Sustaining the Relevance of Transportation Planning and Forecasting in a Fast-Changing World

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ABSTRACT
Transportation planning and forecasting have long been essential in guiding investment decisions and shaping transportation systems. However, rapid technological advancements, shifting societal values, and the lingering effects of the COVID-19 pandemic have challenged the relevance and accuracy of traditional forecasting models. This paper examines the evolving context of travel behavior, highlighting the limitations of existing models in capturing new trends such as telework, e-commerce, and induced demand. It advocates for the development of more dynamic, data-driven, and context-sensitive modeling approaches that can better accommodate these changes. The paper also discusses the need for planners and forecasters to engage with stakeholders to ensure that models remain effective tools for decision-making in an increasingly complex and uncertain world.

Keywords: Transportation Planning, Forecasting, COVID-19 Pandemic

1. INTRODUCTION

Historically, long-range transportation planning and forecasting have served as a means of identifying needs and reducing risk for supporting transportation investment decisions. Transportation facilities are built to serve for decades and meet long-term needs (Sciare and Handy, 2017). Therefore, the desire to be able to forecast these needs motivated the development of forecasting tools to gauge future demand and hence be able to build facilities that can be located and scaled to address that demand (Transportation Research Board, 2006). Both the time to implement projects and their useful lives necessitate having insights into future demand in order to make informed decisions.

Ever-growing computing capabilities, data availability, and modeling capabilities have expanded the application of these tools for a broader spectrum of issues and projects with such models now also able to offer insights relevant to policy and operating decisions, including insights into the magnitude and distribution of impacts. Such tools have served the profession well for several decades and have been instrumental in shaping major elements of transportation systems, especially major roadway and transit network investments in urban areas.

The COVID-19 pandemic and its residual impact on travel behaviors, best exemplified by robust levels of telework and accelerated e-commerce, served as a catalyst for recognizing the need for reflection on the state of travel demand modeling (Wang et al., 2024). A host of additional factors are also at play. There are meaningful changes in people's values and priorities. Enhanced sensitivity to equity in access to mobility options and exposure to externalities of transportation, heightened environmental sensitivities exemplified by concerns about climate change, a recognition of the role that transportation and land use play in influencing people's health and safety, and other considerations are changing personal choices and policy priorities. Technologies are changing rapidly and influencing travel. While telework and ridehailing are perhaps the most well-recognized example of technologies fundamentally impacting travel behavior, technologies have changed a multitude of attributes of virtually all travel choices. Trip planning and scheduling, fare payment, safety, comfort, operator assistance aids, traveler amenities, security features, emissions levels, and other factors are changing travel choices and their attributes. Feature changes not only affect key attributes such as cost and speed but also change more intangible considerations such as comfort, convenience, reliability, safety, and image.

The ability to substitute communication for travel has impacts well beyond telecommuting as information communication capabilities can enable individuals to forego personal travel by arranging delivery of products or services or performing activities online rather than in person. In addition, convenient access to information can inform choices on trip destinations, trip timing, and travel mode choices, for example, enabling someone to compare product prices and check inventories before initiating a trip.

The consequences of these changes as well as other changes in demographics, governance, and economic conditions have resulted in a critical need to review the capabilities and practices of planning and travel behavior modeling in a search to ensure that these efforts continue to offer value for decision-making. Figure 1 characterizes the major factors influencing travel behavior changes.

