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Scenario Modeling of Autonomous Vehicles with Trip-Based Models

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Abstract

While a range of methods have been employed to quantify certain anticipated impacts of connected and autonomous vehicles (CAVs), a comprehensive framework for integrating CAVs into trip-based models, like those used by many metropolitan areas today, is lacking. Without real-world CAV usage data, integrating CAVs into trip-based models today requires speculative modeling assumptions; however, incorporating fundamental parameters into existing travel modeling frameworks is timely for two reasons. First, understanding the range of possible futures from scenario planning or exploratory modeling analysis can assist metropolitan areas anticipate and manage the potential risks and benefits of CAVs. Second, data on the travel behavior of early CAV adopters will become available during the lifespan of many models currently in use or development. This paper summarizes an enhanced trip-based modeling framework incorporating uncertainties related to CAVs initially developed in support of the Michigan Department of Transportation's statewide model. This framework is now being applied in statewide and metropolitan scale models in Michigan, Illinois, Virginia, Indiana, and South Carolina. An important contribution of this framework is its typology of and methods for representing zero-occupant vehicle (ZOV) trips. Additionally, this paper details an exploratory analysis of CAV scenarios in Vermont using a trip-based model incorporating several elements of the framework. In this application, reasonable assumptions related to induced CAV demand, including ZOV trips, resulted in substantial increases in vehicle miles traveled, vehicle hours traveled, and delay despite capacity increases, demonstrating how relatively basic trip-based scenario modeling of CAVs can be a valuable tool for informing and encouraging public policy discussions.

Connected and autonomous vehicles (CAVs) are poised to dramatically alter transportation systems in the United States (*1*). While highly autonomous vehicles—Level 4+ in the Society of Automotive Engineers' international taxonomy for automated driving systems—have not yet reached the market, vehicles with some level of automation have been operational for nearly two decades (*2*, *3*). Today, vehicles with driver assistance systems that provide semi-autonomous functionality are widely available (*4*). As autonomous technologies continue to improve, the market share of CAVs is expected to grow. Alongside the emergence of CAVs, mobility as a service (MaaS) has transformed the way many interact with the transportation system. The dual emergence of these technological innovations presents many possible opportunities and challenges for the transportation sector.

The potential impacts of CAVs on our transportation systems are wide-ranging. CAVs may improve mobility options for populations with mobility constraints, such as elderly and disabled populations (*5–8*). Additionally, households may choose to reduce the number of vehicles owned in response to high-quality ridesharing services offered by shared CAVs (sCAVs) or the option to share private CAVs (pCAVs) within households (*9*, *10*). However, CAVs may also result in zero-person trips. If pCAVs are shared within households, vehicles may need to travel without any passengers to pick up other household members at other locations. Alternately, pCAVs may avoid paid parking by returning home or traveling to a remote parking location after dropping off their occupant or, for shorter duration activities, by circulating nearby streets. sCAVs may also need to travel empty between passenger drop-offs and pick-ups ('dead-heading') and will need to intermittently return to centralized

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depots for fueling/charging, maintenance, and/or during periods of low demand. Finally, CAVs may more efficiently utilize constrained roadway capacity via higher operating speeds and reduced following distances; however, these benefits may be marginal until CAVs constitute a significant portion of the vehicle fleet (*11*, *12*). Thus, while CAVs may more efficiently utilize constrained transportation capacity, they may also induce additional transportation demand. How these countervailing influences will impact our transportation systems will depend on many factors, including decisions made by households and transportation network companies (TNCs) that influence the balance of pCAVs and sCAVs, the percentage of the vehicle fleet that are CAVs, and policy decisions regarding CAV operations. Local and regional governments are increasingly preparing for widespread adoption of CAVs—in the largest urban areas, 60% of long-range transportation plans now include some discussion of CAVs (*13*). For transportation researchers and practitioners, however, CAVs present a unique challenge: planning for the future in the context of an emerging mobility paradigm, the implications of which are dependent on highly uncertain parameters.

