddell, 2014; Waldeck et al., 2020). The inherent uncertainty associated with predicting future conditions poses a substantial challenge to long-term travel demand forecasting.

A third question is whether current behavior is a good predictor of future behavior. In the future, people may not respond to transportation options in the same way that they do today. Travel time might become more or less important, for example, or demand for certain activities might wane. But the static equations at the heart of the model assume that the calculus of individual travel choices remains the same, even as the inputs to the model change. Not only are factors such as technological innovations or shifts in travel preferences difficult to anticipate accurately (El Zarwi et al., 2017; Shaheen & Cohen, 2020), such changes are not easily incorporated into TDMs short of a wholesale recalibration of the model. The models are not built to adapt to fundamental economic and societal changes.

Simplifications

In addition to these substantial uncertainties, TDMs have inherent limitations owing to their simplified representation of travel behavior and the transportation system. Four-step models are more simplified and thus have more limitations than activity-based models, though the limitations of the latter are also notable.

Four-Step Models

Traditional four-step TDMs are characterized by their aggregated representation of travel behavior, based on traffic analysis zones rather than households or individuals. This approach oversimplifies heterogeneity within zones, instead relying on average characteristics within the zone, and tends to create aggregation biases that could affect analyses of proposed projects (Miller, 2020; Davidson et al., 2007). This problem is especially acute for zones with diverse land uses and population characteristics. In addition, these models do not provide spatial detail on travel flows within zones, a significant limitation for the analysis of public transit and non-motorized trips (Davidson et al., 2007). Temporal detail is also limited, in that the models tend to aggregate trips to peak periods rather than predicting the specific time at which trips are made. Simplified behavioral assumptions embedded within these models introduce another limitation (Ben-Akiva et al., 1998; Vovsha & Bradley, 2006).

Although four-step models continue to be widely used in practice, especially in smaller regions with limited resources, the field has increasingly recognized that these models are limited in their ability to account for the dynamic interplay between travel behavior and network conditions. This limits their ability to reasonably represent the effects of transportation policies such as variable road pricing and travel demand management strategies (Rasouli & Timmermans, 2012; Shiftan & Ben-Akiva, 2011). This recognition has led to interest in developing integrated dynamic models that link advanced activity-based demand model components with dynamic network traffic assignment model components (Castiglione et al., 2014).

Activity-Based Models

Activity-based models offer a more complete representation of the complexity of travel behavior by focusing on individual households and the individuals within those households. In doing so they account for heterogeneity within the population with respect to travel needs and preferences, thereby enhancing the fidelity of predictions in demographically varied regions (Davidson et al., 2007). The models account for interactions among household members in the scheduling of activities and their attendant travel choices, including decisions about shared vehicles (Gliebe & Koppelman, 2005; Hu et al., 2023; Vovsha et al., 2003; J. Zhang et al., 2009; Davidson et al., 2007; Vovsha et al., 2011)). They also operate at a finer temporal resolution and thus provide a more accurate representation of dynamics of travel behavior. Their finer spatial resolution enables the analysis of short distance trips, particularly those by public transit and active modes. In these ways, they offer the potential for more accurate forecasts, though they too face issues around uncertainty as discussed above.

In sum, these models not only do a better job of representing real-world travel behaviors than four-step models but also simulate travel demand outcomes at the micro level with respect to spatiotemporal changes in land use, demographic characteristics, employment, income, and diverse transportation modes (Arentze & Timmermans, 2012; Davidson et a. 2007; Ferdous et al., 2012; Walker et al., 2019). They allow for a more detailed and dynamic representation of travel behavior, which, as many argue, make them more suitable for analyzing the effects of various transportation policies (Davidson et al., 2007; Malayath & Verma, 2013; Griesenbeck & Garry, 2007; Shan et al., 2013). Studies demonstrating the higher accuracy of activity-based models compared to four-step models underscores the potential usefulness in policymaking (Padhye et al., 2020; Tajaddini et al., 2020).

Other Considerations

Travel demand models were initially developed to forecast traffic counts and congestion levels, and they continue to support this objective. However, today's MPOs and state DOTs have adopted a broader array of goals, including environmental justice and mobility equity. TDMs are not necessarily well suited to providing information useful to assessing the implications of policies for these goals (Bills, 2024; Bills et al., 2012; Miller, 2020). Regarding equity, certain demographic groups or geographic areas often experience disproportionate negative effects from transportation investments, and these impacts may not be adequately reflected in modeling outputs (Ramadan et al., 2019).