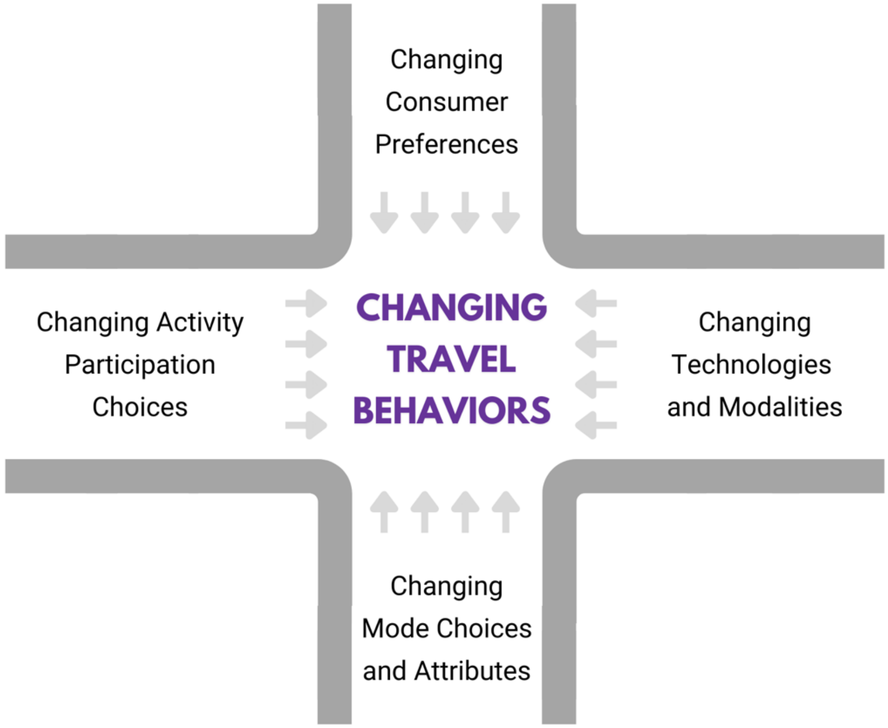

FIGURE 1 Characterization of Factors Influencing Changing Travel Behaviors

This paper explores the challenges to long-range planning and forecasting for transportation in an era where multiple factors impacting transportation are changing at a pace arguably unseen since the development of metropolitan-level transportation planning practices and tools in the U.S. Most of these phenomena are equally important in other geographies. Reviews and scrutiny of modeling tools are certainly not new as the profession has long had various evaluations and reviews that have shaped research agendas and influenced practices and the credibility of modeling systems (Hartgen, 2013). Methods and capabilities have continued to evolve in pace with greater data availability, more powerful computing capabilities, and a more nuanced understanding of travel behaviors and research findings on how to improve the predictive capabilities of data and approaches used in modeling. Examples of this scrutiny include language in the most recent federal transportation program authorization calling for regular reviews (United States Congress, 2021).

> *SEC. 11205. TRAVEL DEMAND DATA AND MODELING …(1) IN GENERAL.— Not later than 2 years after the date of enactment of this Act, and not less frequently than once every 5 years thereafter, the Secretary shall carry out a study that— (A) gathers travel data and travel demand forecasts from a representative sample of States and metropolitan planning organizations; (B) uses the data and forecasts gathered under subparagraph (A) to compare travel demand forecasts with the observed data, including— (i) traffic counts; (ii) travel mode share and public transit ridership; and (iii) vehicle occupancy measures; and (C) uses the information described in subparagraphs (A) and (B).*

Many transportation agencies during the COVID-19 pandemic leveraged alternative data sources and tools, such as real-time GPS data from smartphones, to better understand and predict demand and adjust their services accordingly, since existing data, models, and tools were not as effective in accommodating dramatic shifts in travel behaviors and patterns, such as the rise in telecommuting, the surge in e-commerce, and changes in transit usage (Parker et al., 2021; Hensher and Stopher 2021; Sana et al., 2022; Marra et al., 2022). While the reliability and accuracy of transportation modeling and forecasting tools have always been questioned from many aspects (some of which are decades old; see, Hartgen, 2013), their inability to adapt to changing circumstances during the pandemic has provided us another opportunity to question their effectiveness and relevance once again. These models and tools are often based on economic assumptions that may not fully reflect new realities about employment patterns and consumer behaviors (Bonsall, 2004; Hartgen, 2013; Goulias, 2018). They rely on static assumptions and historical trends, which do not always reflect the dynamic nature of travel behaviors. Models and tools utilizing economic and behavioral theories, such as Random Utility Models (RUM), to provide behavioral insights often oversimplify human decision-making processes by not incorporating many contextual elements that are at play in transportation decision-making, such as attitudes, perceptions, lifestyles, and inter- and intra-household interactions (Gärling, 1998; Morikawa, et al., 2002; Rasouli and Timmermans, 2014; Paulssen 2014; Varotto et al., 2022). This issue has become even more critical as choices and preferences are becoming more diverse in an increasingly heterogeneous population and as schedules and mobility patterns have become more dynamic and less predictable. Advanced hybrid models have attempted to address some of these issues by incorporating latent factors and joint modeling of decisions, but their complexity and data-intensive nature limit their real-time applications (Kim et al., 2014; Varotto et al., 2022; Kim and Mokhtarian, 2023). These limitations, and potentially others, have led to biased estimates and inaccurate predictions in forecasting, at least in many cases (Hartgen, 2013). Moving forward, we need better methods and more dynamic, data-driven, and context-sensitive modeling approaches and tools to enhance the robustness and accuracy of transportation planning and decision-making processes, or at least more explicitly and openly reveal the constraints and uncertainty inherent in the forecasts.

