Federal Highway Administration (FHWA) Connected and Automated Vehicles (CAV) Analysis, Modeling, and Simulation (AMS) Program

Connected, Automated, and Electric: Modeling Traffic and Traveler Choice Considering the Three Mega-Trends

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16. Abstract

The rapid development and deployment of traveler connectivity, automated vehicle (AV), and electric vehicle (EV) technologies are changing the way people use and interact with the transportation system. These behavioral shifts are impacting the accuracy of standard AMS tools due to more complex decision-making processes, new mobility service models, and new interactions with traditional transportation infrastructure. This analysis aims to identify current and potential future behavior changes resulting from traveler connectivity, AVs, and EVs in isolation and when operating together in both cooperative and conflicting settings. Such findings will then be used to identify high-impact future research directions related to the integration of changing travel behaviors into AMS tools and frameworks to model transportation systems in the mega-trend era.

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Table of Contents

List of Tables

No table of figures entries found.

List of Figures

Executive Summary

The purpose of this document is to identify potential travel behavior changes, conflicts, and synergies of three technology mega-trends: 1) automated vehicles (AV), 2) electric vehicles (EV), and 3) traveler connectivity. This analysis focuses on how the adoption of such technologies (one or multiple) might impact travel behavior choices, such as trip generation, route choice, and destination choice. Current methods to capture these changing behaviors in modeling and simulation are also reviewed. A thorough (though not exhaustive) literature review was conducted primarily focused on travel behavior impacts from any one of the three technologies (AV, EV, traveler connectivity) to help inform potential shifts in behavior in the mega-trend era. The overarching goal of this analysis is to identify research activities that can help fill gaps in modeling and simulation approaches to accurately capture shifting travel behaviors resulting from the convergence of three mega-trends.

Three key research questions were used to guide the literature review and to answer the overarching questions of how AVs, EVs, and traveler connectivity technologies will impact travel behaviors and how such behaviors can be integrated into existing modeling and simulation tools.

Question #1: What are the travel behavior impacts resulting from automation, connectivity, and vehicle electrification?

AV, EV, and traveler connectivity technologies impact travel choices in different ways. All three technologies provide numerous benefits to the individual traveler by reducing travel time uncertainty, providing new, convenient alternatives to private vehicle travel, reducing travel costs due to ability to multi-task, and reducing monetary operational costs by smoother driving behaviors and lower costs of electricity (compared to gas). More specifically, several travel behaviors were identified for each technology, and are as follows:

- **Traveler Connectivity**
    - Digital Navigation – Real-time travel information and recommendations has led to selfish travel behaviors and misuse of transportation infrastructure.
    - Shared Service Models – Smartphone connectivity has led to new and convenient mobility service offerings (e.g., ridehailing), which has led to significant growth of these services, which behave and interact with transportation infrastructure in new ways (fleet-based decision making, deadheading behaviors, pickup/drop-off curb interactions).
- **Automated Vehicles**
    - Induced Travel – Lower values of travel time (VOTT) were observed for commute and long-distance trips for AV. This finding indicates that travelers are willing to increase their delays when multi-tasking options are available.

  - Zero Occupancy Travel – Additional travel without a passenger is expected for AV owners because travel costs can be reduced or eliminated by sending empty vehicles to cheaper parking or to pick up family/friends. These behaviors will create additional trips affecting traditional trip generation models. Additionally, travel cost functions will require modifications because monetary factors will become more important compared to travel time and delay costs when vehicles are operating in zero occupancy mode.
- **Electric Vehicles**
  - Complex Decision-making Processes – EV owners must consider their state of charge (SOC) at the origin/destination, battery range, access to charging, charger reliability and wait times, and potential charging at the destination when making travel choices. These complex choices lead to a variety of different travel behaviors, from eco-routing to tradeoffs between detour length and charging speeds/reliability.
  - Risk Attitudes – EV owners exhibit different risk attitudes, which can lead to different choices that are tied to the current constraints of EV technology (range, limited access to charging, large variations in range) and technology unfamiliarity.

Question 2: What are some potential synergies and conflicts between emerging technologies that could alter travel behavior?

The combination of mega-trend technologies was found to be complementary in many settings. However, it is also easy to identify situations where the coupling of two or more technologies led to individual benefits at the expense of system performance. The identified relationships were as follows:

Traveler connectivity + AVs:

- **Network efficiency** [complementary] – Real-time data processing and automated decision making can help shift network behaviors closer to system optimal (especially in fleet settings) in the appropriate policy and regulatory framework.
- **Network inefficiency** [conflicting] – Without policy/regulation, AVs will likely be programmed to maximize individual benefits at the expense of network performance. Enhanced automation capabilities with real-time network information can act upon real-time data from multiple sources to further improve individual decision making resulting in degraded network performance.
- **Transportation affordability** [complementary] – Removing the driver in public mobility systems (e.g., transit, ridehailing) can drastically reduce operational costs, which can be passed on to users in the form of reduced fares and improved service performance.
- **Reduced operational costs** [conflicting] – High upfront costs and low operational costs of AV technologies can lead to greater vehicle miles travelled for affluent populations, which will increase societal costs in a mixed-use environment.

AVs + EVs:

- **Access to charging** [complementary] – Automation expands access to charging and decouples the need to have charging available at specific destination locations. The ability to send AVs to charge reduces EV constraints, leading to greater use and adoption.

- **Regional travel** [conflicting] – AVs provide new, convenient options for regional travel which can be cancelled out by limited range of EVs. This can lead to slower adoption of EVs and increased regional travel with internal combustion engine (ICE) vehicles.
- **Zero-occupancy travel** [conflicting] – Zero-occupancy vehicles will seek to reduce monetary costs (e.g., fuel costs, parking fees) as opposed to minimizing travel time. This could result in electric AVs seeking out congestion and stop-and-go traffic to reduce energy consumption and avoid parking fees.

Traveler connectivity + EVs:

- **Enhanced charging reliability** [complementary] – Real-time information related to routing, charger locations, and wait times will provide travelers with information to ease range anxiety and reduce overall EV travel costs. This will facilitate faster EV adoption and increased EV travel.
- **Selfish routing/charging** [conflicting] – Access to more real-time information can also facilitate increased opportunities for individuals to make utility maximizing choices, which can cause greater network/charging congestion.

Question #3: What are the gaps/challenges related to representing travel behavioral shifts in current AMS tools?

Based on findings from the literature review, four key areas were identified in which current AMS tools have shortcomings when it comes to modeling scenarios in the mega-trend era. The four focus areas and specific details related to gaps/challenges are as follows:

- **Shared service models** – There is a need to integrate changing behaviors resulting from AVs and EVs for fleet-based mobility services with AMS tools, such as how drivers will behave when using EVs (near-term) and how operations will differ when shared mobility services eliminate drivers and use AVs (longer-term). Fleet behaviors differ from individual travelers because different factors are considered when making choices about picking up passengers, traveling between passengers, and dropping off passengers.
- **Zero-occupancy trips –** New types of trips and new interactions with infrastructure are enabled by AVs, such as autonomous charging, self-parking, and pickup/drop-offs. Zero-occupancy VMT is expected to be significant, which will require modeling these types of trips (including the charging phase for electric AVs) to better understand network impacts and design interventions. New tradeoffs will also need to be evaluated (access time vs. parking costs) to gain a deeper understanding about human decision-making when interacting with AVs.
- **Network utilization –** Travel connectivity apps that provide real-time recommendations about routing, charging, and parking can result in significant network delays and misuse. Understanding these new interactions and incorporating them into AMS tools will be important to design strategic interventions. This will likely require a high-resolution representation of the network that includes information such a bridge clearance, steep grades, sharp turns, lane widths, among others and methods to estimate macro-level impacts using multi-resolution modeling frameworks.

- **EV charging/routing –** Travel choices become more complex in the mega-trend era due to numerous new constraints and capabilities. In addition to travel cost and travel time, common travel choices will require information related to SOC at origin/destination, vehicle range, charging supply including charger types, location, pricing information, and wait times. In addition, due to variation in battery range, different risk attitudes will also have to be modeled because route, charging, and cancelation decisions will vary between individuals. Finally, charging itself now represents a significant part of a trip, which can have widespread network implications in not captured in modeling and simulation frameworks.

Based on these findings, the following potential future research directions are presented to guide travel behavior and modeling/simulation research in the mega-trend era.

- Travel choices differ significantly between ICE and EV drivers due to range anxiety, range constraints, and limited (not well distributed) charging infrastructure. EV and ICE drivers traveling between similar origin-destination pairs may take completely different routes and park at different locations based on their vehicle state of charge (SOC), risk attitudes, and charging access at the destination. Therefore, travel behaviors (including risk attitudes) as a function of vehicle fuel type need to be studied further and integrated into current AMS tools.
- Constrained charger supply in both time and space can significantly alter travel behaviors in unforeseen ways, especially when self-charging becomes available using autonomous vehicles. The charging portion of the trip (location, time required, wait times, charger type) is a significant factor impacting travel choices, which is often not considered in EV modeling and simulation. Further research is needed that quantifies travel behaviors as functions of charger locations, queueing at charger, charging times, charger types, and whether vehicles are human driven or autonomous. Real-time charging recommendation systems will also impact travel choices as EVs gain market share, which is another area for future study.
- Real-time recommendations from travel apps, such as Google Maps or Waze, have drastically increased cut-through traffic and have caused problems when local context is not considered (e.g., bridge clearance for large trucks, school zones, steep grades). Such problems will likely increase in the megatrend era with recommendations for charging, eco-routing, autonomous parking, among others. Therefore, there is a need to study human responses to real-time recommendations (across a variety of contexts) and integrate these behaviors into AMS tools. There is also a need to better understand the underlying data that is being used to inform recommendations and the computational tradeoffs of including richer data streams for improved guidance.
- Numerous automobile manufacturers are developing and deploying SAE L2-L3 (hands-free) systems using pre-mapped roads and/or specific operational design domains (ODD). In such ODDs, drivers can monitor the vehicle hands-free (for SAE L2) or can engage in other tasks (for SAE L3), reducing individual travel costs. The rapid development of these systems and scarce publicly available data limits our understanding of human decision making when presented with tradeoffs between travel time and ease of driving. To address this gap, further research is needed to identify changing travel behaviors resulting from commercially available, hands-free features. For example, will travelers select longer routes and/or prioritize pre-mapped routes (usually freeways) if they offered more hands-free driving?
- In the longer-term, highly automated vehicles (SAE L4-L5) bring new capabilities, which can alter the relationship between travelers, vehicles, and infrastructure. For example, zero-

occupancy vehicles can be used to charge/park themselves and potentially run errands (assuming service models evolve with the technology). Such vehicles will utilize different cost functions compared to human drivers, with higher importance placed on monetary costs (e.g., parking costs, fuel costs) and reduced sensitivity to travel time/delay. The potential for zero-occupancy travel to contribute to significant VMT, congestion, and delays highlights the importance of considering these types of trips in modeling and simulation exercises. In the near-term, the majority of SAE L4-L5 vehicles will likely be part of a ridehailing fleet. And if such shared mobility services gain significant market penetration, it will be important to integrate fleet-optimal algorithms (considering both AVs and EVs) and perspectives into AMS tools, which is an area with limited research.

1 Introduction

1.1 Background

Emerging transportation technologies and services are changing the way people use and interact with the transportation system. Three technologies of special interest to both transportation decision makers and users are automation, connectivity, and electric vehicles, which are characterized in this document as “mega-trends” due to their potential to significantly disrupt travel behavior and transportation system use. Widespread adoption of mega-trends promises significant benefits to safety, efficiency, and sustainability; however, it is unclear how the mega-trend technologies will interact with each other, potentially cancelling out benefits without strategic interventions. Up to this point, numerous studies have forecasted travel behavior change due to automation, connectivity, and electrification technologies in isolation. This review considers these technologies together to glean realistic insights related to complementary and/or conflicting relationships between the various technologies that can affect system performance. The overall goal is not to answer all potential questions related to travel behavior change resulting from the coming together of three mega-trends, but to gather related literature and pose important questions to help guide future research efforts.