Resource constraints in terms of available funding and human capital pose practical challenges to developing and maintaining sophisticated travel demand models. Regions or agencies lacking the necessary resources may struggle with regular model updates or improvements (D'Cruz et al., 2020; Kisgyörgy & Vasvári, 2017; Y. Zhang & Zhang, 2019). Activity-based models especially demand detailed data and computational resources, potentially limiting their applicability in situations where such resources are scarce (Moekel et al., 2020).

Agencies must also consider community engagement. If the public lacks trust or understanding of the modeling process, it can lead to resistance and hinder the successful implementation of transportation policies (Givoni et al., 2016b; Marsden et al., 2009;

Volker et al., 2020). Effective communication and collaboration among stakeholders is paramount to building trust in modeling results so that they are actually used to inform transportation policies (Angelelli et al., 2022; Ben-Akivai et al., 1996). The two types of models present different challenges on this front. On one hand, the complexity of activity-based models may be off-putting to stakeholders (Givoni et al., 2016), on the other, their behavioral realism may be easier for stakeholders to grasp.

These challenges underscore the ongoing need for research and innovation in the field to advance the capabilities of travel demand modeling and its application in shaping sustainable and equitable transportation systems. Addressing these constraints necessitates a concerted effort to enhance data collection, refine modeling techniques, and bolster the integration of travel demand modeling with other planning processes.

VALIDITY AND SENSITIVITY TESTING

The validity – or accuracy – of the forecasts generated by TDMs cannot be directly assessed at the time of the forecasts. Instead, TDMs are generally validated based on their ability to replicate current patterns of travel, though sometimes they are validated using a "back-casting" approach in which the accuracy of forecasts for earlier years are compared to actual traffic counts for those years. It is generally accepted that forecasts have a high degree of uncertainty, particularly on specific segments of the network, though this uncertainty is not always highlighted or acknowledged.

Several studies have explored the accuracy of different components of models or different types of models, as in the following examples:

> Gibb (2023) analyzed a more modern trip distribution model, developed for the Sacramento Council of Governments' SACSIM activity-based model. SACSIM uses a multinomial logit (MNL) model rather than the traditional gravity model. The author tested this model both with and without attraction constraints, which have historically been employed to simulate the real-world constraints that people experience in their daily travels (Gibb, 2023).
>
> Pulugurtha et al. (2019) evaluated the accuracy of the Charlotte regional TDM's travel time estimations by comparing them to real-world data. The model in question was a traditional four-step model. The study found that correlations between forecasted and actual travel times was strongest in suburban and rural areas, and weakest in urban and inner-ring neighborhoods (Pulugurtha et al., 2019). These results suggest that travel demand forecasts are most accurate when vehicular congestion is minimal and route choice is more constrained.
>
> Shan et al. (2013) and Zhong et al. (2015) conducted a comparative analysis of the Tampa Bay Regional Planning Model (TBRPM), an existing traditional four-step model for the same area, and an activity-based model developed using travel diary data from the Tampa Bay Region in Florida. The analysis showed that the activity-based model provided a more accurate representation of travel behavior, though the four-step model out-performed the activity-based model in some respects (Shan et al., 2013; Zhong et al., 2015).

Sensitivity analysis, in contrast, involves the systematic variation of input parameters, including variables such as travel costs, time considerations, socioeconomic factors, and infrastructure attributes, to test their impact (Al-Salih & Esztergár-Kiss, 2022b; Xu et al., 2023). The TDM is run for distinct sets of parameter values to determine resultant changes in model outputs, including mode choice, trip distribution, and overall travel demand patterns (Castiglione et al., 2014; Du & Chen, 2022)). Identifying the parameters having the greatest influence on outputs can provide direction for efforts to improve data accuracy, refine assumptions, and bolster the reliability of the model (Al-Salih & Esztergár-Kiss, 2022a; Gu et al., 2022).

The literature underscores the pivotal role of sensitivity analysis in assessing the responsiveness of TDMs to transportation policy questions. These analyses provide decision-makers with a systematic methodology for understanding the complex interplay of input parameters. They can be used to produce a ranking of parameters based on the sensitivity of the TDM to each parameter, providing decision-makers with a clear hierarchy of influential factors shaping travel demand model results (Al-Salih & Esztergár-Kiss, 2022b; Yang et al., 2013). These insights can provide the basis for the development of policy scenarios. However, hyper-sensitivity of the models to policy inputs, when small alterations in policy assumptions lead to consequential variations in model outputs, complicate the use of TDMs for policy evaluation (Shiftan & Ben-Akiva, 2011; Yang et al., 2013).