2. CHANGING CONTEXT SURROUNDING THE USE OF TRAVEL FORECASTING MODELS

Not only have the factors that influenced travel behavior changed but the context in which travel forecasting is carried out has also shifted significantly since the formative years of travel modeling. In general, the total U.S. population is growing far slower than in previous decades, and its growth is highly dependent on policy-driven immigration levels (Frey, 2021). Per capita travel demand has been stable or declining for most of the 21st century. While redistribution of population can create the need for additional capacity even in the absence of overall national demand growth, many urban areas are predicted to see lower population and demand in the future. In the last half of the past century, the U.S. had annual increases in vehicle miles of travel (VMT) in the 4-5 percent range, whereas at the end of 2023, annual VMT was less than 10% higher than at the end of 2005.

In many cases, communities are behind in addressing needs so resources can be directed to meet very apparent current or past needs and not be reliant on forecasts of future needs. A study by researchers at the University of Chicago concluded that over 40% of the nearly 30,000 U.S.

cities are at risk of facing a 12-23% population decline by 2100, with more of the at-risk cities in the North and Midwest compared to the South and West (Sutradhar et al., 2024). The obvious implication is that expanding capacity to accommodate growth will be of diminished significance going forward in light of existing and emerging trends regarding surface travel demand. Thus, the foundational role of long-range demand forecast to help guide the development of transportation system deployment may well play a more modest role in overall transportation planning and policy decision-making. Furthermore, as many of our core metropolitan transportation systems are in place, the era of developing new high-capacity roadway systems or high-capacity transit services is of diminished relevance in most metropolitan areas. Changes are far more likely to be incremental and highly influenced by existing network configurations.

The relevance of demand is also diminished by virtue of the fact that decision-making for transportation investments is now more likely to be impacted by a plethora of goals ranging from impacting economic development, public health, equity of opportunities, minimizing impacts, enhancing resilience, integrating safety considerations, facilitating intermodal connections, and other concerns that result in information about demand competing for attention with multiple other goals in policy and project decision-making (Sciara and Handy, 2017; Pan et al., 2024).

The use of demand forecasts to influence transportation priorities is also diminished due to the highly constrained context that exists in many urban areas where the range of feasible options is constrained by environmental, financial, political, or other factors. In other contexts, the political culture favors prescribing the future rather than predicting the future. Prescriptive planning rather than predictive planning has won favor among many planning professionals and many decision-makers are similarly inclined.

Transportation planning and demand forecasting are also subject to the prospect of diminished relevance due to declining public confidence in government institutions and information. While not unique to transportation, uncertainty creates challenges for the credibility of forecasts and a cynical public, or policymakers can more easily rationalize ignoring professional forecasting results (Pew Research Center, 2023). Increasingly partisan transportation policy-making risks exacerbating the challenges to credibility as, for example, challenges to models' sensitivities to induced demand behaviors can undermine confidence in travel models (ITDP, 2023). Attitudes about roadway expansion, transit viability, and equity-focused investments leave fewer people open to actually using forecast results. Also, now there are often alternative sources of forecasts from think tanks and special interest groups that can undermine or reduce confidence in models used by agencies.