In this paper, we refer to *travel behavior* as the choices, decisions, and patterns that travelers exhibit when moving between locations throughout the transportation network. A strong understanding of these choices and behaviors are needed for analysis, modeling, and simulation (AMS) tasks to realistically evaluate network impacts and bound uncertainty across a variety of alternative scenarios prior to investing in large transportation infrastructure projects with long service lives. Out of this need to capture realistic travel behavior patterns, a travel behavior research community has emerged that focuses on broad activities that includes real-time decision making at the micro-level (e.g., individual travel choices, multimodal trip chaining) all the way to long-term planning choices (e.g., where to live/work depending on available transportation options). To provide specific AMS examples, agent/activity-based methods are at the *micro*-level because they model decisions at the individual/household/tour level, whereas traditional four-step models are at the *macro*-level because they capture aggregate behaviors at the level of a traffic analysis zone across larger regions. Micro-level AMS tools are used to evaluate outcomes at high resolution in time and space (e.g., tactical/operational decisions). Macro-level AMS tools evaluate regional outcomes across long time horizons (e.g., strategic decisions, long-term planning). Travel behaviors, such as route choice, destination choice, departure time, parking decisions, etc., which are required for traffic simulation tasks, fall somewhere in-between micro- and macro-level modeling. This analysis focuses on these behavior changes resulting from the convergence of three mega trends. More specifically, what are the impacts of automation, connectivity, and electrification on the standard sequence of travel choices that one typically goes through starting with the decision to make a trip and ending with choices that happen at the trip destination, such as parking location. Other decisions include mode, destination, departure time, trip cancelation, and route choices.

The rapid development and deployment of automation technologies (e.g., Tesla Autopilot, Waymo, Cruise), connectivity through real-time travel applications/services (e.g., Google Maps, Waze, public transit apps, traveler information messages), and affordable electric vehicles (EV) enabled by steep declines in battery production costs (82% decline in battery price in the last 10 years [1]) are impacting travel behavior in diverse ways. These emerging trends coupled with a constantly evolving technology, policy, and infrastructure landscape are creating challenges for the AMS community to accurately capture shifting travel behaviors. This analysis aims to address these challenges by connecting technology characteristics to factors affecting traveler choices both in isolation and in realistic environments where new technologies and services coexist. Gaps in current AMS tools will be identified and potential strategies to integrate new methods to capture shifting travel behavior will also be discussed. Specific high-level questions this paper aims to address are as follows:

- *What are the travel behavior impacts resulting from automation, connectivity, and vehicle electrification?*
- *What are some potential synergies and conflicts between emerging technologies that could alter travel behavior?*
- *What are the gaps/challenges related to representing travel behavioral shifts in current AMS tools?*

1.2 Emerging Technologies in Transportation

1.2.1 Connectivity

In the context of this analysis, connectivity refers to digital communications between devices, systems, vehicles, and infrastructure. *Vehicle* connectivity refers to vehicles that can send and/or receiving data via wireless communications. These technologies enable communication between the vehicle and other vehicles (V2V), infrastructure (V2I), and everything else (V2X). *Traveler* connectivity technologies are tools, devices, or platforms that are used to improve an individual's (or group's) overall travel experience. Examples of such technologies are mobile applications and traveler information services that provide real-time information (e.g., Google Maps, Waze, public transit apps) or access to new services (e.g., Uber/Lyft, micro-mobility, bike share). *Vehicle* connectivity technologies primarily focus on safety and operational efficiency while *traveler* connectivity technologies aim to improve traveler experience through information provision. Based on these primary objectives, it is anticipated that larger-scale travel behavior change will be due to *traveler* connectivity enhancements, and for this reason, *traveler* connectivity technologies are the focus of this study.

Traveler connectivity is not a new concept. The earliest examples date back to the 1930's with the in-car radio designed to provide traffic reports to the driver [2]. Other communications technologies, such as OnStar and electronic toll collection, have incrementally enhanced traveler experiences throughout the years. However, the introduction of modern smartphones and Wi-Fi-enabled vehicles in 2007 and 2008, respectively, have changed the landscape in terms of traveler connectivity for several reasons. First, smartphones are equipped with GPS that enabled a massive new source of speed and travel time data. In addition, GPS is necessary for new mobility service models that rely on real-time locations of travelers and vehicles for assignment and routing. Second, the proliferation of smartphones and the ease of integrating new platforms/services has resulted in smartphones becoming the default platform for disseminating detailed and tailored navigational support (Google Maps) and travel information (multi-modal / public transit apps). The growing use of smartphones and innovations to data collection, processing, and optimization has led to numerous individual benefits in terms of travel time reductions, improved reliability, and access to new mobility services. However, at the same time, numerous societal costs have also been observed due to unforeseen behavioral shifts (e.g., mode shift from public transit to Uber/Lyft leading to increased congestion [3], misuse of existing transportation infrastructure [4]).

1.2.2 Automated Vehicles

Concepts and pioneering research into automated vehicle (AV) technologies began in the early 1900's and continued through the end of the century. However, the automated vehicle grand challenges initiated by the Defense Advanced Research Projects Agency in 2004 and 2007, respectively, spearheaded commercial interest by showcasing what can be possible with vehicle automation technologies. The combination of new commercial interest (and investment) and advancements in key enabling technologies (e.g., sensors, software, computation) has pushed forward AV development in the last decade to a point where AVs are now commercially operating on U.S. roadways [5], [6].

Six levels of vehicle automation are defined by the Society of Automotive Engineers (Level 0 – Level 5) [7]. Level 0 – Level 2 refers to lower levels of automation, such as driver assistance and partial automation. High vehicle automation (Levels 3-5) refers to situations when the vehicle can be in full control of driving tasks in the appropriate operational setting. In terms of macro-level travel behavior, high automation is likely to cause the biggest shifts due to its ability to significantly change an individual's travel cost function. Therefore, highly automated vehicles are the focus of this analysis due to their potential to cause widespread behavioral change.

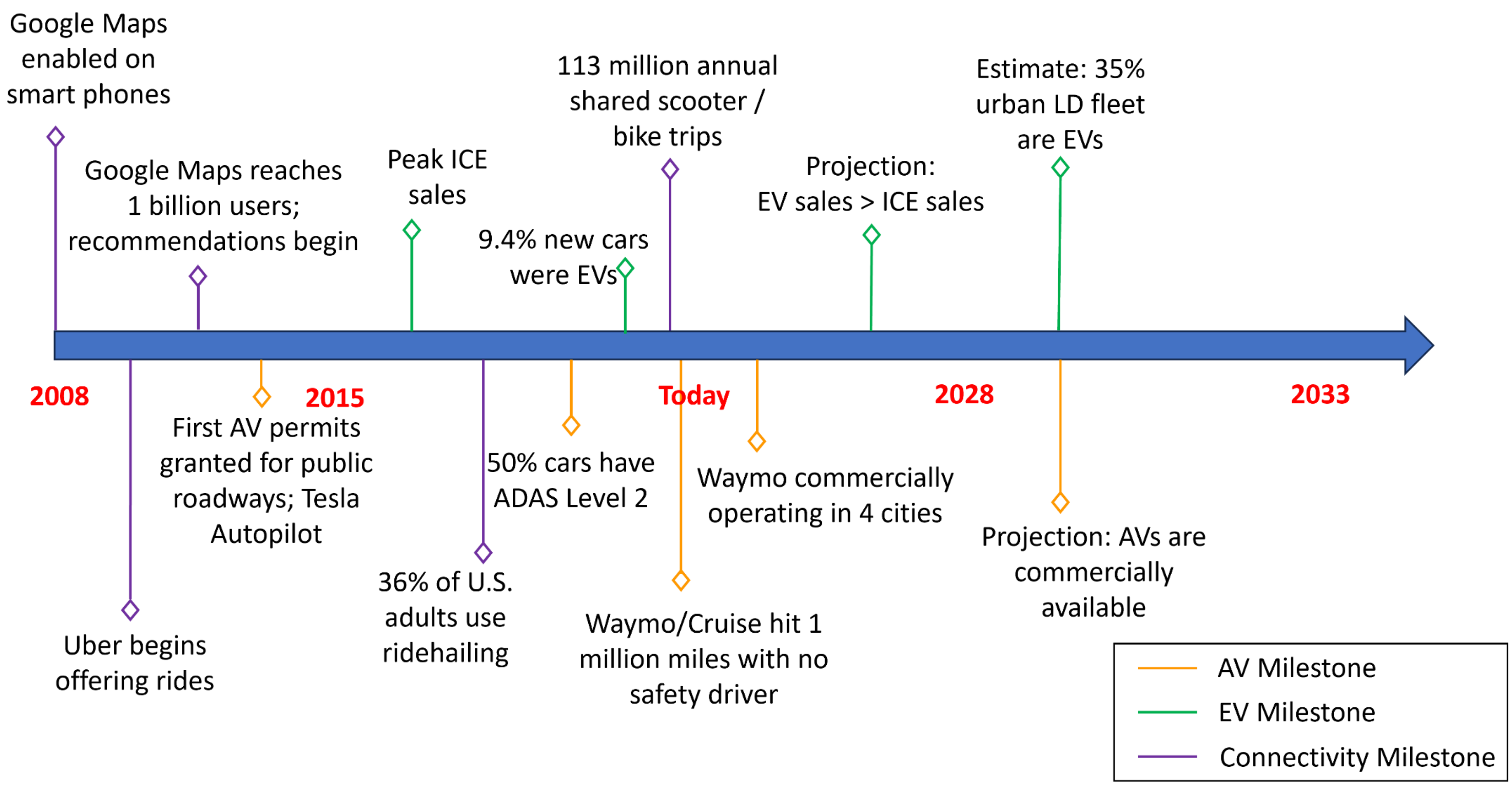
Finally, behavioral change from AVs is largely dependent on the service model. Currently, two primary models exist: privately owned vehicle model and shared use model. To date, the most advanced systems are being operated as shared, ridehailing services (Waymo, Cruise), which can facilitate safer, more affordable on-demand mobility service. The private ownership model (e.g., Tesla Autopilot) can also provide numerous individual benefits with potentially higher costs to society due to increased vehicle miles traveled (VMT) [8]. This analysis addresses both models to determine potential implications if either (or both) take hold.

1.2.3 Electric Vehicles

The race to decarbonize the transportation sector (which is currently the highest greenhouse gas (GHG) emitting economic sector accounting for 1/3 of total U.S. emissions [9]) has led to large investments in EV technology. These investments have paid off as battery costs have come down 82% in the last ten years ($780/kWh in 2013 to $139/kWh in 2023) [1]. These steep reductions in battery costs coupled with numerous federal, state, and local incentives have led to exponential growth in EV sales increasing from 0.7 million to 13.7 million between 2016-2023 [10]. The rapid adoption of new power train technologies can have significant impacts on travel behavior as new factors must be considered prior to making a trip (e.g., battery range, state of charge, access to charging). While these factors will likely evolve with improvements in battery range and charging infrastructure, the physical constraints posed by the electric grid (e.g., location, capacity) will continue to limit fueling flexibility for the foreseeable future.

For the purposes of this analysis, privately owned EVs are the focus. Other modes are also transitioning from internal combustion engines (ICE) to electric motors (public transit, micro-mobility); however, the fuel type alone is not likely to produce large shifts in travel behavior unless traveler costs can be drastically reduced. From a behavioral perspective, EVs serve as a clean-fuel replacement for ICE. Therefore, travel behavior change caused by EVs will be closely tied to their new benefits and constraints compared to their ICE counterparts. For example, battery range and availability of charging infrastructure are new constraints an EV owner must consider when making travel choices, which will alter their travel behavior compared to ICE vehicles.

Figure 1 presents key milestones for connectivity, automated vehicles, and electric vehicles over the last 15 years. Notice the rapid technology development and deployments during recent years, and how the different technologies are all expected to reach widespread deployment in the near-term. Therefore, there is an urgent need to improve AMS capabilities to capture these emerging trends.



Source: ITS JPO

Figure 1. Important Milestones and Deployment Timeline for AVs, EVs, and Traveler Connectivity Technologies

1.3 Travel Behavior Modeling

Travel behavior modeling is an approach used to estimate and forecast travel choices and their resulting network impacts using mathematical and statistical models. These models can then be used to evaluate various planning and operational designs quickly and cost-effectively to help inform policy, planning, and infrastructure investments. The field of travel behavior modeling is broad and consists of a series of modeling approaches developed to answer specific questions from intersection signal timing to long-range regional planning. The specific behavioral impacts of interest for this study are related to the sequence of choices an individual (or group) must make to initiate/complete a trip: 1) whether to make a trip or not, 2) destination choice, 3) mode choice, 4) route choice, 5) departure time, 6) trip cancellation/abandonment, and 7) parking decisions. This sequence of choices can then be integrated with the appropriate AMS tools (e.g., mesoscopic, macroscopic) to study macro-level behavior change and resulting network impacts.