The potential impacts of CAVs have been explored using a range of modeling approaches, from activity-based models (ABMs)—models which first predict individuals' daily activity patterns and, in turn, their travel choices—to simple extensions of traditional trip-based models—models which first predict trips, distribute these trips across a region, estimate travel mode, and finally assign trips to the transportation network. A recent study in Jacksonville, Florida, employed an ABM with dynamic traffic assignment to explore how estimated vehicle-miles traveled (VMT) and delay vary over a range of CAV adoption scenarios, including different distributions of pCAVs and sCAVs in the vehicle fleet (*13*). An application of a dynamic traffic assignment model coupled with direct replacement of conventional trips with sCAV trips in Austin, Texas, found that CAVs may reduce vehicle ownership needs but increase VMT because of dead-heading between trips (*14*). Similarly, a study of the impacts of pCAV adoption in Atlanta, Georgia, combined a greedy scheduling algorithm, which seeks to maximize the number of activities that can be completed given scheduling constrains, with a model to estimate household vehicle reduction potential and optimize routing of occupied vehicles, the results of which were then applied to a synthesized trip profile and fed into a trip assignment model. This work found that widespread adoption of pCAVs would allow households to reduce vehicle ownership while increasing average daily household VMT by around 30 mi per day because of empty vehicle trips (*15*). Finally, simple extensions to traditional four-step models in Toronto, Canada and Austin, Texas, including increases in network capacity and trip generation, have also been used to estimate how CAV adoption may affect VMT, congestion, and transit ridership (*16*, *17*). While a variety of modeling approaches have been employed to explore the potential impacts of CAVs, a generalizable framework for assessing CAV impacts has yet to emerge.

The lack of a generalizable approach to incorporating CAVs into travel demand models conflicts with the desires of transportation agencies to plan for future CAV adoption. While advanced ABMs offer a more nuanced understanding of potential CAV impacts, many transportation agencies do not have such models and instead use trip-based travel demand models to support transportation decisions. However, applications of traditional four-step models to explore CAV impacts to-date have lacked a structure and robust accounting of uncertainties throughout the modeling process. Scenario planning—a structured way for organizations to think about the future via a limited number of possible scenarios—has been applied extensively in transportation and land-use planning (*18*). When systems can be expressed in mathematical terms or represented with a model, exploratory model analysis (EMA) is also a useful tool. EMA allows analysts to systematically vary model input assumptions and assess potential scenarios along key dimensions of uncertainty to identify input assumptions that most influence model outcomes (*19*). Identifying key sensitivities and developing reasonable scenarios enables the development of plans and policies that are robust in the face of uncertainty, allowing policymakers to mitigate risks in an uncertain future. As more certainty is gained over time, EMA supports narrowing the range of plausible values for key model uncertainties and clarifying policy decisions. While CAVs may soon dramatically alter our transportation systems, prevailing travel demand models used by many metropolitan areas do not adequately consider CAVs. This paper highlights work to incorporate CAVs into trip-based travel demand models in a systematic way that explores uncertainty and provides flexibility to update models as early CAV adopters provide information on real-world use, focusing on a recent application of portions of this framework in Vermont, and on-going efforts to fully incorporate the framework for models in Michigan, Illinois, Virginia, Indiana, and South Carolina.

Methods

Given the broad range of uncertainty about how widespread adoption of CAVs and MaaS may impact transportation systems, a systematic approach to incorporating uncertainty into trip-based modeling framework was pursued. Broadly, uncertainty can be