Finally, the relevance of forecasting can also be diminished in light of the evidence of high degrees of uncertainty regarding the future. The pace of change in technologies and behaviors is such that forecasting is highly speculative. Even the fundamental understanding of future development/land use is difficult to forecast as communication substitution for travel, crime, disaster risk exposure, and other factors overwhelm the traditional power of accessibility in forecasting future land use. There is even evidence of political culture influencing migration trends, behavior, and technology acceptance. The prospect of automated vehicles and their uncertain impact on travel, changing sensitivity and personal and policy reactions to climate change, additional influence of ever-improving communications substitutes as an alternative to travel, acceptance of emerging micromobility modes and business models for delivering mobility, and other factors are changing at an unprecedented pace that makes forecasting exceptionally challenging. Models may remain useful tools for testing scenarios and assessing impacts, but they may lose their significance as forecasting tools if forecasting the core inputs and the attributes of the travel choices are not possible with a degree of confidence that instills trust.

The collective consequences of these considerations suggest planners and travel forecasters should carefully assess their contexts and engage with users of their products and services to ensure that all possible steps are taken to be responsive to the needs of decision-makers.

While understanding the context is critical there are several specific challenges confronting forecasting. Some of these are discussed in the remaining sections of this paper.

3. CHANGING TRIP MAKING RATES

Survey data has indicated declining average person trip rates over the past few decades. Historically, trip making has been highly correlated with real income, but average trip rates are declining despite real income increases (FRED, 2024). This trend predates the spike in e-commerce and telework associated with the COVID-19 pandemic but may reflect the emergence of communications as a substitute for other travel as social media platforms, texting, online business transactions, online gaming, and related activities replace some travel during the past several years. Other contributing factors may be a saturation in travel demand as high levels of auto availability have been reached. An aging population may be a contributing factor as might the stabilization of household sizes. Additionally, some persons may be minimizing personal travel by contracting for activities and services that they might previously have handled personally and involved personal travel. In any case, an understanding of causal factors for person trips and a theoretical framework for modeling and measuring their future trend merits review in the context of evaluating travel demand forecasting capabilities in an era where virtual engagements are destined to continue to increase.

Figure 2 shows the reported trip rates according to the American Time Use Survey (ATUS). Even pre-COVID, there was a consistent downward trend in daily trip rates of U.S. residents. That trend is confirmed by data collected by the National Household Travel Survey (NHTS) series conducted by the U.S. Department of Transportation as shown in Figure 3. While slightly different definitions and sample specifications are used, the downward trend is confirmatory across these data sources.

Gaining a richer understanding of the interrelationship between trip generation and decisions to conduct activities via communication capabilities and or the decision to, in effect outsource the delivery or conduct of services in lieu of incurring personal travel is important to explore in the context of future trip generation rates. At a minimum, the basis for future trip generation rates should be evaluated in light of the clearly documented decline in trip making.

Somewhat related, understanding trip attraction in an era of information and communications technology (ITC) substitution and reduced trip making is also important. The variability across metropolitan areas and market segments and the geographic implications on trip tables are critical, particularly in light of the persistence of telework. Understanding the distribution of home ends for teleworkers and their subsequent travel patterns will be important as will understanding modifications to trip attraction rates by employment location.