The challenge with analyzing travel behavior change from emerging technologies is the lack of real-world deployments/data. However, data collected from surveys can help forecast behavioral shifts based on how the new technology or service impacts factors that influence travel choices. Many factors impact travel decisions that include socioeconomics, demographics, residential/work locations, etc., however, the focus of this analysis will be based on factors that affect the generalized travel cost function: 1) travel time and 2) monetary cost for travel (parking, fuel, tolls, fares, etc.). Reliability, convenience, vehicle ownership, and other factors that impact travel choices will also be discussed in terms of high-level impacts resulting from the three mega-trends.

To summarize, the convergence of three technology mega-trends (automation, connectivity, and electrification) are expected to disrupt the transportation sector in the coming years. At this point, is it unclear how these technologies will impact travel behavior, and if such travel behavior shifts are net positive or net negative. This analysis begins to address these questions at a high level by gathering relevant studies and comparing technologies to best understand how the different technologies will interact, and what roles they will play in modern transportation systems. Based on initial findings, new questions will also be posed to guide future research focused on travel behavior shifts resulting from mega-trend technologies. Finally, network level impacts and methods to integrate new shifting behaviors into existing AMS tools will also be discussed.

1.4 Purpose

The purpose of this document is to identify potential impacts from AVs, connectivity, and EVs as they relate to travel behavior to update, integrate, and operationalize AMS tools. The overarching goal is to improve accuracy and reduce uncertainty for AMS tools when modeling the coming together of three mega-trends.

1.5 Scope of Document

The primary focus is at the vehicle and/or traveler level. More specifically, how will AVs, *traveler* connectivity, and EVs impact *individual* decision making. Potential synergies and conflicts between the various technologies will also be discussed. Future research directions will be identified based on a review of relevant literature related to the integration of shifting travel behaviors with currently available AMS tools.

1.6 Report Organization

The remainder of this white paper is organized as follows:

- Chapter 2 presents a summary of the literature review of existing studies focused on travel behavioral change from automation, connectivity, and electric vehicles.
- Chapter 3 discusses potential relationships (complementary / competitive) between automation, connectivity, and electrification based on findings from Chapter 2.
- Chapter 4 summarizes modeling gaps/challenges and discusses various ways to integrate and operationalize behavioral shifts with current AMS tools.
- Chapter 5 summarizes the conclusions, including responses to important research questions posed, and identifies future research directions.

2 Literature Review

This chapter presents an overview of findings related to travel behavior shifts resulting from traveler connectivity technologies, AVs, and EVs. The various methods and approaches used to model and simulate emerging technologies will also be discussed. The chapter will conclude with key findings and gaps/challenges.

2.1 Travel Behavior Impacts

2.1.1 Traveler Connectivity

The smart phone has changed the way traveler's make choices. Since its introduction in 2007, numerous mobility applications have been developed to improve the traveler experience. Generally, the various applications can be divided into two groups: 1) traveler information and 2) mobility services. Traveler information apps equip travelers with data to inform decision making (e.g., Google Maps, Waze). More information leads to more rational decisions and improved individual benefits. Information apps can be real-time (e.g., traffic congestion along route) or offline (e.g., multimodal planning based on timetables). Service apps, on the other hand, are new modes and services enabled by smartphone connectivity. Ridehailing (e.g., Uber/Lyft) and other micro-mobility services (e.g., bikeshare, shared scooters) are two service models made possible by smartphone connectivity that have shifted travel behavior resulting in significant network disruption over the last decade [3], [11], [12]. The following section will focus primarily on these two groupings of traveler connectivity apps, and how access to information and new services have impacted travel behavior.

Travel decisions informed by real-time information are largely en-route decisions, such as route choice, trip abandonment, and parking decisions. Factors affecting these decisions are delays/congestion, incidents, weather, and parking supply/cost. Prior to this information being made available through connectivity, travelers would continue taking their "best" routes that were learned through experience, which might not always be user optimal. Therefore, real-time information can help increase individual benefits and enable more rational behavior. Evidence of improved decision making was found in several studies dating back to traffic reports in the early 1990's. One study found that commuters were more likely to change their route choices and departure times to minimize travel costs after listening to traffic reports if their route was congested [13]. A different study found that travelers' route choice behavior was more rational when real-time information was presented through dynamic message boards [14]. Improved rationality leads to more predictive behavior, which is consistent with how current AMS tools model route choice behavior. However, improved individual decision making doesn't always lead to positive outcomes and can create new modeling challenges based on new traveler-infrastructure interactions. For example, one study found that while digital navigation increased the usable capacity of the road network by diverting traffic to lesser-used roads, many of the roads were not being used as intended. For example, local traffic was now using motorways designed for long-distance travel (adding to congestion) and long-distance travelers were now using local roadways not intended for high traffic volumes (increasing negative environmental impacts) [15]. This behavior was corroborated by other studies in London and California [15], [16]. These observations were occurring because travel information providers (Google Maps, Waze, etc.) work in isolation (not with local transportation officials) and provide “selfish” routing recommendations. Simple heuristics are also used to make recommendations in real time, which require roads to be broken down into a few simple classes with no local contextual information. Finally, acceptance of routing recommendations is extremely high among app users (~75% follow recommendations more than 80% of the time [17]). These simplifications of the road network and high compliance among app users creates numerous problems for city traffic officials as they can no longer manage traffic as intended, often leading to increased congestion and traffic accidents (e.g., school zones, difficult to cross intersections, difficult roads with steep grades and blind spots, truck rerouting along on roads without appropriate accommodations, e.g., bridge clearances, sharp turns, steep grades) [4]. These observed trends can also increase overall network delays when large numbers of travelers divert to smaller roads instantaneously (assuming recommendations are provided based on real-time data, i.e., no predictions), which can create unexpected queues due to the recommended route’s inability to accommodate the sharp increase in demand [18]. From the user benefits perspective, several studies found that travelers place high value on reducing travel time uncertainty. [15] concluded that the biggest benefit from digital navigation was its ability to reduce travel time uncertainty, while [14] found that travelers with sufficient experience between specific OD pairs tend to shift from the lowest expected travel time routes with high variation to more reliable routes. Finally, from the parking perspective, several studies observed reduced circling for parking when information was available [19], [20]. [20] found that travelers behaved more rationally (in a cost-minimizing fashion) when parking information (cost, availability) was provided, and time flexibility was considered. To conclude, the types of travel behavior shifts that can be anticipated from real-time traffic information vary based on what is important to the user and how the information is presented. When all information is presented and travelers have time to make choices between alternatives, individuals tend to be more rational. Real-time traffic apps can also reduce travel uncertainty, which is an important factor for travelers making choices about whether to take the trip or not, departure time, and route choice. Finally, recommendation systems play an enormous role in en-route travel behavior, especially when the traveler is unfamiliar with the region.

Travel decisions informed by offline information are often pre-departure decisions, such as mode choice, departure time, and other trip planning decisions. Multimodal planning and transit apps are primary examples. The research in this area is limited, however, [21] used a survey of 3,000 multi-modal app users to find that 38% of users drove less, 1/3 of respondents increased their use of alternative modes, and half of the respondents reduced their wait times. Improved access to information will improve reliability and reduce travel costs for alternative modes, which will likely cause mode shift in regions where robust alternative services exist and costs to own private vehicles is high.

Finally, the rise of service-based apps enabled by connectivity has grown rapidly since Uber and Lyft began offering rides in 2010 and 2012, respectively. Also included in this category are all bike share and micro-mobility systems that require a mobile app to lock/unlock devices, pay for services, and locate devices. The improved convenience of such technology-enabled services has led to rapid growth in the use of these services. In 2019, 36% of U.S. adults reported using ridehailing services, which was up from 15% in 2015 [22]. In 2022, 113 million trips were taken by e-scooter and bike share systems, up from 320k in 2010 [23]. These numbers indicate a mode shift and/or induced demand that should be considered for planning purposes, especially as younger, more tech savvy generations reach working age. However, more importantly are the sheer number of new fleet vehicles on U.S. roadways. In New York City alone, Uber operates a fleet of 80,000 vehicles compared to only 13,000 taxis [24]. From a traffic perspective, large fleets of on-demand vehicles (ridehailing, delivery, etc.) will impact network performance in unforeseen ways because fleet vehicles behave differently compared to individual drivers. First, fleets are centrally coordinated and profit maximizing during assignment. This behavior was found to increase system costs at low fleet penetration rates [25]. Next, a different set of behaviors is exhibited between trips (deadheading) in search for demand, which can be further influenced by policies, pricing, and/or regulation [26], [27], [28]. Finally, parking is no longer a consideration, which can reduce circling but can also create congestion at pickup/drop-off locations. [3] found that average pickup/drop-off times for ridehailing services in San Francisco to be 1 minute, significantly impacting local congestion.

2.1.2 Automated Vehicles

Numerous automation technologies exist within the transportation ecosystem; however, highly and fully automated vehicles (defined by SAE as L4-L5) are the focus of this study because they can facilitate widespread behavioral change. However, it is worth noting that numerous hands-free automation systems are being developed and deployed by different manufacturers that could impact travel behaviors. For example, General Motors (GM) recently extended their hands-free Super Cruise (SAE L2) network to 750,000 miles (in the U.S.) based on pre-mapped roads that have been approved for use by GM [29]. Other manufactures have taken similar approaches (e.g., Ford BlueCruise [30], Nissan Pro-PILOT 2.0 [31]) with SAE L2 capabilities using pre-mapped roads. Recently, Mercedez-Benz received approval for Drive Pilot (SAE L3) to operate in Nevada and California when speeds are below 40 mph [32]. A few studies have considered/analyzed different travel behaviors based on different levels of automation. For example, [33] assumed a 5% reduction in travel costs for SAE L2 systems and 50-80% reduction in travel costs for SAE L3-L4 systems. A different study used a driving simulator for both SAE L3 and SAE L4 features and stated preference surveys to find that drivers were willing to spend 30-50% longer traveling if they did not need to drive the whole trip themselves [34]. This finding would indicate that drivers of vehicles with SAE L2-L4 features would likely deviate from their normal route (up to a point) to access pre-mapped corridors or other operational design domains defined by the automation feature. Due to recent technology deployments and limited data on the subject, travel behavior change resulting from SAE L2-L4 systems is not well understood, indicating an important area for future research. For highly/fully automated systems (the primary focus of this paper), there tends to be two general pathways for AV adoption / deployment: 1) private ownership model and 2) shared services model. The pathway that dominates will also govern the resulting travel behavior changes. This literature review investigates both pathways to capture all potential scenarios that could unfold.

The most agreed upon finding in the literature is that the value of travel time (VOTT) decreases when traveling in an AV because travelers can now use their time to do other tasks (working, reading, etc.). This assumption is supported by several studies and is consistent for both private and shared models. However, the reduced VOTT was only observed for work travel/commutes and long-distance travel [35], [36]. Estimates of VOTT reductions were between 20-50% [37]. These findings indicate that if vehicles are designed to accommodate work tasks during commutes, then the reduction in VOTT could increase peak hour congestion because individual travel time costs decrease while departure time penalties remain unchanged. This results in travelers being less sensitive to delays when making travel decisions. Along these same lines, the ability to multi-task (or sleep) during longer distance travel is a clear advantage for AVs. This idea has led to several studies estimating rather large mode shifts between short-haul flights to AVs for trips between 100-500 miles [37], [38].

AVs can also decrease travel costs by reducing/eliminating parking costs. Traditionally, parking costs in downtown central business districts are high to help balance supply and demand. The parking choice for individual drivers come down to the monetary cost of parking versus walking time tradeoff. This tradeoff is different for AVs depending on the how long the traveler plans to spend at the destination. For short duration trips, travelers prefer wait times less than 10 minutes, which means that the access/egress costs can be relaxed because AVs are much faster than walking. For longer duration trips, the parking location decision is simply a cost minimization problem (operational + parking) because access time is no longer an issue [39]. Finally, trip termination for AVs is more like a ridehailing service, in that passengers can be picked up and dropped off anywhere. This represents a behavioral shift as to how curb space is used, which can result in harmful impacts if not considered in planning and operational designs.