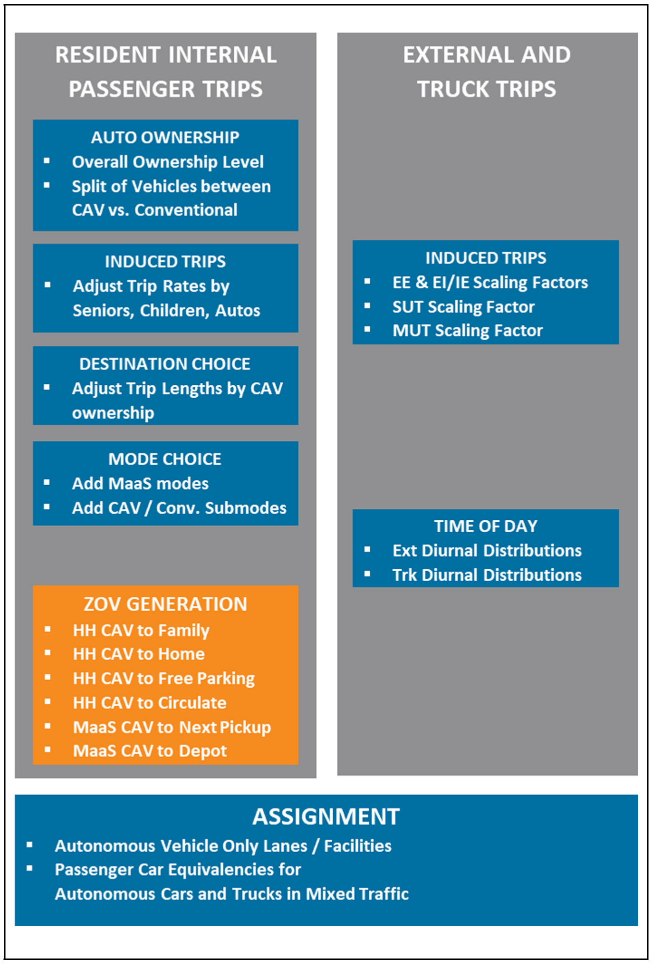

Figure 1. Enhanced trip-based model conceptual framework.

characterized as demand uncertainty and supply uncertainty. These sources of uncertainty affect different steps of trip-based travel demand models in different ways, requiring structural changes and/or assertions regarding parameter values (Figure 1).

Demand Uncertainty

Market Penetration of CAVs and Market Segmentation. In response to wider availability of CAVs and MaaS, households will likely alter behaviors along several dimensions, including decisions on whether to purchase their own CAVs and how many total vehicles to purchase (*8*, *9*). To incorporate these decisions into trip-based models, a new household segmentation schema was developed designed for easy extension of existing vehicle ownership models: 1) no vehicles; 2) fewer vehicle than adults with no CAVs owned; 3) fewer vehicles than adults but with at least one CAV; 4) as many or more vehicles than adults with no CAVs owned; and 5) as many or more vehicles than adults with at least one CAV owned. Implicitly, the distribution of households along the CAV ownership dimension reflects CAV market share as well as the relative dominance of private ownership versus shared mobility. Additionally, incorporating this expanded household segmentation enables the model to consider the degree to which households may choose to reduce vehicle ownership based on CAV use (e.g., a household may be able to meet its mobility needs with CAV rather than two conventional vehicles, or reduce its vehicle holdings in response to the availability of MaaS). The resulting market segments, though simple, allow the representation of differences in travel behavior based on vehicle ownership in general as well as specifically ownership of a CAV. Moreover, replacing a traditional three-market schema (no vehicles, vehicle insufficiency, vehicle sufficiency) with five market segments avoids substantially increasing model requirements in relation to file storage, memory, and runtime.

Induced Trip-Making. Given expected induced demand because of CAVs, trip generation rates can be scaled up based on household characteristics for the population as a whole, with higher scaling factors for households for which CAVs will reduce existing barriers to mobility, such as households with disabled person(s), households with seniors, and households with children (*6*–*8*). Increasing evidence suggests that MaaS with conventional vehicles is already inducing trip-making even among drivers. Moreover, a recent study emulating CAV ownership by providing study participants with a chauffeur for two weeks found travelers increased trip-making by over 80%. While the study sample was small and novelty may have inflated this finding, studies such as these begin to present evidence of potential for significant increases in trip-making at least among households that own their own CAVs (*20*).

Trip Distribution. Passengers in CAVs may be able to use in-vehicle travel time for other activities, such as working, relaxing, or sleeping. Having the option to use travel time for other productive uses may make passengers more willing to spend more time in vehicle, thereby reducing the marginal cost of travel. However, this effect would presumably be more significant among CAV owners both because CAV owners could purchase customized vehicles capable of supporting activities in line with their interests (e.g., exercise machinery, comfortable beds, big screen entertainment systems, etc.) as well as because sCAV services will result in a marginal cost of travel being passed to travelers which will presumably mitigate the tendency to travel farther.