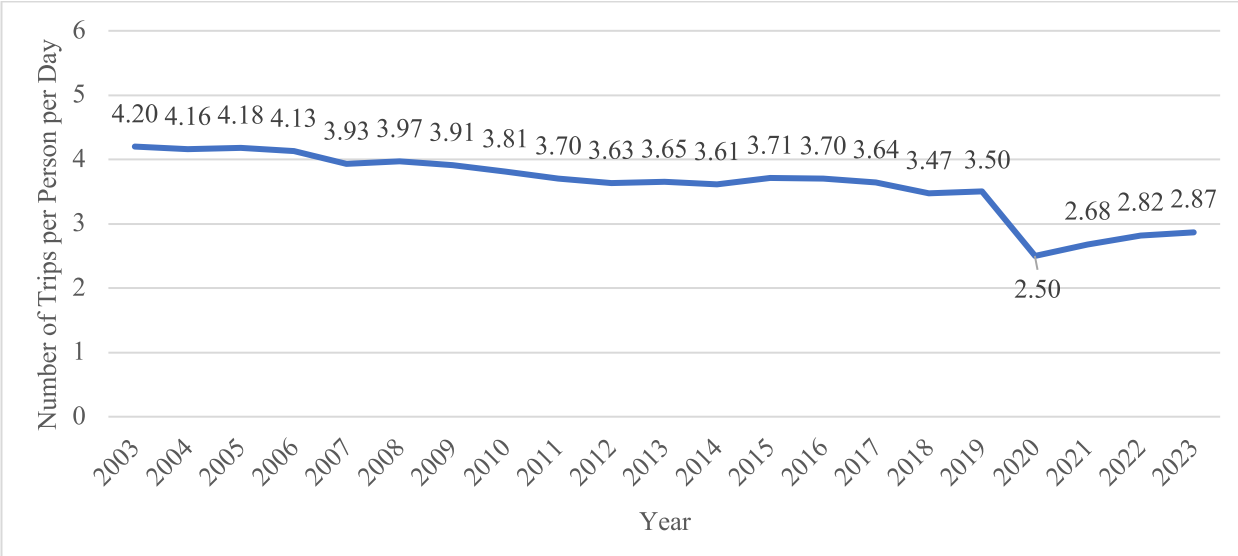

FIGURE 2 Per Capita Daily Trip Rate in ATUS (BLS, 2024)

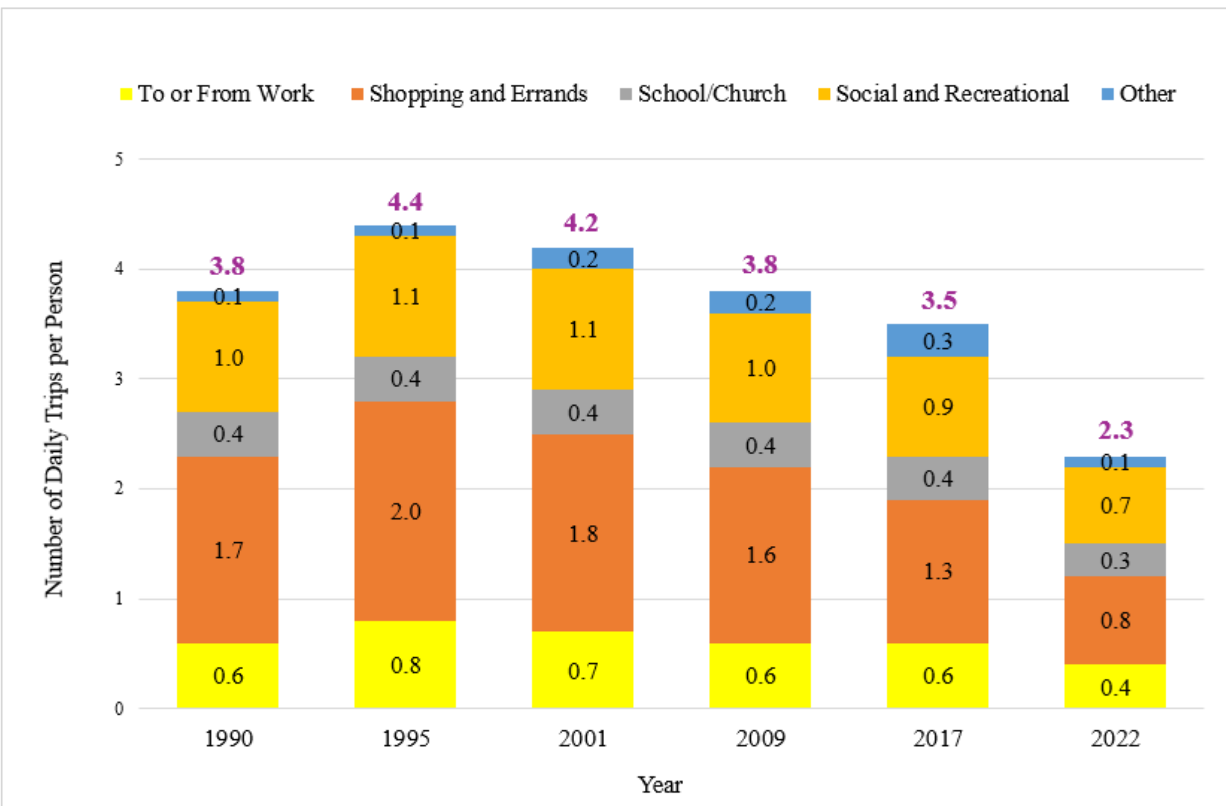

FIGURE 3 Per Capita Daily Trip Rate by Trip Purpose in NHTS (USDOT, 2024)