The combination of reduced travel time costs (i.e., lower VOTT) and reduced monetary costs compared to human driven vehicles (e.g., reduction in parking costs, improved driving efficiency) will likely result in increased mode share for AVs at the expense of alternative modes. Several studies have found that public transit mode share will likely decrease with greater access to highly and/or fully automated vehicles (SAE L4-L5) due to reduced travel time disutility and lower operational costs provided by autonomous vehicles [40], [41], [42]. However, this shift will depend on access and efficiency of nearby public transit and travelers' willingness to use AVs [43], [44].

Perhaps the biggest uncertainty related to AV behavior is related to zero-occupancy trips. The ability for AVs to travel throughout the network without a driver fundamentally changes how people and vehicles interact with the transportation system. When a person is in the AV, travel choices will be similar to conventional vehicles (balancing travel costs, travel time, reliability, etc.) with marginal shifts due to reductions in VOTT. However, when an AV is traveling without a driver, these costs and objectives change. For example, the travel time component of cost becomes irrelevant, and autonomous vehicles will simply look to minimize operational/parking costs. The unfortunate fact about the operational cost minimization strategy is that traveling at slower speeds is the most cost effective solution, thus incentivizing congestion [45]. In the case of parking, AVs will select the parking locations where the summation of operational costs and parking fares are minimized. In many cases, this might result in AVs returning home for free parking and doubling vehicle miles traveled (VMT) [8], [46]. An alternative optimal solution for dense urban cores might be for AVs to simply cruise, as operational costs can often be cheaper than sending the vehicle home or paying for parking [45]. The key takeaway here is that VMT is expected to increase with AVs and a significant portion of induced VMT will likely be in the zero-occupancy state. One previous study using a chauffeur to simulate AV travel behavior found that VMT increased by 85% with 21% of the increase coming from zero occupancy trips [47]. These zero occupancy vehicles move about the network and make decisions based on a very different cost function compared to conventional vehicles, which can negatively impact network efficiency without the appropriate policies in place (e.g., congestion pricing).

Shifting to the shared autonomous vehicle (SAV) model, which can be thought of as a shared fleet of AVs that operates like a ridehailing or on-demand public transit service. According to several studies, SAVs can reduce car ownership, reduce waiting time and trip costs compared to traditional public transit, are more efficient (serve demand with smaller fleets), improve accessibility for non-driving populations, among many others [48]. One reason why there is so much interest around shared automated services is that eliminating driver costs (accounting for up to 70% of expenses in public transit systems) can drastically reduce operational costs and resulting affordability. One study estimated that shared, autonomous ridehailing could be 10-40% cheaper per mile compared to private conventional vehicles in the next decade. Compared to traditional ridehailing, fully autonomous fleets can reduce mobility costs by 70-80% [49]. If technology developments continue to progress and cost reductions are realized, significant growth in the use of these services is anticipated. From a modeling perspective, large, centrally operated vehicle fleets behave and interact differently with existing infrastructure and other network users. Fleet optimal algorithms will be used to advance operator objectives (likely profit maximizing objectives). Empty vehicle miles between drop-offs and subsequent pickups (also known as deadheading) will be unpredictable and based on private demand data collected by the operator. Finally, interactions with the curb will drastically change as on-street parking will be less in demand and pickup/drop-off zones will be needed to remove vehicles from traffic streams to prevent congestion.

A large shift towards greater use of SAVs was also found to reduce mode share for both private vehicles and public transit due to low operational costs and reduction in VOTT [40], [50]. However, it is difficult to determine if the net effects of mode shift towards SAVs are positive or negative from congestion and VMT perspectives without a more detailed analysis that considers local conditions, built environment, and travel behaviors.

AVs will also provide mobility services to new, non-driving populations (e.g., elderly, disabled, youth), which by some estimates, can increase vehicle miles traveled (VMT) by 14% for the adult population [51]. A deeper understanding related to travel behaviors associated with such populations is needed to accurately model and simulate behavior change resulting new traveler types.

Finally, it is worth mentioning that AVs exhibit programmed behavior, which can be very different than driver behavior. A conservative driving style that is fully compliant to all rules and regulations could impact network efficiency when coupled with other potential AV behaviors. For example, selecting low-speed local routes to minimize travel costs might present problems due to higher-than-normal pedestrian traffic (e.g., multiple crosswalks present through a school zone). The lack of social cues in such scenarios can drastically slow travel and create unnecessary congestion.

2.1.3 Electric Vehicles

The transportation sector accounts for 1/3 of total U.S. emissions, of which, light duty vehicles contribute to 49% [9]. To combat the growing impacts of climate change, the transportation sector will need to leverage a variety of technologies and strategies to promote more sustainable travel. The transition from ICE to EV vehicles is one of the most important components for most decarbonization strategies. At the same time, EVs have a different set of constraints compared to ICE vehicles that travelers must learn and consider when making travel choices. This section focuses on these choices, and how travel behavior might change as the light-duty fleet electrifies.

First, it is important to remember that EVs serve as a replacement for ICE vehicles. The main differences between the two are that EVs have more efficient power trains and are powered with electricity. This translates to lower energy costs (70% reduction in energy costs for EVs compared to ICE vehicles [52]) but more complex decision making due to new constraints around battery range, reliability, and access to charging infrastructure. The consistent finding from the literature is that most day-to-day travel choices will be directly impacted by battery and charging conditions. One study found that state of charge (SOC) at the origin is the most important factor for deciding to charge while estimated SOC at the destination was the most influential factor for route choice decisions. Additionally, when en-route charging was required, travelers tended to choose routes with charging close to the origin with minimal wait/charging times [53]. A different study found that in addition to SOC at origin and destination, the presence of charging at the destination, charger types, and charging wait times also impact route choice [54]. Findings also suggest that when SOC at the destination is low, travelers choose local streets with slower speeds to reduce energy consumption. If charging is required, travelers prefer arterials with access to fast charging [54]. Finally, from a departure time perspective, one study points out that EVs can increase peak-period congestion by not altering their departure time. Congestion related costs for EV drivers are expected to be lower due to improvements in energy efficiency at low speeds. In some cases, the added congestion costs are lower than penalties incurred by departing early or late [55]. Other research has also shown that reduced fuel costs are likely to lead to increased trips [56], [57], [58] when battery range is not an issue. However, trip cancelation / abandonment rates are also expected to increase when estimated SOC at the destination is low [59]. Range reliability is also an issue affecting trip taking behavior, as EVs range can vary significantly based on travel speed, road grade, driving behavior, and temperature [59]. The key takeaway from this section is that trip choice and destination are both highly dependent on SOC. Departure time to avoid congestion might also be impacted due lower energy costs while in congested conditions. For EVs in general, the generalized cost function for route choice becomes more complex because travelers must now consider battery SOC and charging access in addition to travel time and cost. Parking choices are also impacted when SOC is low at the destination.

The rapid adoption of EVs might also impact travel behaviors for ICE vehicle owners. According to a report by Boston Consulting Group, 25-80% of the fuel market could be unprofitable in the next 15 years due to EV adoption and the increased use of mobility-on-demand [60]. If gas stations plan to accommodate both EVs and ICEs, they will need to relocate to areas with more land to provide services for longer durations (lower turnover with EVs), which will impact area travel behaviors as gas stations relocate from urban to suburban locations. This transition will also have equity implications as smaller urban gas stations (without room to expand) will likely be the first to close, resulting in decreased access and longer travel times for urban ICE owners. The most likely gas stations to survive this transition are ones that diversify their offerings and accommodate EV charging, which in many cases, will be based in areas with favorable utility rate structures [61] and outside of affluent, urban neighborhoods where home charging is an option [62]. In scenarios where access to gas stations becomes increasingly difficult (affluent, urban neighborhoods), ICE owners will likely have to alter travel behaviors or have their fuel delivered [63].

EV drivers also exhibit different driving behaviors compared to the general population. One study surveyed 350 EV owners in the United States and found that EV drivers exhibited calmer driving behavior and were more likely to engage in more fuel-efficient driving habits, such as trip chaining and taking eco-routes [64]. At the same time, a rebound effect has also been observed, as EV owners perceived EV travel as significantly more environmentally friendly than public transit, leading to an increase in private vehicle trips [65]. In addition, eco-routing behaviors may also increase total system costs due to delays and increased congestion in a mixed traffic environment as EVs owners may seek out stop-and-go traffic to save energy thus causing more congestion for all network users, including ICE vehicles.

2.2 Modeling Methods

A rich literature exists related to the integration of AV, vehicle and traveler connectivity, and EV driving behavior into micro-simulation models. However, less attention has been paid to modeling macro-level behavioral shifts, which is the focus of the following section.

2.2.1 Traveler Connectivity

The three primary areas of interest identified from the literature review related to connectivity technologies were behavioral response to real-time travel info (e.g., digital navigation apps, such as Google Maps or Waze), behavioral shifts due to greater access to multimodal information (both real-time and offline), and the potential widespread adoption of fleet-based services enabled by connectivity technologies (Uber, eScooters, bikeshare, etc.). For fleet-based services, the shifts in "behavior" are due to new types of vehicles and services interacting with the network in new ways.

First, from a real-time information perspective, several studies have identified a shift towards more rational decision making when real-time information was provided [14], [66], [67]. Different studies have modeled this behavior by assuming travelers will select the route with the lowest expected travel time based on real-time network conditions. This choice is presented at each time step to model en-route behavior [18], [68]. [18] found that providing real-time information to a small portion of travelers resulting in improved network performance. No real-time information led to higher congestion on freeways and major arterials. Providing real-time information to a high percentage of travelers caused more intensive use of smaller roads with bottlenecks, which also increased total network delays. This is because large numbers of travelers may all decide to use the instantaneous optimal route, which may lead to unexpected queues on routes not designed to accommodate all of the diverted travelers. [68] observed similar results for parallel networks (providing real-time information to only 30% of travelers was optimal). However, network performance improved as a function of the proportion of travelers provided with real-time information for grid and ring networks. Other studies have found oscillatory behavior amongst rational travelers when provided real-time information on simplified networks [66], [69], [70]. This behavior was due to the time lag between providing shortest path route recommendations to drivers and the subsequent congestion caused by more drivers using the recommended route. The current route then becomes the shortest path due to fewer drivers, which will now become the recommended route resulting in an oscillating pattern of congestion. This pattern has been shown on theoretical, simplified networks, however, further research is needed to understand how real-time information impacts actual drivers on real-world networks.

Next, from a multimodal perspective, access to transportation planning apps and real time transit information leads to improved performance of alternative modes. For example, when using a multimodal/transit app, wait times were reduced, thus lowering the total cost of the trip [21], [71]. Research studies were not identified that specifically modeled travel behavior response from improved access to multimodal information. However, multimodal travel behavior has been extensively studied and can be integrated into traditional travel demand models using behavior choice studies. Based on previous research, correlation was found between smartphone use (and transportation app use) and greater probabilities to use alternative modes. One study found that millennials (who were also found to use smartphone apps at increased rates) were three times more likely to use Uber or Lyft and five times more likely to take a shuttle to work or school compared to Generation X respondents [72]. Modeling frameworks for multimodal travel have been developed for research applications, however, emerging modes (ridehailing, scooters, bikeshare, etc.) are often not considered [73], [74]. The current method of choice for capturing mode shift to alternative modes (or multimodal travel) is to use agent-based models (ABM). ABMs are flexible modeling frameworks that simulate actions and interactions at the individual-level based on a set of predefined rules/behaviors. Using this framework, heterogeneous behaviors can be modeled in the multi-modal context that includes emerging modes. ABMs are extremely flexible and different modeling approaches exist, however, the general approach for transportation ABMs begins with tour assignment (based on area activity patterns) using empirical data and discrete choice models. A simulation step then follows that assigns traveler tours to specific routes. Finally, a replanning phase is initiated to allow individuals to make alternative plans based on utility maximization. These steps are repeated until population utilities stabilize [75]. This framework allows for easy integration of alternative modes based on how each mode impacts an individual's utility.