Mode Choice. Because CAVs and MaaS are substantially different from and will be a substitute for other

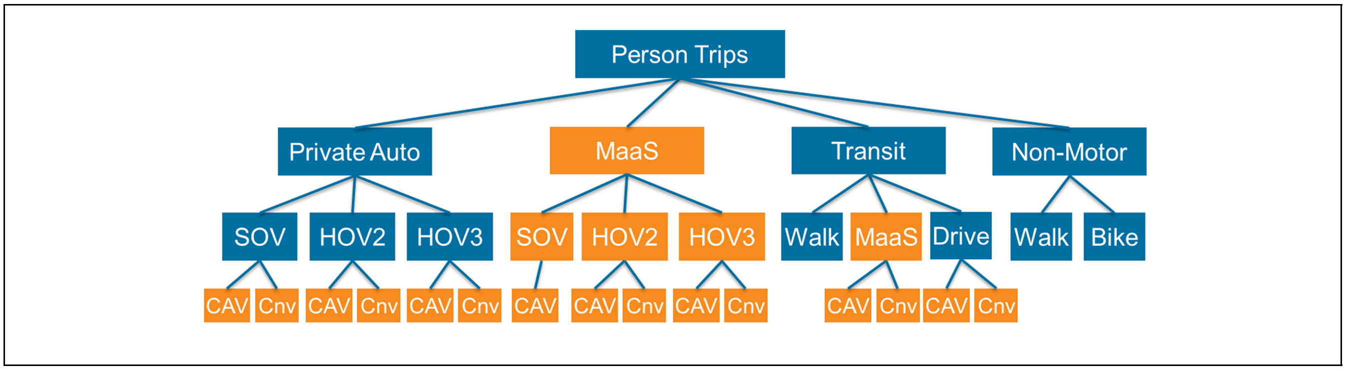

Figure 2. Enhanced mode choice nesting structure, with new modes in orange.

transportation modes, traditional mode choice models must be expanded to reflect the increased choice set for travelers. Within CAV modes, the distribution of trips taken in pCAVs and sCAVs is critical to the operational characteristics of CAVs. To include these additional choices in our models, MaaS was first added as a new mode in the top level of the mode choice model with SOV, HOV2, and HOV3 options nested underneath. MaaS was also added as a transit access mode alongside walking and driving. Finally, conventional and CAV submodes were added under all vehicle modes in the model (private auto SOV, private auto HOV2, private auto HOV3, MaaS SOV, and so on) (Figure 2).

Time-of-Day and Long-Distance Demand. Trucks and long-distance travelers may choose to use traveling hours for sleeping and, as a result, shift long-distance trips to nighttime hours. This temporal shift in long-distance travel may help offset induced trip-making which may be significant for this market segment since CAVs would substantially decrease the cost of long-distance travel, for instance, by obviating the need to pay for a hotel en route to a destination.

Zero-Occupant Trips. The introduction of CAVs into the vehicle fleet will result in a new type of trip: zero-occupant vehicle trips (ZOVs). The characteristics of ZOVs will depend on whether a CAV is privately owned or operated by a TNC. For pCAVs, car-sharing among members of the same household may result in ZOV trips if a pCAV drops one household member off at some destination and subsequently travels to some other location to pick up another member of the same household. To incorporate within-household pCAV car-sharing ZOV trips into our trip-based framework, the zonal origins and destinations of an assumed percentage of household person trips were inverted and fed into a gravity model. Additionally, pCAVs may return to their home location after dropping an occupant off to avoid paid parking. These ZOV trips were included in our framework by inverting the trip origins and destinations of an assumed percentage of home-based trips to Traffic Analysis Zones (TAZ) with paid parking. Alternatively, pCAVs may travel to some other remote (non-home) location to avoid paid parking. These trips were incorporated into our framework by creating trips between TAZs with paid parking and a nearby TAZ with non-paid parking as a function of long duration activities at zones with paid parking. Finally, pCAVs may circulate after dropping off an occupant for a short-duration activity in lieu of parking. Circulating trips were modeled by assuming some percentage of home-based other and non-home-based trips with short activity durations resulted in the generation of additional VMT. This VMT was then apportioned to the network within a buffer of the zone dividing by the length of each segment to convert the VMT into vehicle volumes which were preloaded on the network before assignment.

Zero-occupant vehicle (ZOV) trips will also occur for sCAVs. After dropping off a passenger, sCAVs will often need to dead-head to a different location to pick up the next passenger. Dead-heading was incorporated into our modeling framework by inverting all passenger origins and destinations and feeding into a gravity model. Additionally, sCAVs will need to return to centralized depots intermittently, either to re-charge or when demand is low. These trips can be modeled in our framework by first asserting that some TAZs contain depots with set capacities, generating trips based on assumptions regarding vehicle charging requirements and/or variation in demand between periods and employing a gravity model between sCAV origins and destinations and TAZs containing sCAV depots.