FORECASTING VMT

Much of the recent literature on the regulatory capabilities of TDMs has been centered on their potential role in accurately forecasting reductions in vehicle miles traveled (VMT), and in turn, greenhouse gas emissions, stemming from various policies. VMT reduction policies may involve some combination of transit improvements, land use changes, and/or auto pricing intended to decrease the attractiveness of driving relative to less impactful alternatives.

TDMs are not always well suited, however, to assessing the effects of such strategies. Rodier (2009) reviewed literature analyzing the capabilities of various regional travel demand models in forecasting changes in VMT and GHG emissions over various time horizons and in response to various policy scenarios. The regions highlighted in the review varied both in population and the level of transit service provided, allowing for the marginal impact of transportation policies to be measured across various scales. Regional agencies simulated policy scenarios in isolation as well as in pairs and triplets, such as a pairing of transit expansion with congestion pricing as in a study for the San Francisco Bay Area. However, the review found that the regional models were limited in their ability to predict the effects of land use change and transit expansion at a granular level. The reliance of measures of the quantity rather than quality of transit service was another notable limitation. At of the time of this review, the ability of TDMs to combine these metrics and evaluate the overall quality of transit service in a region was still limited (Rodier, 2009). Many agencies forecast active travel “off model” since these modes are not directly represented in the models (Handy, 2008).

The accuracy of the VMT estimates is another important question. Metz (2021), for example, analyzed the accuracy of a travel demand model in predicting travel time savings from widening a 16-mile section of London’s M25 motorway from three lanes to four lanes per direction. The SATURN software model had projected an increase in both traffic volumes and average speeds from the road widening. These projections contributed to favorable economic cost-benefit projections during the planning of the project. According to the analysis, the project did reduce travel times immediately following its 2014 opening, but much of the time savings disappeared in subsequent years. Over time, as traffic volumes increased, average roadway speeds returned to the status quo before expansion, thereby wiping out the benefits on which the project was justified. On both local and national scales, the study found that improvements to roadway infrastructure did not lead to reductions in travel time but rather to increases in road travel. This finding points to a notable disconnect between the economic forecasts presented to the public and the actual economic impacts post-completion (Metz, 2021).

Critical to the accurate forecasting of VMT is the accurate forecasting of induced VMT, that is, the increase in VMT that can be attributed to highway capacity expansion itself. Caltrans requires the estimation and mitigation of induced VMT as a part of the environmental review process under the California Environmental Quality Act, a requirement implemented in response to SB 743 (Caltrans, 2020). Capacity expansion reduces the cost of travel, leading to short-term changes in behavior, including longer trips, shifts in travel mode, route changes, and entirely new trips. Longer-term changes in residential and commercial locations as well as changes in land development patterns can also occur (Downs, 1962; Caltrans, 2020; Handy, 2005).

TDMs typically do not capture all of these possible changes because they do not reflect all of the ways that changes in travel speeds can reshape travel behavior (Naess et al., 2012; Milam et al., 2017; Deakin et al., 2020). In four-step models, the issue is whether the model includes feeds the forecast of congested travel times that the model produces as an output back into earlier components of the model. Although the forecasted times are usually fed back into the route assignment and mode choice submodels, they are less often fed back into the trip distribution submodel and rarely into the trip generation submodel. Also rare are feedback loops between the forecast of travel times and the land use scenario that is input into the model. This means that while models generally capture induced VMT associated with changes in route and mode choice, they generally do not capture induced travel associated with changes in trip destinations, trip generation, residential and commercial location, and land development patterns. As a result, they tend to underestimate VMT induced by the expansion and thus total VMT following the expansion. The result is overly optimistic forecasts of benefits in terms of increased travel speeds and reduced congestion but also overly optimistic forecasts of costs in terms of GHG emissions and other impacts (Naess et al, 2012; Volker et al., 2020).

Activity-based models offer the potential to both represent policies other than highway capacity expansion (e.g. transit improvements, investments in active modes, pricing strategies) and to capture more of the connections between decisions that result in induced VMT. The higher temporal detail in activity-based models is also helpful in accurately capturing induced VMT by accounting for shifts in trip departure times in response to changing levels of congestion. But even these models often lack feedbacks to trip generation and to land development patterns (Milam et al., 2017).

CONCLUSION

Travel demand forecasting models are essential to the transportation planning process and to the assessment of the environmental impacts of proposed projects. Although activity-based models represent an improvement over traditional four-step travel demand models in terms of their more realistic representation of travel behavior and their greater level of spatial and temporal detail, both types of models necessarily offer simplified representations of the actual transportation system and produce forecasts with a high level of uncertainty. Validity and sensitivity testing help analysts understand uncertainties and inaccuracies in the model forecasts. Of particular concern from a policy standpoint is the ability of these models to accurately account for the induced VMT effect of highway capacity expansions.

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