Lastly, and perhaps the most impactful, are travel behavior shifts due to emerging services and technologies enabled by connectivity. Modeling efforts that consider the different objectives (fleet optimal versus user optimal) have been conducted in research using mixed-traffic equilibrium, where both fleet vehicles and private vehicles must reach fleet optimal and user optimal conditions, respectively [25], [76]. However, deadheading and queueing created during pickup/drop-off were not considered. A different study used optimal control theory to characterize ridehailing dynamics including the deadheading portion of the trip [77]. However, other traffic was not considered. Finally, different modeling methods have been developed to analyze impacts from the pickup/drop-off portion of the trip. [78] used ABMs and constrained pickup/drop-off zones to parking areas (both on-street and off-street) where the probability of available parking supply was high based on parking data. [79] developed a bi-modal equilibrium model with a queueing component to capture network impacts of ridehailing pickup and drop-off.

2.2.2 Automated Vehicles

From the private ownership perspective, highly automated vehicles can significantly impact network efficiency by reducing VOTT for travelers and through zero occupancy travel. From a shared service model perspective, automation can enable affordable new mobility services (e.g., ridehailing, on-demand transit) that can impact network performance through new fleet-based objectives, added VMT from deadheading, and new interactions with the curb. Numerous studies have developed different ways to model these behavioral changes, however, no studies have modeled automation impacts in aggregate to gather realistic insights.

First, the general approach to modeling AV travel, for both private and shared models, is to reduce VOTT and operational cost parameters and simulate travel outcomes [40]. To evaluate resulting impacts, activity- and agent-based models were most often used due to their flexibility to consider new modes and behaviors. The general approach to represent AVs in macroscopic models was to modify demand (e.g., passenger car unit factors) and/or supply based on reduced headways between AVs [80], [81]. For travel demand models, new AV modes (private, ridesharing) can be easily integrated into the mode choice step by adding an AV option to the choice set with modified cost and travel time parameters [80]. Modifications to VOTT and travel costs were also used to represent long-distance AV travel compared to conventional driving, air, and rail travel [82], [83].

Next, one large difference between conventional driving and AV travel is related to what happens before and after the trip when vehicles are in a zero-occupancy state. Several studies have looked at this from a parking choice perspective. The most common approach is to select a parking location based on total cost minimization (operational, tolls, parking fares). [84] used an ABM to model parking choices based on minimizing parking and driving costs in Seattle and found that VMT increased between 5.6-13.5km per day with AVs. A different approach was also developed to consider both trip segments (origin → destination + destination → parking) to more accurately represent AV travel and quantify resulting impacts [85]. The parking location was assumed to be known a priori based on minimizing costs between the destination and final parking spot. The total travel cost can then be calculated based on both trip segments and represented in a network equilibrium model [85]. [45] used similar travel cost functions to determine parking locations (free on-street parking or returning home). In addition, SUMO modeling software [86] was used and cruising behaviors were modified to seek the most congested routes to minimize cruising costs. Based on demand data in San Francisco, the study found that cruising was the cheapest option for 37% of the trips for ICE vehicles and 39.9% of trips for EVs [45]. Modeling parking decisions—which is one motivation for zero-occupancy travel—is a well-researched topic area that comes down to minimizing monetary costs of travel and parking fares. However, other zero-occupancy behaviors are likely to arise (e.g., errands, delivery, picking up friends/family [47]), which can have significant impacts on network conditions. Modeling these situations and designing appropriate interventions will be integral in managing future traffic networks with highly/fully automated vehicles.

From a shared use perspective, the most common modeling approaches use ABMs and modify travel cost parameters to represent private and shared AVs in the network. One study used MATSim [75] and reduced cost parameters for private and shared AVs to capture mode choice decisions and subsequent operational impacts when traversing through the network [87]. Shared AVs must also include disutility factors for sharing rides with others and wait/detour times. Other modeling considerations (fleet-optimal decision making, deadheading, and curb interactions) are similar to those of ridehailing fleets discussed above. The primary difference between the two services (ridehailing with drivers versus ridehailing with AVs) is related to expected costs of travel and deadheading behaviors. Lower costs for AV-based services are expected, which will likely facilitate a more rapid modal shift. Cruising behaviors between passengers will also likely be different. AV services will likely reposition based on historical data and fleet optimal decisions. Driver-based ridehailing behavior will be based on driver experience.

2.2.3 Electric Vehicles

The key finding from the literature was that EV drivers must consider new constraints when making travel decisions due to technology limitations and lack of a convenient and reliable charging network. Important factors such are SOC at the origin and destination, locations of different types of charging infrastructure, and routing decisions to conserve energy when the cost of en-route charging is high (detours, wait time, monetary cost, etc.) must all be considered in addition to travel time and cost.

From a modeling perspective, battery range constraints and charging decisions can alter the way EV drivers utilize the transportation network. To capture range anxiety, several studies have modeled EV travelers with different risk attitudes [53], [88]. For example, risk averse drivers will select slower routes with improved access to charging. These risk behaviors were considered in the shortest path calculation by placing higher weight on the risk term when calculating route costs [88]. Based on this assumption, EV drivers will take different routes between the same origin-destination pairs based on their risk tolerance. A similar study analyzed EV driver data and recommended to include SOC origin, SOC destination, and en-route charging access as well as risk attitudes in the route cost formulation [53]. User equilibrium models have also been developed to include EV charging behavior by adding charging costs to link cost functions based on where charging stations were located [89]. ABMs have also been used to model EVs due to their flexibility is creating rules and/or using heuristics to simulate travel behavior. For example, [90], [91] both use SOC thresholds to send vehicles to charge when operating in an on-demand, shared service setting. Finally, eco-routing behaviors have been observed for EV drivers [64]. Therefore, factors that impact energy consumption (stop-and-go conditions, slower speed roads, grade, etc.) should be considered when calculating shortest cost paths for EV drivers.

2.3 Key Findings

The key findings listed below are based on a review of existing literature related to travel behavior changes resulting from traveler connectivity, AVs, and EVs, and modeling approaches to quantify network impacts from such changes. The first and second sets of key takeaways focus on behavioral impacts and modeling approaches, respectively.

Behavioral impacts:

- A significant behavioral shift towards the use of new, fleet-based mobility service models (enabled by connectivity) has led to new interactions between travelers and infrastructure (fleet-optimal behaviors, user optimal deadheading behavior, and new interactions with the curb).
- Greater access to real-time information has led to more rational behavior, greater use of alternative modes, and new traveler-infrastructure use patterns.
- A research gap exists that studies traffic impacts of real-time recommendations (e.g., oscillations in congestion/recommendations between alternative routes) due to limited access to digital navigation data.
- Algorithms that make travel recommendations in real-time (Google Maps, Waze) can have significant impacts on individual decision making because travelers are continuously looking

to minimize travel time and uncertainty. This has led to misuse of transportation infrastructure.

- Highly and fully automated vehicles (L4-L5) reduce travel disutility for work and long-distance trips. This means that travel time costs felt by individuals are less when using an AV because that time can be used to pursue other activities. This is positive for individual travelers because they experience the direct benefits of automation. However, this also means that individual travelers are less impacted by congestion and delays, which could increase system level costs.
- Zero occupancy travel will make decisions based on monetary cost minimization with little sensitivity to travel time.
- Zero occupancy travel behavior is highly uncertain. Most studies have focused on parking; however, new uses and service models are expected with full automation.
- SAE L2-L3 systems are being developed/deployed by many manufacturers using pre-mapped roads. A research gap exists that explores potential travel behavior change resulting from these new automation features that are constrained to specific locations and operational design domains.
- The expected reduction in costs for shared AV mobility systems (operating like a ridehailing platform) will likely result in significant mode shift from both public transit and private vehicles.
- Travel decision making becomes much more complex for EV drivers as they must consider SOC at origin, estimated SOC at destination, en-route charging access, and charging availability at the destination when making mode and route choices.
- Different EV drivers exhibit different risk behaviors when it comes to range anxiety, which can dramatically shift their travel choices.
- EV drivers tend to exhibit more eco-friendly driving behaviors, such as trip chaining and eco-routing.

Modeling approaches:

- New modeling approaches are being developed to capture changing travel behaviors resulting from emerging technologies. However, most methods are specific to one or a few use cases and development is mostly being conducted in the research setting.
- ABMs provide the flexibility needed to model heterogeneous travel behaviors, emerging modes, and complex/dynamic interactions. Interpretability and feature sensitivity remains an issue due to numerous complex interactions between travelers and infrastructure.
- Numerous models have been developed/proposed to simulate fleet-based services that include fleet optimal decision making, deadheading behavior, and pickup/drop-off behaviors. However, model simplifications are needed to isolate impacts and interpret findings.
- AV and EV travel behaviors can be incorporated into existing tools by modifying demand, supply, and travel cost functions used to model travel choices. For example, travel costs and VOTT can be reduced for AV travel, or SOC and charging availability can be integrated into route cost functions for EV drivers.

- The impacts from real-time routing recommendations are typically modeled by allowing travelers to deviate from their original route based on real-time information using simplified, symmetrical networks. However, evaluating such behaviors, such as oscillations caused by a time lag in congestion after numerous travelers deviate from their original routes, has not been studied using real-world behaviors and realistic network configurations.
- Zero occupancy travel choices have been modeled based on monetary cost minimization (operational costs + parking fares).

3 Potential Synergies and Conflicts

Numerous travel behavior shifts have been identified resulting from AV, traveler connectivity, and EV technologies in isolation, all with potential to significantly impact network efficiency and performance. However, a deeper understanding is needed as to how these mega-trends interact with one another in realistic environments where the three technologies coexist. There is also a need to integrate these findings into current AMS toolsets to better estimate impacts of these technologies and inform requisite policies and/or designs that maximize societal benefits. The following section takes findings from the literature review to help identify potential relationships (complementary or competitive) between the various technologies and guide future research activities.

3.1 Automation & Connectivity

Network efficiency [complement]: Assuming that policy/regulatory frameworks are in place to ensure that automated decision-making is in the best interest of society (i.e., AVs programmed to maximize system benefits), the pairing of automation and connectivity technologies can improve data processing and optimization times to react quicker to incoming data resulting in improved safety and efficiency. Connectivity also provides an improved representation of surrounding conditions to augment data received from onboard sensors to further improve decision making tasks. From a travel behavior perspective, this combination of technologies has the potential to shift en-route travel decisions (departure time, routing, parking) from user to system optimal.

Network inefficiency [conflict]: Previous studies have shown that drivers make rational (or selfish) decisions when real-time information is provided. This behavior, coupled with recommendation systems that use simple heuristics, can lead to transportation network misuse and increased congestion. If AVs are privately owned and programmed to maximize user utility (which is likely), it is expected that these issues will only be exacerbated. In addition, local context (e.g., steep grades, one lane roads, school zones) will be even more important to consider when making routing decisions as AVs will have less experience in such scenarios, which will result in increased risks.

Affordable mobility alternatives (shared service model) [complement]: The combination of automation and connectivity can enable new mobility service models that are more convenient, efficient, and affordable. Currently, labor costs for public transit service are close to 70% of the total operating costs. If labor costs can be removed, the costs of shared mobility systems will decrease drastically resulting in improved access and potentially reduced vehicle ownership. Connectivity and automation technologies also enable more flexible (on-demand) and convenient (door-to-door) service, which can result in numerous benefits to access, efficiency (fewer, high utilization vehicles serving the same demand), and sustainability. From a behavioral perspective, if such a model takes hold, we can expect mode shift between both public transit and private vehicles to a more shared, on-demand system. Vehicle behaviors will shift from user optimal to fleet optimal (which can result in system optimal conditions at high enough fleet penetration levels [25]), repositioning strategies between passengers will be profit maximizing, and interactions at the curb will be more short-term (pickup/drop-off) as opposed to longer-term parking.

Lower costs to travel (private ownership model) [conflict]: The combination of automation and connectivity can lower marginal costs of travel by allowing travelers to disengage from all decision making. In this situation, the generalized cost of travel decreases for the user due to lower stress and travel time sensitivity. Additionally, efficiency gains can be achieved through more efficient driving maneuvers (e.g., smaller headways, smoother driving, platooning). The high upfront costs for connected automated vehicles will reserve these benefits to higher-income populations and lead to increased driving (and congestion) as the service gap between personal driving and alternative modes (public transit) continues to grow. From a travel behavior standpoint, we can expect increased driving from affluent populations due to lower costs for travel. The combination of connectivity and autonomy also provides additional uses and flexibility for zero occupancy trips (e.g., delivery, errands, cruising, collaboration to create congestion to reduce cruising costs), thus increasing VMT. This scenario will lead to high societal costs due to costs felt by conventional drivers in a mixed environment.