Supply Uncertainty

Operation in Mixed Traffic

One of the most widely touted benefits of CAVs is their ability to reduce crash rates and provide improved safety to travelers (*21*). However, this benefit would likely come

Table 1. Summary of Demand Uncertainty

Model step	Structural change(s) in model	Required parameter assertions
Vehicle ownership & household segmentation	Expanded segmentation: 1. Zero vehicles 2. Vehicles < adults; no CAVs 3. Vehicles < adults; CAVs > 0 4. Vehicles ⩾ adults; no CAVs 5. Vehicles ⩾ adults; CAVs > 0	Change in vehicle ownership patterns. Market penetration of privately owned CAVs
Trip generation	Segmentation of HBO trips (on non-work tours) by activity duration (greater or less than 30 min)	Changes in trip generation rates especially for households with disabled persons, seniors, and/or children and households that own CAVs
Trip distribution	No changes required	Reduced sensitivity to travel time, particularly for households that own CAVs
Mode choice	New mode choice options: 1. MaaS added at upper level with SOV, HOV2, and HOV3 nested underneath 2. MaaS added as a transit access mode 3. Conventional and CAV submodes added under all vehicle modes	Mode shares for new modes not observed or minimal in the model base year and submode shares by market segment Vehicle occupancy shares within MaaS cost of CAV MaaS
Time-of-day	No changes required	New, shifted diurnal distributions of long-distance passenger and freight travel
ZOV trips	New trip types: 1. pCAV: car-sharing within household 2. pCAV: park at home 3. pCAV: other remote free parking 4. pCAV: circulating in lieu of parking 5. sCAV: dead-heading between passenger pick-up and drop-off 6. sCAV: to/from depots	Generation rates and trip lengths / distribution parameters for each type of ZOV trip

Note: CAV = connected and autonomous vehicle; HBO = home-based other; HOV = high occupancy vehicle; MaaS = mobility as a service; pCAV = private connected and autonomous vehicle; sCAV = shared connected and autonomous vehicle; SOV = single occupancy vehicle; ZOV = zero-occupant vehicle.

at the cost of increased consumption of capacity by CAVs in mixed traffic. CAVs would reduce crash rates by driving more conservatively than humans, leaving more space between vehicles, and thereby reducing throughput. This effect can easily be incorporated in static user equilibrium assignment models through the use of passenger car equivalency (PCE) factors. While the traditional use of PCEs was to reflect trucks' consumption of more roadway space/capacity, the same technique can be applied for CAVs.

Operation in Fully Autonomous Traffic

If operating on dedicated infrastructure, CAVs may immediately see operational improvements before full market penetration. Under these conditions, CAV will likely allow for higher operating speeds, reduced following distances or increased capacities, reduced waiting times at intersections, and fewer operational disruptions related to crashes.

Application of Trip-Based CAV Framework

An initial application of the framework described in this paper was employed to develop CAV scenarios as a component of the 2018 Chittenden County, Vermont Environment, Community, Opportunity and Sustainability (ECOS) Plan. The ECOS plan is a combined regional plan, metropolitan transportation plan, and comprehensive economic development plan that strives for a healthy, inclusive, and prosperous community and was adopted in June 2018 (*22*). In 2015, Chittenden County had a population of 161,382 in 63,498 households and 135,511 jobs. By 2050, the region's population is expected to grow to 183,172—a 14% increase—and add around 47,000 jobs. The county is home to two major attractions, the University of Vermont and Lake Champlain. Burlington, VT is the county seat and the county's largest city. To help the region anticipate potential transportation and land-impacts of CAVs, two scenarios were included in the plan: a scenario envisioning 80% market penetration of CAVs by 2050 (Scenario 1) and a full adoption scenario assuming 100% market penetration (Scenario 2). From these scenarios, performance measures were derived and compared vis-à-vis the baseline scenario without CAVs. The assumptions made to support this work are detailed in turn below, following the framework detailed in the previous section.