Data analysis reveals a wide variation in telework shares across geographies. For example, analysis of the 2021 American Community Survey (ACS) data set on reported usual commute mode recorded the highest remote work commuting zone was Washington, DC with 33.6% and the lowest reported was 2.4%. Across the top 50 commuting zones, telework shares ranged from 33.6% to 19% (Ozimek and Carlson, 2022). The analysis also revealed the well-recognized relationship between telework and education, compensation, and job type. Other factors known or hypothesized to be significant include commute trip length, congestion levels, parking/toll costs, corporate culture, and community culture among others. The variation across regional geography suggests that knowledge of causal factors and integration into forecasts will require context-specific information.

Understanding the implications of telework on household-level trip generation will also be required to integrate this new phenomenon within travel models. While income and education are recognized factors and some measures of access distance to telework conducive employment opportunities may be able to be developed, it may be more challenging to reflect telework implications on household-level trip generation. This issue is also compounded by an emerging understanding of how telework participation influences household travel patterns, trip rates, travel modes, and trip distances.

While telework behaviors are still maturing and fluctuating, there appears to be little consensus regarding a new normal other than the expectation that telework will remain substantially more pronounced than was the case pre-COVID. There are similar expectations that over time if current trends towards a larger share of employment opportunities being information-type jobs continue and communications capabilities and strategies and tools for integrating telework into business operations keep improving, one might expect to see growing telework participation.

It is important to note that the influence of teleworking is not universally consistent across travel modes. Historically, public transportation's market focus has been on central business districts with their concentration on office, government, and information-type employment. Accordingly, the impact of the COVID-19 pandemic and its induced telework has been most pronounced for public transportation in the United States. According to the 2022 ACS, the share of commuting by personal vehicle alone or shared declined by 11.2% whereas the share of people commuting by public transportation declined by 38% (Polzin et al., 2023). Telework has similarly impacted the temporal distribution of daily travel with generally lower morning peaks, higher midday travel, and flatter evening peaking trends (Polzin and Choi, 2021). Depending upon their intended application, travel models will have to reflect these emerging behaviors.

4. EMERGING CONSIDERATIONS IN TRAVEL DEMAND ANALYSIS

4.1. Incorporating Induced Demand

Another current high-profile aspect of demand forecasting in the U.S. that merits attention is assessing the sensitivity of forecasts to the phenomenon of induced demand. Practitioners and interest groups do not have confidence that travel forecasting accurately reflects induced demand behaviors. The ability of forecasting tools to accurately reflect these behaviors and the validation of that sensitivity is critical for forecasting. The lack of confidence in travel models' sensitivity to induced demand has been reflected in actions such as its reference in the reauthorization of the U.S. transportation legislation, a 40-page critique document authored by a consortium of 40 environmental groups in response to federal solicitation of input, and ramped up research on induced demand by both the Transportation Research Board (TRB) and the U.S. Department of Transportation (United States Congress, 2021; ITDP, 2023; NASEM, 2024).

Several induced demand calculators have been proposed and there has been extensive commentary regarding induced demand and its implications on transportation planning and policy (Zipper, 2021; Mintz, 2021; Duncan, 2021; Deakin et al., 2020). The sensitivity to the issue of induced demand merits the modeling community making efforts to evaluate modeling tools to discern their effectiveness in addressing this issue. Understanding how models react is critical to preserving confidence in the models and in attempting to realistically characterize the changes associated with new capacity. This would mean assessing the sensitivity to trip generation, geographic trip distribution, temporal trip distribution, and mode choice. Interestingly, the foundational logic of induced demand would imply that other system changes beyond roadway improvements that enhanced the capacity of alternative modes or increased throughput with features such as signal optimization would also induce additional travel. For example, the development of a competitive public transit alternative would induce roadway travel to consume some of the roadway capacity freed up as a result of diversion to the alternative mode.