3.2 Automation & Electrification

Improved access to charging [complement]: The primary constraints for EVs compared to traditional ICE vehicles are related to battery range and access to charging. However, the ability to send EVs to charge when convenient is a huge advantage which will facilitate faster adoption of EVs. From a behavioral perspective, the influence of certain factors (e.g., SOC at destination, destination choice, availability of charging at destination, eco-routing, trip cancelation / abandonment) on travel choices will become less sensitive with the ability to expand charging “catchment areas” and decouple the need for charging at travel destinations.

Regional travel constraints [conflict]: Automated vehicles reduce VOTT for long-distance trips (primarily for trips between 100-500 miles) and allow for resting/sleeping while traveling. This shift in travel time flexibility can lead to induced demand and significant mode shift from short-haul flights due to drastic reductions in travel costs. This change in travel behavior can be beneficial to the environment with EVs, however, range limitations negate the benefits by adding travel time and inconvenience due to required charging along the route. This will be especially detrimental for overnight trips. From a travel behavior perspective, this limitation will likely lead to slower adoption of electrified AVs and increased ICE AV purchases to ensure AV benefits are fully realized.

Empty vehicle routing [conflict]: Automation enables zero occupancy travel, which can lead to a significant increase in VMT. Based on the literature, zero occupancy travel decisions will largely be based on monetary cost minimization. Therefore, there will be an incentive to route automated EVs on local roads because EVs are most efficient at slow speeds and in stop-and-go conditions. The combination of technologies can significantly impact network efficiency without the appropriate policies in place.

3.3 Connectivity & Electrification

Enhanced charging reliability [complement]: The most important factors affecting travel choice for EV users are related to battery and charging constraints. Connectivity technologies that provide real time charging information (wait times, charging costs, locations, charging types) to EV travelers can drastically reduce associated travel costs related to range anxiety and reliability. The combination of the two technologies can lead to faster adoption of EVs and more rational travel and charging behavior.

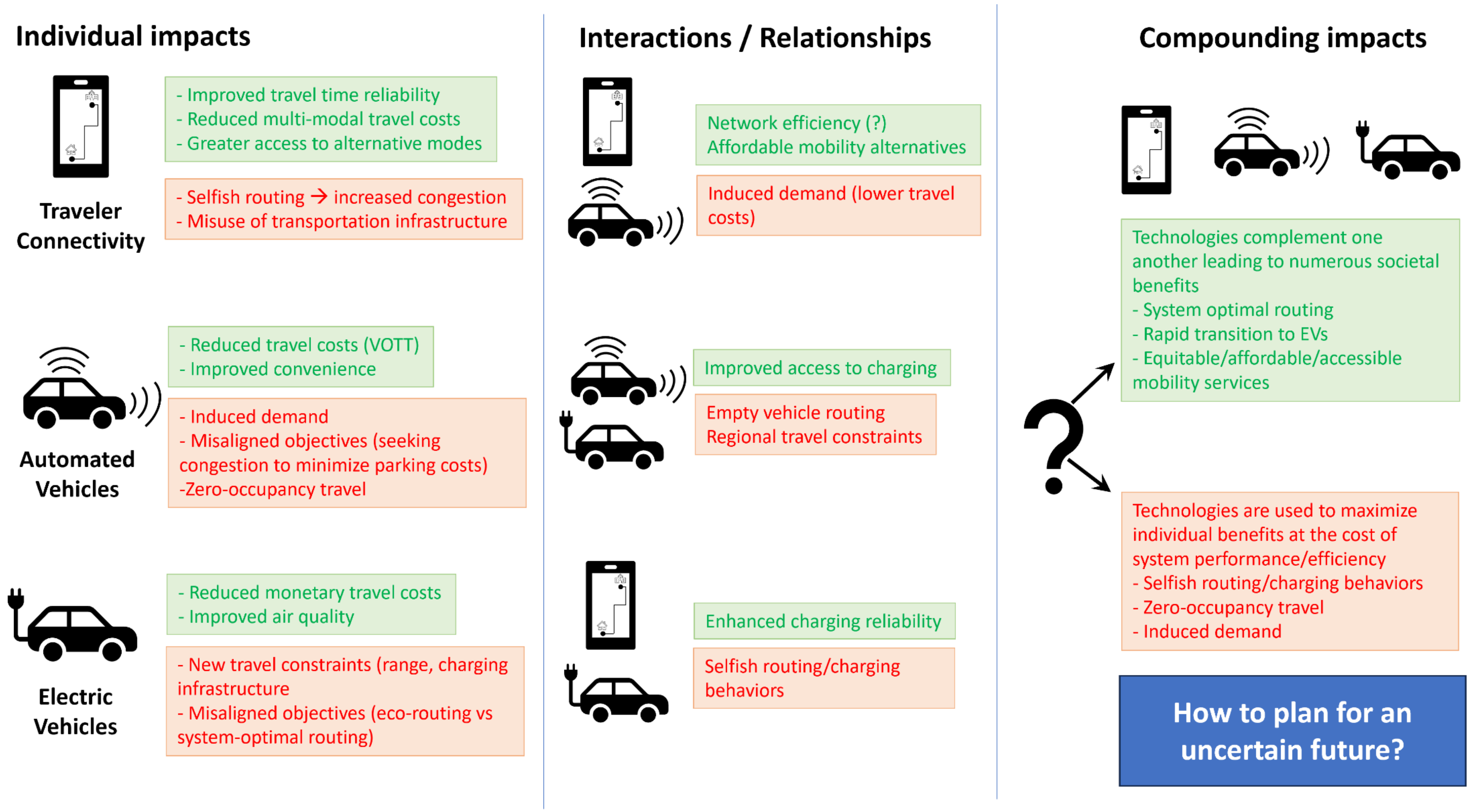
“Selfish” routing and charging [conflict]: While reliable access to charging information can promote faster EV adoption, the same algorithms that recommend selfish routes for network travelers (e.g., Google Maps, Waze) can behave similarly when recommending charging, thus exacerbating congestion and wait times. From a travel behavior perspective, it is anticipated that EV drivers will look to maximize individual utility when user optimal routing and charging recommendations are provided. In this environment, negative system level outcomes are expected for the same reasons why increased congestion is observed for “selfish” routing algorithms (use of heuristics, lack of full picture of network conditions, no context specific information, etc.).

3.4 Travel Behavior Change Due To The Convergence Of Three Mega-Trends

The convergence of three mega-trends will drastically impact the way travelers use and interact with the transportation system. Based on the literature reviewed, significant travel behavior shifts are already occurring due to traveler connectivity technologies and electric vehicles. From a traveler connectivity standpoint, access to new information and services have increased benefits for *individual* travelers through improved travel time reliability, convenience, and greater access to alternative modes. At the same time, *social* costs have been observed in the form of increased congestion and misuse of transportation infrastructure due to selfish routing and simple heuristics used by digital navigation apps. The opposite was observed for EVs, as battery range constraints and lack of reliable access to charging has increased *individual* travel costs (e.g., range anxiety, more complex decision-making, battery reliability) and reduced *social* costs through emissions reductions. Highly and fully automated vehicles promise both individual and societal benefits, which will largely depend on which operational model that takes hold (private versus public). However, due to limited deployments, the impacts from AVs remain speculative.

Thinking towards the future when L4-L5 AVs are also available, it is expected that individual benefits will be magnified through cheaper, more convenient travel options. Social benefits are also expected through enhancements to safety, efficiency, accessibility, and sustainability. However, when thinking a little deeper about the various technologies, their interactions, and likely use cases, it is also easy to dream up scenarios where significant societal costs are incurred due to decisions that maximize individual utility. System level impacts of such behaviors will be more pronounced in the connected, autonomous, and electrified era because charging and parking choices will have greater impacts on network performance. For example, charging type, locations, and pricing will impact behavior more compared to ICE vehicles and gas stations because of range anxiety, fewer charging options, and larger variation in fuel pricing (e.g., time of day pricing). The same goes for parking, as decisions become more impactful as options increase (e.g., send car home, send car to charge, seek congestion to avoid paying parking fares, among others). In addition, growing system complexity will result in greater reliance on simple recommendation systems (e.g., apps that provide recommendations for charging, parking, and routing), which can lead to increased system delays. And research has already shown that close to 75% of app users follow recommendations more than 80% of the time [17], which can result in significant impacts. In conclusion, widespread behavior shifts are expected, however, large uncertainty still exists as to how the three mega-trends technologies will be used and their resulting impacts—positive or negative—to the transportation system. Many realistic scenarios exist where complementary relationships between the technologies lead to greater societal benefits. However, such relationships are not guaranteed, and strategic interventions will likely be needed to ensure societal net benefits. A summary of findings from the literature related to potential behavioral shifts and their resulting impacts are shown in **Figure 2**.

It is also important to note that traveler connectivity, automation, and electric vehicle technologies also enable decision makers to rethink how fueling (more specifically, the electric grid) interacts with transportation infrastructure. Automation and connectivity enhance fueling flexibility, which is currently needed due to numerous grid constraints. At the same time, regional electricity generation is usually managed and operated by one decision making entity. Therefore, there is opportunity to institute various pricing and incentive strategies to help manage both charging demand and traffic conditions. In such a setting, travel behaviors can be managed to maximize system-level benefits. Therefore, it will be important to study behavioral responses to new and innovative dynamic pricing schemes that can vary in space and time enabled by the three mega-trend technologies.



Source: ITS JPO

Figure 2. Summary of Findings Related to Travel Behavior Changes Resulting from AVs, EVs, and Traveler Connectivity Technologies.

4 Modeling EV/AV/CV with AMS tools: Gaps, Challenges, & Recommendations

Based on the literature, several behavioral shifts due to traveler connectivity, AVs, and EVs were identified that can significantly impact AMS results if they are not considered during modeling and simulation tasks. The general finding considering all three technologies is that travel costs are expected to decrease resulting in increased VMT. Mode shift is also expected from alternative modes to electric AVs (both in private and shared service models) due to improved convenience and reduced travel costs. Generally, these behavioral shifts are straightforward to model within current AMS tools by altering travel time and travel cost functions. Other potential shifts in travel behavior were also identified that present new modeling challenges due to shifts in how travelers use and interact with transportation infrastructure. These observed and projected behavioral changes are the focus of the following section, and are as follows:

- Shared service models are growing in popularity due to a seamless travel experience enabled by connectivity (e.g., door-to-door, on-demand, frictionless payment, driver/passenger rating systems, information provision). As fleets grow to accommodate rising demand, new travel behaviors and vehicle-infrastructure relationships will need to be captured in modeling and simulation tasks, such as fleet optimal behaviors, deadheading decisions, and pickup/drop-off interactions with the curb.
- Zero-occupancy trips will be significant contributors of increased VMT in a highly automated environment. Zero-occupancy travel choices will also differ from conventional drivers, and in many cases, will lead to high system costs without the appropriate policies in place. For example, cost minimizing behavior for autonomous EVs would be to seek out congestion to conserve energy. There is also uncertainty as to what types of trips will be taken by zero-occupancy vehicles (e.g., EVs to charge), and how goods/services providers might alter their business models to accommodate a highly/fully automated environment (e.g., grocery, drycleaning, pickup/delivery). All of this is to say that significant zero-occupancy travel is a realistic outcome of automated vehicle technologies, and new travel behaviors and service models need to be considered to realistically capture network impacts.
- No roads are off limits. Digital navigation apps are designed to consider all road types with no local context, which can lead to widespread misuse of transportation infrastructure. Examples include the re-routing of tractor trailers along local roads with insufficient clearance and/or sharp turns and steep grades and re-routing commuter traffic along local roads with significant pedestrian use. AMS tools are designed to capture network impacts when travelers use the infrastructure as intended. However, in the new era of digital navigation, it will be important to capture the impacts of new individual decision-making systems and their misuse of the transportation infrastructure system. AVs and EVs can exacerbate these issues when similar recommendation systems are also used for charging and autonomous parking.

- EV drivers must consider new factors (SOC at origin, SOC at destination, locations of charging, energy-efficient routes, and risk behaviors) when making travel choices. These factors can lead to different travel choices between individuals traveling between the same origins and destinations. Heterogeneous behaviors, spatial layout of charging, and potential charging supply/demand mismatches must all be considered to capture realistic EV travel behavior. In addition, autonomous EVs will also behave in unforeseen ways as self-charging now becomes feasible and zero-occupancy travel will likely seek out highly congested routes to minimize energy consumption and resulting costs.