Table 2. Summary of Supply Uncertainty

Model step	Structural change(s) in model	Required parameter assertions
Developing transportation network	If needed, can include dedicated CAV-only infrastructure	Changes in link capacity, by functional classification. Changes in intersection capacity, by intersection type
Assignment	Create additional vehicle class for CAVs	Effective vehicle length (PCE) for capacity consumption in mixed traffic

Note: CAV = connected and autonomous vehicle; PCE = passenger car equivalency.

Table 3. Summary Chittenden County Plan Assumptions

Model step		Model parameter	Assumed change, relative to baseline	
			Scenario 1	Scenario 2
Demand uncertainty	Household segmentation	CAV market penetration	80%	100%
	Trip generation	Children/elderly HBO trip rate	5% increase	5% increase
	ZOV trips	Circulating trips for pCAVs	Yes	Yes
		ZOV travel tax policy	No	Yes
		MaaS dead-heads	Yes	Yes
	Mode choice	pCAV/sCAV split	50/50	35/65
		MaaS CAV occupancy	No change	2.5 persons/car
	Trip distribution	Sensitivity to in-vehicle travel time	No change	No change
Supply uncertainty	Link capacity, by type	Freeways	100% increase	200% increase
		Rural arterials	No change	75% increase
		Urban arterials	No change	50% increase
		Rural arterials	No change	50% increase
		Rural arterials	No change	50% increase
	Intersection capacity, by type	Signalized	5% increase	80% increase
		1, 2, 3 way stop	No change	10% increase
		On-ramp yield	No change	10% increase
		Yield	No change	10% increase
		All-way stop	No change	10% increase
	Assignment	Effective vehicle length	10% increase	na

Note: CAV = connected and autonomous vehicle; HBO = home-based other; MaaS = mobility as a service; na = not applicable; pCAV = private connected and autonomous vehicle; sCAV = shared connected and autonomous vehicle; SOV = single occupancy vehicle; ZOV = zero-occupant vehicle.

An initial application of the framework described in this paper was employed in the Chittenden County model. Superficially, demand-related assumptions were made for trip generation, pCAV/sCAV split, and ZOV trips (Table 1) and supply-related assumptions were made for link and intersection capacity and following distance (Table 2). These assumptions are summarized in Table 3 and discussed in turn below. The assumptions were not to be understood as particularly likely but simply meant as an initial exploration of possible future scenarios involving CAVs.

Demand-Related Parameter Assertions

Trip Generation. To capture trips induced by CAVs in households with mobility constraints, modest (5%) increases in the generation of home-based other trips were assumed in both the 80% and 100% CAV penetration scenarios.

pCAV/sCAV Split. In Scenario 1, it was assumed that 50% of all CAV trips were taken in pCAVs and 50% in sCAVs; in Scenario 2, 35% of CAV trips were assumed to be in pCAVs and 65% in sCAVs. Additionally, average vehicle occupancy was assumed to remain constant in Scenario 1 and increase to 2.5 persons per car in Scenario 2.

Circulating Trips. To account for ZOV circulating trips, it was assumed that 50% of pCAV home-based other and non-home base trips in destination zones in downtown Burlington with constrained parking (Figure 3) resulted in two additional trips—one from the destination zone to the nearest neighboring zone and one back to the destination zone. In the 80% CAV scenario these trips were non-constrained; in the 100% CAV scenario it was assumed that a progressive tax policy regarding ZOV travel reduced occurrence of circulating trips by 90%.

Figure 3. Scenario assumptions for Chittenden County, Vermont.

Constrained Parking. For zones located in downtown Burlington, it was assumed that pCAVs would return home after dropping the occupant off at work resulting in an additional trip to or from the subject zone for each home-based work trip in Scenario 1 and Scenario 2.

MaaS Dead-Heads. To model ZOV trips for sCAVs, one additional trip was added between passenger pick-ups and drop-offs. In addition, 10 TAZs distributed throughout the study region were assumed to contain depots operated by TNCs (Figure 3). When a surplus of MaaS vehicles on the network occurred, sCAVs returned to the nearest depot. Conversely, sCAVs were dispatched from depots when a deficit of MaaS vehicles occurred. These new trips were added using a short-distance gravity model.