4.2. Accommodating Emerging Modes and Technology Features

New modes, new business models, and technology features that meaningfully change the attributes and customer experience using various modes can result in travel behavior changes and different choices. Thus, characterizing the attributes of the modes or multimodal trips in ways that enable accurate forecasting is increasingly challenging. The choice of modes is both more complex and more dynamic. Ridehailing, scooters, e-bikes, shared cars, and eventually automated vehicle options are changing the choice set confronting travelers, certainly for long-range forecasts. A multitude of other changes in technologies and policies similarly have an effect. For example, dynamic tolling and congestion pricing can influence behaviors. In post-COVID, we are seeing substantial experimentation on transit fare structures enabled by technological improvements. For example, third-party payment is more readily available and income-based pricing strategies are similarly more able to be implemented and administered. Strategies such as fare capping and accommodative pricing for less than full-time commuters, similarly, change the cost experience for public transportation travelers.

Modal features are also changing with the presence of Wi-Fi, far more convenient and flexible fare payment strategies, real-time information and trip scheduling capabilities, and other comfort, safety, and convenience features being deployed across modes. Does acquiring an electric vehicle (EV) diminish the motivation for an environmentally sensitive traveler to choose public transportation? Does the presence of security cameras in stations and vehicles enhance the prospect that travelers will choose public modes? Developing credible strategies for accommodating these changes and understanding their significance in traveler decision-making is important. While not all of these features and attributes will be significant enough or broadly enough deployed to meaningfully impact regional forecasts, the modeling community will certainly be asked to expound on the sensitivity of their tools to these issues.

4.3. Understanding Non-Household-Based Travel Demand

The foundation for urban travel forecasting has always been a strong reliance on household travel and work trip travel in particular. Households' share of all travel is declining significantly. Travel by freight, and especially commercial and service vehicle travel collectively constitute over an estimated 40% of all travel. These sectors are responsible for a still larger share of roadway capacity, energy use, emissions, safety risk, noise, and other externalities. Table 1 shows the share of total U.S. VMT that is explained by household travel as estimated by contrasting household VMT estimates from the National Household Travel Survey series with count data on VMT. Both data sets are collected and maintained by the Federal Highway Administration.

TABLE 1 Analysis of Household VMT Share Trends (FHWA, 2024)

<table>
<tr><th rowspan="2">Attribute</th><th colspan="2">2009</th><th colspan="2">2017</th><th colspan="2">2022</th></tr>
<tr><th>Household VMT</th><th>All Roadway VMT</th><th>Household VMT</th><th>All Roadway VMT</th><th>Household VMT</th><th>All Roadway VMT</th></tr>
<tr><td colspan="7">Household Travel</td></tr>
<tr><td>Commuting</td><td>27.8%</td><td rowspan="4">76.0%</td><td>30.2%</td><td rowspan="4">70.4%</td><td>30.1%</td><td rowspan="4">56.9%</td></tr>
<tr><td>Work Related/Business</td><td>9.0%</td><td>3.2%</td><td>8.9%</td></tr>
<tr><td>Other Household Travel</td><td>63.2%</td><td>66.6%</td><td>61.0%</td></tr>
<tr><td>Subtotal</td><td>100.0%</td><td>100.0%</td><td>100.0%</td></tr>
<tr><td colspan="7">Public and Commercial Travel</td></tr>
<tr><td>Public Vehicle Travel</td><td rowspan="4">--</td><td>2.0%</td><td rowspan="4">--</td><td rowspan="2">20.5%</td><td rowspan="4">--</td><td rowspan="2">32.7%</td></tr>
<tr><td>Utility/Service/Commercial Travel</td><td>12.0%</td></tr>
<tr><td>Heavy Freight and Goods</td><td>10.0%</td><td>9.1%</td><td>10.4%</td></tr>
<tr><td>Total</td><td>100.0%</td><td>100.0%</td><td>100.0%</td></tr>
</table>

Note: Non-household travel may include other travel by household members not reported on the NHTS survey.