The key takeaway from the above findings is that the transportation system is growing in complexity and there is a need to integrate these more complex and varied decision-making processes into AMS tools. Traveler connectivity has enabled new modes and service models that are affordable and convenient. Significant growth in the use of these services will require AMS tools to model heterogeneous vehicle behaviors with different objectives. Additionally, new situations will need to be integrated, such as the ability to pickup/drop-off anywhere or at managed curbs designed to optimize short term parking situations, which will become prevalent in the age of ridehailing and autonomous vehicles. Vehicle powertrain types will also be important to include when modeling travel choices. From the literature, EV driver decisions, starting with mode choice and ending with parking decisions all factor in SOC and charging availability. New utility functions that also include risk behaviors and spatial-temporal charging conditions will need to be integrated with current AMS tools to accurately capture EV driving behaviors. Finally, fully automated vehicles no longer require drivers, which can fundamentally change how people interact with the transportation system. It is anticipated that zero-occupancy vehicles will behave in a cost minimizing fashion, which can lead to increased congestion, especially with high EV penetration rates. AMS tools need to incorporate these behaviors and develop a deeper understanding of how these behaviors may evolve as new modes and services enter the market.

Historically, AMS tools have been developed to manage vehicle flows throughout the transportation network. However, recent efforts have been made to incorporate new modes and travel behaviors to capture realistic insights due to the integration of new technologies and services. The following section characterizes current AMS capabilities and identifies potential shortcomings related to the various travel behavior shifts mentioned above.

Shared service models: Due to the rapid growth in ridehailing and other on-demand services, many commercially available AMS tools, such as PTV Group (Visum, Vissim, MaaS Modeler) and Aimsum, have developed on-demand fleet management packages to help inform strategic, tactical, and operational decisions for fleet managers and city/regional planners alike. In both cases, fleet optimal algorithms can be specified, and resulting congestion impacts from access/egress can be computed. The drawback to these tools is that they were developed for transportation engineers/fleet managers faced with decisions about the deployment of on-demand services, fleet sizes, and service areas. Actual driver behaviors associated with ridehailing services (trip cancelations, deadheading, and pickup/drop-off) are not captured and modeled for realistic network impacts. In addition, the changing behaviors and operational models related to vehicle automation and electrification are not captured by existing AMS tools.

For example, automation drastically cuts travel costs, which would incentivize more aggressive repositioning strategies for fleet vehicles (i.e., willingness to travel further distances to serve more expensive trip requests). On the other hand, EV drivers will likely exhibit more conservative repositioning strategies or choose to take more energy-efficient local roads to minimize energy costs and charging instances and maximize profits. These behaviors are particularly important as both Uber and Lyft have pledged to be zero-emissions platforms by 2030 [92], [93]. Overall, commercial tools do exist to model some of the impacts from shared fleet operations. However, additional capabilities are needed to capture the new driver behaviors that might result from autonomous and electric vehicle technologies, and are as follows:

- Repositioning strategies – how will EV drivers/AVs behave between passenger drop-offs and subsequent pickups? And how will they differ from current operations?
- Routing decisions – profit maximizing routes might shift for EV drivers as vehicles are more efficient at slower speeds.
- Pickup/drop-off – AVs will likely be programmed to seek areas outside of traffic streams, while EVs might seek zero/low-emissions curbs.
- Fleet behavior – AV fleets will be centrally operated and compliant, which will behavior closer to fleet optimal compared to driver-based ridehailing where drivers can still make individual decisions. EV fleets will also need to consider charging during operations, which might lead to different routing and deadheading choices to maximize EV fleet performance.

Zero-occupancy trips: There is a rich literature related to integrating AVs into microscopic modeling frameworks by modifying supply and capacity characteristics to mimic reduced headways and reaction times with commercially available tools. Outputs from such models can be used to simulate impacts at the network level using a multi-resolution modeling framework. However, missing from these tools are the zero-occupancy driving state, which exhibits different behavior and can be a significant contributor to VMT. The types of behaviors exhibited by zero-occupancy vehicles will differ depending on trip type and duration. Lower duration trips will still place value on being able to hail the vehicle in a reasonable amount of time. Longer duration decisions will likely be monetary cost minimizing, which could result in cruising behaviors that seek congestion to avoid parking fares. Electrification adds further issues as EVs are most efficient at slow travel speeds and in stop-and-go traffic. The ability to charge autonomously will also play a role in how vehicles move throughout the network seeking charging options that minimize total costs. Currently, AMS tools do not model these trips, which can account for significant VMT. Further research is also needed related to new travel behaviors resulting from electric EVs, such as travel cost functions and self-charging behaviors.

Network utilization from digital navigation apps: Starting in 2013, digital navigation apps began offering routing recommendations [4]. This new offering has fundamentally changed how travelers move through and interact with the transportation network. City planners and engineers design the transportation network based on hierarchical roadway types and various controls to help manage system efficiency. This design framework is how AMS tools are developed to help inform designs and investments based on a general understanding of how the network will be used. However, routing recommendation apps fundamentally change how the network is used by oversimplifying the infrastructure and providing selfish routing recommendations. This has led to numerous problems that includes higher volumes of traffic using low-speed local streets with many pedestrians and routing vehicles on streets with limited site distances and narrow lanes, leading to increased delays and collisions [4]. These issues will be exacerbated with automated and electric vehicles because similar heuristic routing strategies will be used for charging and parking recommendations, which can lead to significant network delays. Additionally, AVs will likely be programed to behave conservatively, which might result in further delays when presented with new situations recommended by real-time navigation apps (e.g., narrow steep neighborhood roads versus arterials). In the absence of improved coordination between app providers and transportation decision makers, AMS tools need to capture this behavior to flag problem areas for strategic interventions. Capturing these behaviors would require higher resolution network representations and relaxed assumptions. Multi-resultion modeling frameworks will also be needed to capture local characteristics and their resulting network-level impacts.

EV behaviors: Numerous models exist that were developed to help guide the transition for electric vehicles, such as Aimsum's battery consumption modeling capabilities [94], HIVE's EV fleet modeling tools [90], and EVI-X's tools to inform large-scale charging deployments [95]. However, the more complex individual decision-making processes that include risk behaviors, SOC, and charging accessibility are not currently captured in commercially available AMS tools. And according to the literature, these factors can have significant impacts for EV travel choices that include the choice to take a trip or not (dependent on vehicle range, charging accessibility, and current SOC), mode choice, departure time (current SOC), trip cancelation, route choice (charging accessibility, energy-efficient route) and parking decisions (access to charging). These choices will also vary based on risk attitudes due to unfamiliarity with EV technologies and variability in battery range due to factors such as weather and road grade. In addition, automation will add new considerations when modeling EVs in the transportation network. First, in the zero-occupancy state, autonomous EVs will seek out low-speed, stop-and-go routes to conserve energy and minimize costs when travel time is not a consideration. Therefore, an improved understanding of wait time and travel cost sensitivities are needed for autonomous EVs. Next, automation relaxes spatial constraints related to charging, which are currently governing many EV travel behaviors. Travelers can now choose destinations without considering SOC and access to charging as vehicles can now drive themselves to charging opportunities. These behaviors are not well understood and are not currently captured by AMS tools. In conclusion, the rapid proliferation of EVs (expected to reach 62-88% of new car sales by 2030 by some estimates [96]), will shift travel behaviors for the majority of drivers, which are fundamentally different than those exhibited by ICE vehicle drivers. AMS tools must consider these changes through an improved representation of EV decision making processes and integration of charging conditions (for all charging speeds) to capture realistic network behaviors. The charging process itself will also require modeling to estimate waiting and re-routing behaviors during peak charging periods.

Based on the review of available AMS tools, several gaps were identified in their abilities to capture and model changing travel behaviors in the connected, automated, and electrified era. Shortcomings identified in the previous sections were used to inform recommendations related to AMS tool enhancements, and are as follows:

Shared service models:

- Develop deeper understanding related to AV and EV fleet behaviors deployed as ridehailing services, such as how routing, charging, cost of travel, and parking/curb interactions will likely change compared to current driver-based services.
- Integrate fleet (% EV and % AV), individual (risk attitudes for EVs), and vehicle level (SOC, range, fuel type) characteristics to more accurately model travel choices at a higher level of granularity.

Zero-occupancy trips:

- Model vehicle travel that begins at the destination and makes cruising/parking decisions based on zero-occupancy travel cost functions.
- Model new, potential zero-occupancy scenarios, such as “self-charging” for EV vehicles or running errands/deliveries.
- Integrate new decision-making processes/choices, such as tradeoffs between parking costs and estimated pickup wait times for private AVs and quantifying this relationship as a function of duration of time spent at the location.
- Modify travel cost functions and the relative importance of different factors (e.g., travel cost, travel time, reliability) for zero-occupancy trips based on trip types.

Network utilization:

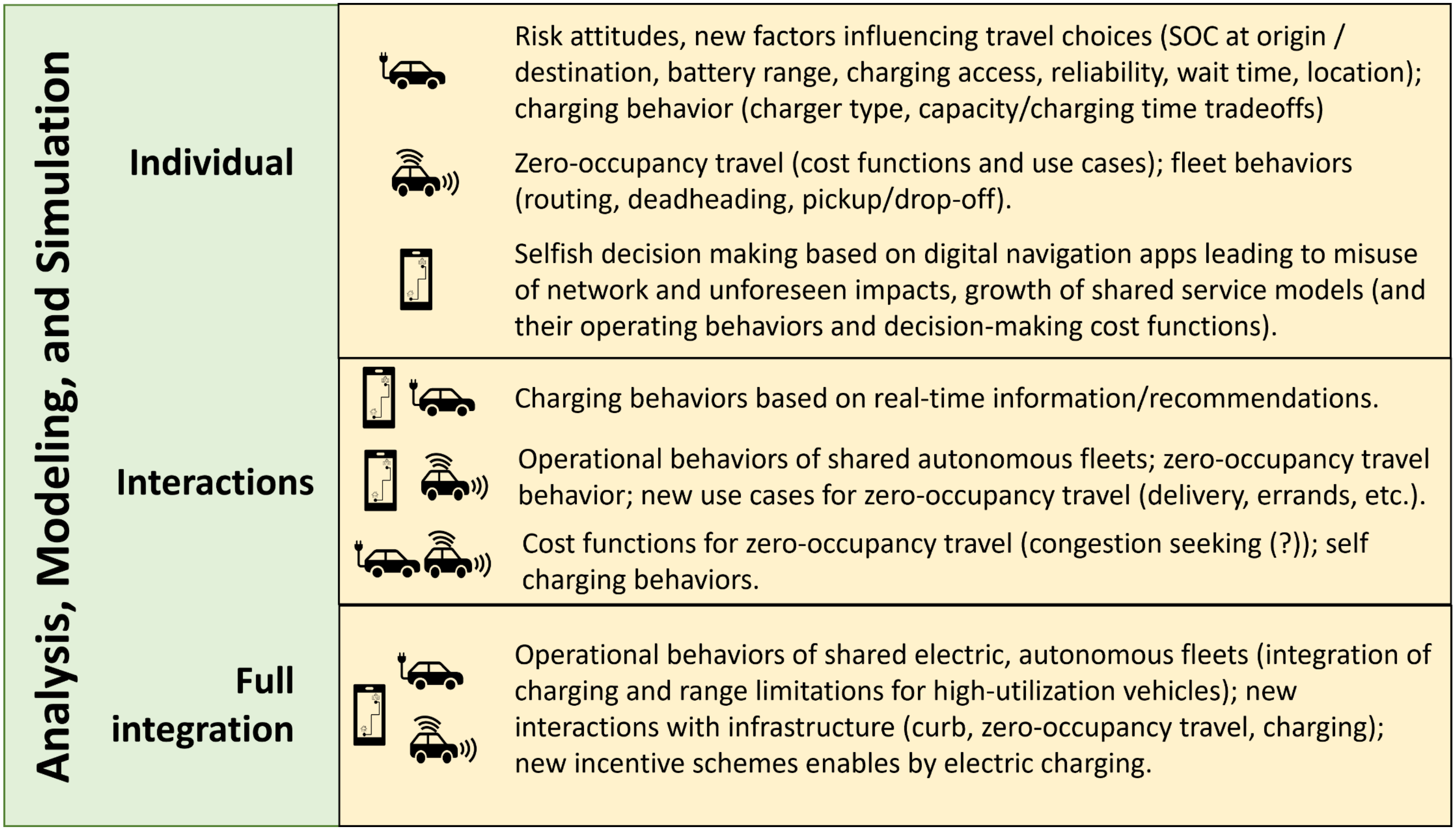
- Relax assumptions related to facility use and integrate context-specific information that could impact network performance if the road is not used as intended (e.g., bridge clearances, difficult roads [narrow, steep grades, etc.]).
- Develop methods to model rational decision-making in the EV charging and AV parking contexts.