Supply-Related Parameter Assertions

Link Capacity. To capture the ability of CAVs to more efficiently utilize existing roadway capacity, the capacity of all freeway links was increased by 100% in Scenario 1 and 200% in Scenario 2. In addition, link capacities were increased by 75% for rural arterials and 50% for urban arterials, major collectors, and ramps in Scenario 2 only.

Intersection Capacity. In Scenario 1, signalized intersection capacity was assumed to increase by 5% while capacity at all other intersections was assumed to remain constant. Much more aggressive capacity improvements were assumed in the 100% CAV penetration scenario: signalized intersection capacity was increased by 80% based on the elimination of lost time (6 s y+ar), 4 phases per cycle, a 120 s cycle length, and a 50% reduction in headways; one- two- and three-way stop intersection capacity was increased by 10% because of less error in judging gaps; on-ramp yield intersection and yield intersection capacities were increased by 10% because of cooperative merging; and all-way stop intersection capacity was increased by 10% because of elimination of confusion and hesitation over who has right-of-way.

Following Distance. Because CAVs may need to operate with a higher factor of safety when sharing the network with conventional vehicles, a PCE factor was introduced that increased effective vehicle length by 10% in Scenario 1. No PCE factor was used in Scenario 2.

Table 4. Chittenden County Plan Model Results

Performance measure	Baseline	Scenario 1	Relative to baseline	Scenario 2	Relative to baseline
Total VMT	5,407,153	7,246,070	*+1,838,917*	5,778,606	*+371,453*
Total VHT	156,847	225,473	*+68,626*	163,905	*+7,058*
VMT/person	29.5	39.6	*+10.1*	31.5	*+2.0*
VHT/person	0.9	1.2	*+0.3*	0.9	*0*
VMT/person-trip	5.96	6.02	*+0.06*	4.53	*–1.43*
VHT/person-trip	0.24	0.33	*+0.09*	0.3	*+0.06*
Total delay (min)	1,686,780	3,056,799	*+1,370,019*	1,441,049	*–245,731*
Delay/person	9.21	16.69	*+7.48*	7.87	*–1.34*
Delay/vehicle-trip	2.53	3.17	*+0.64*	1.79	*–0.74*
Average trip length (mi)	8.65	7.5	*–1.15*	7.17	*–1.48*
Average trip length (min)	16.02	14.01	*–2.01*	12.2	*–3.82*
All vehicle trips	666,388	965,533	*+299,145*	805,927	*+139,539*
ZOV trips	none	295,009	*+295,009*	269,646	*+269,646*
Percent ZOV	0%	30.6%	*+30.6%*	33.5%	*+33.5%*

Note: VHT = vehicle-hours traveled; ZOV = zero-occupant vehicle. Italics indicate changes relative to the baseline while plain font indicates absolute numbers.

Results

Compared with the baseline scenario, both CAV market penetration scenarios estimate increases in VMT, vehicle-hours traveled (VHT), and total vehicle trips (Table 4). Interestingly, VMT and VHT are only marginally higher in Scenario 2 compared with the baseline (increase of 2 VMT/person) but are substantially higher in Scenario 1 (increase of 10.1 VMT/person). Similarly, total VHT increases by nearly 70,000 hours in Scenario 1 but only 7,000 hours in Scenario 2. Total trip-making increases by large amounts in both Scenario 1 (299,000 additional trips) and Scenario 2 (140,000 additional trips); however, VMT/person-trip remains largely flat in Scenario 1 and is reduced by 1.43 mi/person-trip in Scenario 2. Conversely, average trip length is reduced by a similar amount in both Scenarios 1 and 2.

In addition to assuming 100% CAV penetration, Scenario 2 assumes an increase in vehicle occupancy for sCAV travel. The results demonstrate the degree to which vehicle occupancy impacts overall VMT. Policies encouraging the literal sharing of sCAVs, along with policies regarding ZOV travel, could play a key role in limiting future increases in VMT.

Results from this exercise were presented to stakeholder groups during the development of the Chittenden County Regional Planning Commission's Metropolitan Transportation Plan (MTP). Ensuing discussions regarding CAVs were a first step for the region in planning for the impending CAV future, and illustrated for the first time for some members the specific challenges and opportunities associated with large-scale CAV and MaaS adoption. The potential for CAV induced sprawl (extended trip lengths) and extreme increases in VMT conflict with many CCRPC goals. Understanding the potential challenges associated with CAVs is an important first step for planners to develop policies and plans to counter the potential negative impacts of CAVs and to best capitalize on the potential benefits.