This travel is often in specialized vehicles, is less amenable to alternative modes, and often the underlying travel decisions are made by corporate or other entities who may not have the same sensitivity to costs or other behavior influencing policies. Long-distance travel is similarly often captive to the vehicle and itinerary influenced by the overall trip and hence, less likely to be influenced by choices and characteristics of the particular urban area. Less is known about factors that influence travel decisions for these market segments. Given their growing and now very significant share of total travel and given the impact of travel by this market segment, it will be important to ensure that travel models show appropriate sensitivity to the behaviors of these markets.

5. DEFINING A PATH FORWARD FOR TRAVEL MODELING

Much of the prior discussion refers to large-scale regional activity-based travel models and their role in transportation planning and challenges in light of the changing context. Planners have a host of methods and modeling tools they use to provide information support for decision-making. Large-scale activity-based models inherently received a great deal of attention due to their scale and historic significance in shaping regional long-range travel plans. However, moving forward it may be prudent to reflect on the information needs of decision-makers, the capacities and confidence in the modeling tools, the level of knowledge and data available to support applications of various tools or types of models, and the context for the target geography. For example, several entities have developed induced demand calculators to supplement other models in light of their lack of confidence in regional models to correctly account for induced demand (e.g., Volker et al., 2020; Rocky Mountain Institute, 2023). Perhaps more significantly, the vast majority of metro areas seeking discretionary federal funding for public transit investments have chosen to use the Simplified Trips-on-Project Software (STOPS) model (Federal Transit Administration, 2020). This model is a federally supported model that provides a more standardized and transparent model that enables consistent methodologies across entities that are competing for funds. The use of induced travel calculators and the STOPS model for transit raises questions as to how more traditional advanced activity-based models fit in the mix of planning tools for metropolitan areas.

While forecasting ridership or vehicle volumes has historically been the focus of forecasting, more recently models are being used to do things like measure energy use, access equity, measure accessibility, and explore the incidence of impacts. While these purposes can be related to forecasting demand, models prescribed for these intentions might be specified and developed differently with different expectations regarding inputs, outputs, frequency of validation and calibration, appropriate design year for application, and degrees of confidence. For example, measures of accessibility do not require demand forecasts. Similarly, there is a variety of simulation, sketch planning, and other models that are being used to address policies and other more micro changes in the transportation system.

There also seems to be a substantial level of interest in forecasting customer acceptance of various changes including pricing strategies, various control strategies, willingness to share rides, and uptake of new technologies such as electrification and automation that may require their own types of models or model specifications.

Table 2 exemplifies the characteristics of the levels of risk associated with various transportation investments or policies. Reflecting on the risk levels gives insight into the criticality of accuracy in the forecast. Higher risk justifies additional investment in forecasting but does not necessarily mean that additional investments in more sophisticated models will be able to provide high-quality forecasts if there is not strong evidence of relevant behaviors and an ability to forecast the necessary model inputs.

TABLE 2 Decision Risk Spectrum (Adapted from Polzin, 2019)

Low Risk Decision		**High Risk Decision**
Low cost		High cost
Reversable/redeployable		Permanent/irreversible
Near term impacts		Long term impacts
Routine/widely deployed		Rare/unique

The pace of change in behaviors, travel options, and data and tools is such that transportation forecasting will be expected to be far more dynamic to keep up with the most current expectations including integrating the most current data and methods and being responsive to the most current issues and concerns. While models have typically focused on evaluating capital plans for the community, many future transportation initiatives will consist of sets of policies or portfolios of investments such as those that might be part of a complete streets initiative or Vision Zero program. While models can be helpful in evaluating policies, policies are also conducive to experimentation, trial and error, case study analysis, and other methods for gauging the influence of various policy initiatives on system operation. The extent to which it is important to build policy analysis capabilities into regional activity travel models merits consideration.

The ultimate challenge facing travel modelers is to take stock of current conditions and evaluate and then develop the appropriate set of tools to support transportation decision-making. Ignoring or minimizing the challenge that currently exists risks diminishing the relevance of travel forecasting and could result in less well-informed decisions.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: S. Polzin, I. Batur, R.M. Pendyala; data compilation: S. Polzin, I. Batur; analysis and interpretation of results: S. Polzin, I. Batur, R.M. Pendyala; draft manuscript preparation: S. Polzin, I. Batur, R.M. Pendyala. All authors reviewed the results and approved the final version of the manuscript.

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