EV charging/routing:

- Capture different risk behaviors related to EV charging and routing.
- Integrate the details needed to capture realistic EV travel behavior: 1) vehicle range, 2) SOC at origin and destination, 3) charging supply including charger types (L1, L2, DCFC), location, pricing information, and estimated wait times. And how travel choices (trip abandonment) might change as a function of battery reliability (weather conditions, energy-intensive routes, etc.)
- Consider zero-occupancy charging behavior that includes modified travel cost functions and the influence of charging reliability, speed, pricing, and wait times on self-charging choices.
- Model the charging process itself based on supply/demand (e.g., queueing, reliability, charging time as a function of outside conditions) and vehicle/charger technology. Recommendation systems, constrained supply, and longer fueling times will impact the

surrounding network in unforeseen ways. The charging phase of a trip will also become much larger, which should be integrated with travel choice models.

Figure 3 summarizes the above findings for the three mega-trend technologies in isolation and when interacting in a real-world setting. Specific gaps/challenges related to both behavioral response to emerging technologies and modeling limitations are identified for the different deployment scenarios.



Source: ITS JPO

Figure 3. Summary of Gaps/Challenges Related to AMS Tools in the Era of Traveler Connectivity, AVs, and EVs.

5 Conclusions and Next Steps

This analysis set out to gather research related to the travel behavior impacts of connectivity, AVs, and EVs. The scope of the work was narrowed down to focus on traveler connectivity (access to real-time information through smartphone apps and new modes and services enabled by connectivity), highly/fully automated vehicles, and personal EVs due to their potential to significantly impact travel behaviors. Significant literature exists focused on connectivity, AVs, and EVs, which is difficult to fully capture in one white paper. However, specific questions were addressed, and a summary of findings are provided below.

5.1 Responses to key questions

What are the travel behavior impacts resulting from automation, connectivity, and vehicle electrification?

All three mega-trend technologies impact travel choices in diverse ways. Traveler connectivity, AVs, and EVs provide numerous benefits to the individual traveler by reducing travel time uncertainty, providing new, convenient alternatives to private vehicle travel, reducing travel costs due to ability to multi-task, and reducing monetary operational costs by smoother driving behaviors and lower costs of electricity (compared to gas). The specific travel behaviors identified for each technology are as follows:

- Digital Navigation [traveler connectivity] – Real-time travel information and constant recommendations has led to selfish travel behaviors and misuse of transportation infrastructure (e.g., using local roads for long-distance travel and freeways for local travel).
- Shared service models [traveler connectivity] – Smartphone connectivity has led to numerous new and convenient mobility service offerings, which has led to significant growth of these services, which behave and interact with transportation infrastructure in new ways (fleet-based decision making, deadheading behaviors, pickup/drop-off curb interactions).
- Induced travel [automated vehicles] – Lower VOTT were observed for commute and long-distance trips for automated vehicles, leading to more travel and lower travel time sensitivities. This finding also indicates that travelers are more willing to experience delays when multi-tasking options are available.
- Zero occupancy travel [automated vehicles] – Additional travel without a passenger is expected for AV owners because travel costs can be reduced or eliminating by sending empty vehicles to cheaper parking or to pick up family/friends. These behaviors will create additional trips affecting traditional trip generation models. Additionally, travel cost functions will require modifications because monetary factors will become more important compared to travel time and delay costs when vehicles are operating in zero occupancy mode.

- Complex decision-making processes [electric vehicles] – EV owners must consider SOC at origin/destination, battery range, access to charging, charger reliability and wait times, and potential charging at the destination when making travel choices. These complex choices lead to a variety of different travel behaviors, from eco-routing to tradeoffs between detour length and charging speeds/reliability, among many others.
- Risk attitudes [electric vehicles] – EV owners also exhibit different risk attitudes, which can lead to different choices that are tied to the current constraints of EV technology (range, limited access to charging, large variations in range) and technology unfamiliarity.

What are some potential synergies and conflicts between emerging technologies that could alter travel behavior?

The combination of mega-trend technologies was found to be complementary in many settings. However, it is also easy to identify situations where the coupling of two or more technologies led to individual benefits at the expense of system performance. The identified relationships were as follows:

Traveler connectivity + AVs:

- Network efficiency [Complementary] – Real-time data processing and automated decision making can help shift network behaviors to be more system optimal (especially in fleet settings) in the appropriate policy and regulatory framework.
- Network inefficiency [Conflicting] – Without policy/regulation, AVs will likely be programmed to maximize individual benefits at the expense of network costs. Enhanced automation capabilities with real-time network information can act upon real-time data from multiple sources to further improve individual decision making resulting in degraded network performance.
- Transportation affordability (shared service models) [Complementary] – Removing the driver for public mobility systems can drastically reduce operational costs, which can be passed on to users in the form of reduced fares and improved service performance.
- Reduced operational costs (private service model) [Conflicting] – High upfront costs of AV technologies and low operational costs can lead to greater VMT (and congestion) by affluent populations, which will increase societal costs in a mixed-use environment.

AVs + EVs:

- Access to charging [Complementary] – Automation expands access to charging and decouples the need to have charging available at specific destination locations. The ability to send AVs to charge reduces EV constraints, leading to greater use and adoption at the expense of increased VMT.
- Regional travel [Conflicting] – AVs provide new, convenient options for regional travel which can be cancelled out by limited range of EVs. This can lead to slower adoption of EVs to increased regional travel with ICE vehicles.
- Zero-occupancy travel [Conflicting] – Zero-occupancy travel will seek to reduce monetary costs as travel time costs become irrelevant in many cases. This could result in electric AVs seeking out congestion and stop-and-go traffic to reduce energy consumption and associated costs.

Traveler connectivity + EVs:

- Enhanced charging reliability [Complementary] – Real-time information related to routing, charger locations, and wait times will provide travelers with information to ease range anxiety and reduce overall travel costs related to EV travel. This will facilitate faster EV adoption and more travel using EVs.
- "Selfish" routing/charging [Conflicting] – Access to more real-time information can also facilitate increased opportunities for individuals to make utility maximizing choices, which can cause greater network/charging congestion.

What are the gaps/challenges related to representing travel behavioral shifts in current AMS tools?

Based on findings from the literature review, four key areas were identified in which current AMS tools have shortcomings when it comes to modeling scenarios in the age of traveler connectivity, AVs, and EVs. The four focus areas were: 1) Shared service models, 2) Zero-occupancy trips, 3) Network utilization, and 4) EV charging and routing. More specific details regarding gaps and challenges are as follows:

- **Shared service models** – Need to integrate changing behaviors resulting from AVs/EVs for fleet-based mobility services with AMS tools, such as how drivers will behave when using EVs (near-term) and how operations will differ when shared mobility services eliminate drivers and use AVs (longer-term). These behaviors are different compared to individual travelers because different factors are considered when making choices about picking up passengers, traveling between passengers, and dropping off passengers. Fleet decision-making also comes into play, as both driver-based and autonomous on-demand fleets are centrally operated.
- **Zero-occupancy trips –** New types of trips and new interactions with infrastructure are enabled by AVs, such as autonomous charging, parking, cruising, and pickup/drop-offs. Zero-occupancy VMT is expected to be significant, which will require modeling these types of trips (including the charging phase) to better understand impacts and design interventions. New tradeoffs will also need to be evaluated (access time vs. parking costs) to gain a deeper understanding about decision-making in the mega-trend era.
- **Network utilization –** Travel connectivity apps that provide real-time recommendations about routing, charging, and parking can result in significant network delays and misuse. Understanding these new interactions and incorporating them into AMS tools will be important to design strategic interventions. This will likely require a high-resolution representation of the network that includes information such a bridge clearance, steep grades, sharp turns, lane widths, among others and methods to estimate macro-level impacts using multi-resolution modeling frameworks.
- **EV charging/routing –** Travel choices become more complex in the mega-trend era due to numerous new constraints and capabilities. In addition to travel cost and travel time, common travel choices will require information related to SOC at origin/destination, vehicle range, charging supply including charger types, location, pricing information, and wait times. In addition, due to variation in battery range, different risk attitudes will also have to be modeled because route, charging, and cancelation decisions will vary between individuals.

Finally, charging itself now represents a significant part of a trip, which can have widespread network implications in not captured in modeling frameworks.

Overall, the key takeaway from this study is that transportation systems are growing in complexity resulting in more complicated decision-making processes and new interactions and relationships between users, vehicles, and infrastructure. Individuals have different perspectives, risk attitudes, and internal utility functions that need to be captured in a more rigorous way as new services, information, and technologies flood the transportation landscape. The vehicles themselves will also exhibit different behaviors depending on if they are autonomous, part of a fleet, or electric. To capture these changing behaviors and interactions, AMS tools will need to develop methods to consider heterogeneous behaviors and characteristics at the individual, vehicle, and infrastructure component level. Charging network characteristics will also be increasingly important as EV market share continues to climb. Information such as charging speed, reliability, supply/demand characteristics at specific locations, inductive charging capabilities, among others will all influence EV travel behaviors in different ways.

5.2 Recommendations for Future Research

Travel choices differ significantly between ICE and EV drivers due to range anxiety, range constraints, and limited (not well distributed) charging infrastructure. EV and ICE drivers traveling between similar origin-destination pairs may take completely different routes and park at different locations based on their vehicle state of charge (SOC), risk attitudes, and charging access at the destination. Therefore, travel behaviors (including risk attitudes) as a function of vehicle fuel type need to be studied further and integrated into current AMS tools.

Constrained charger supply in both time and space can significantly alter travel behaviors in unforeseen ways, especially when self-charging becomes available using autonomous vehicles. The charging portion of the trip (location, time required, wait times, charger type) is a significant factor impacting travel choices, which is often not considered in EV travel behavior studies. Further research is needed that quantifies travel behaviors as functions of charger locations, queueing at charger, charging times, charger types, and whether the vehicles are human driven or autonomous. These findings can help inform new traveler behavior models that capture complex decision-making processes for EV drivers and automated EVs.

Real-time recommendations from travel apps, such as Google Maps or Waze, have drastically increased cut-through traffic and have caused problems when local context is not considered (e.g., bridge clearance for large trucks, school zones, steep grades). Such problems will likely increase in the megatrend era with recommendations for charging, eco-routing, autonomous parking, among others. Therefore, there is a need to study human responses to real-time recommendations (across a variety of contexts) and integrate these behaviors into AMS tools. There is also a need to better understand the underlying data that is being used to inform recommendations and the computational tradeoffs of including richer data streams for improved guidance.

Numerous automobile manufacturers are developing and deploying SAE L2-L3 (hands-free) systems using pre-mapped roads and/or specific operational design domains (ODD). In such ODDs, drivers can monitor the vehicle hands-free (for SAE L2) or can engage in other tasks (for SAE L3), reducing individual travel costs. The rapid development of these systems and scarce publicly available data limits our understanding of human decision making when presented with tradeoffs between travel time and ease of driving. To address this gap, further research is needed to identify changing travel behaviors resulting from commercially available, hands-free features. For example, will travelers select longer routes and/or prioritize pre-mapped routes (usually freeways) if they offered more hands-free driving?

In the longer-term, highly automated vehicles (SAE L4-L5) bring new capabilities, which can alter the relationship between travelers, vehicles, and infrastructure. For example, zero-occupancy vehicles can be used to charge/park themselves and potentially run errands (assuming service models evolve with the technology). Such vehicles will utilize different cost functions compared to human drivers, with higher importance placed on monetary costs (e.g., parking costs, fuel costs) and reduced sensitivity to travel time/delay. The potential for zero-occupancy travel to contribute to significant VMT, congestion, and delays highlights the importance of considering these types of trips in modeling and simulation exercises. In the near-term, the majority of SAE L4-L5 vehicles will likely be part of a ridehailing fleet. And if such shared mobility services gain significant market penetration, it will be important to integrate fleet-optimal algorithms (considering both AVs and EVs) and perspectives into AMS tools, which is an area with limited research.

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