Discussion

Trip-based travel demand models can be enhanced to capture many of the dimensions of uncertainty about CAVs. The application of the enhanced travel demand model in Chittenden County, Vermont, illustrates how addressing CAVs in all model steps, accounting for pCAV and sCAV mode splits, and including ZOV trip components can provide decision-makers with a more focused picture of what widespread CAV adoption may entail for our transportation systems. Critically, trip-based travel demand models enhanced to include potential impacts of CAVs can be a tool to foster conversation and policy debate relevant to CAVs despite the uncertainty of many model parameters. Additionally, the results of the model application in Chittenden County are broadly aligned with findings of other work, some of which employ more complicated models that are infeasible for many metropolitan planning organizations (MPOs). Models in Austin and Atlanta found that adoption of sCAVs and pCAVs may allow households to reduce total vehicle holdings; however, concomitant increases in total VMT are likely to occur because of ZOV trips (*14*, *15*). These findings are mirrored in our application of the enhanced trip-based framework described in this paper. Additionally, the application of an ABM in Jacksonville found that the distribution of pCAV and sCAV users is a key model parameter influencing VMT and delay—a finding once more echoed by the trip-based approach employed here (*13*).

As CAVs are increasingly adopted in the vehicle fleet, early adopters will provide valuable information to reduce uncertainty related to model parameters. By pursuing a structured approach to incorporate CAV uncertainty into trip-based models, the framework presented in this paper is able to flexibly adapt as real-world evidence of the behavioral impacts of CAV adoption emerges and certain parameter uncertainties are reduced while simultaneously supporting the current needs of transportation agencies seeking to make policy decisions in the context of CAVs. Further, incorporating CAVs into established models empowers users to think pragmatically about the potential impacts of CAVs and develop policy approaches to mitigate potential future risks now rather than waiting for the development of advanced ABMs or other approaches to estimate CAV impacts and compare policy options. While only one application is described in this paper, on-going efforts are under way to apply the enhanced trip-based CAV framework in Michigan, Illinois, Virginia, Indiana, and South Carolina. These additional applications will demonstrate the validity of this framework in different geographic contexts and spatial scales (metropolitan and statewide).

This work has several limitations. First, long-term land-use impacts of CAVs are not explicitly considered within the modeling framework developed in this paper. Reductions in the generalized cost of driving have historically precipitated urban sprawl in the United States; introducing the potential for CAVs to exacerbate sprawl may undermine some of their expected benefits (*23*). However, future land-use impacts will manifest within a complex regulatory context, and urban and transportation planners may use models like the one described in this paper to inform policies aimed at curbing deleterious CAV impacts, including land-use effects (*24*). Second, CAVs may eventually serve as a substitute for some public spaces, thereby reducing the need to travel for certain activities. Finally, the treatment of uncertainty pursued in this work, while providing robust decision support, does not provide a quantitative depiction of the probabilities of various outcomes. Several methods, including Monte Carlo simulation, Bayesian melding, and response surface modeling, may be integrated with the approach described in this paper to further quantify uncertainties associated with the CAVs (*25*).

Conclusion

Transportation systems may soon be fundamentally transformed by widespread adoption of CAVs. While current modeling approaches for CAVs are not necessarily aligned with the needs of many metropolitan areas, the enhanced trip-based modeling framework described in this paper can support planning and policymaking efforts in the context of CAVs. An initial application of portions of the framework described in this paper, applied in Chittenden County, Vermont, illustrated how CAVs may result substantial increases in VMT, VHT, and delay despite capacity increases. On-going applications in Michigan, Illinois, Virginia, Indiana, and South Carolina will demonstrate the validity of this framework across differing geographic contexts and spatial scales. This framework will empower decision-makers to identify key sensitivities related to CAV adoption and develop plans and policies that are robust in the face of a highly uncertain future for our transportation system.

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Author Contributions

The authors confirm contribution to the paper as follows: framework conception and design: VLB; draft manuscript preparation: TM; framework implementation and code development: HS; model application: BS, SB. All authors reviewed the results and approved the final version of the manuscript.

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