Guidance on Considering CAVs in Travel Demand Models

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Leta Huntsinger, Ph.D., P.E.
Si Shi
Fahim Kafashan
Ali Hajbabaie, Ph.D.
Shoaib Samandar, Ph.D.
Vince Bernardin, Ph.D. (Caliper Corp.)
Kyle Ward (Caliper Corp.)
Institute for Transporation Research and Education
North Carolina State University

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16. Abstract

NCDOT uses a data-driven process to inform the funding of transportation infrastructure. The primary analytical tool supporting this data-driven process is the travel demand model (TDM). The TDM is used to develop traffic forecasts that inform project decisions and the spending of tens of millions of dollars. The introduction and deployment of Connected and Automated Vehicles (CAVs) have the potential to significantly change traffic forecasts and may result in the Department unnecessarily spending tens of millions of dollars, or on the other hand, leave them unprepared for the disruption that CAVs may create in our transportation system.

This study focuses on the consideration of CAVs in TDMs and aims to provide guidance to NCDOT on the consideration of CAVs in travel demand models developed by or for NCDOT in support of transportation planning analysis and traffic forecasts across the state. Key findings from this research support the use of strategic scenario planning both within an existing model design (Tier 1) and design modifications (Tier 2) to evaluate the potential impact of CAVs on both system-level performance measures and project-level traffic forecasts. System level performance measures for both the Tier 1 and Tier 2 analysis showed increases in daily vehicle miles traveled (VMT) but decreases in congested VMT and delay for both a high (95%) and medium-high (70%) CAV adoption level. The project level analysis showed improvements in the demand-to-capacity ratio (D/C) and delay cost savings, but CAVs did not always indicate that project construction would no longer be necessary. The Tier 3 evaluation of NCDOT's Regional Travel Demand Model (RTDM) suggests first that CAV results may not be as intuitive in a small area with little congestion, but also that a deeper dive into the functionality and assumptions of this model is needed.

The study concludes that applying travel models in a scenario planning context is an effective way to understand the potential risks and benefits of CAVs on traffic forecasts. While model design (Tier 2) is the preferred method, this approach is more time and resource-intensive and requires a certain level of model development expertise. On the other hand, using an existing model (Tier 1) is an approach that could be implemented without delay on most, if not all, upcoming traffic forecasts. While not as realistic a representation of travel behavior, the results are shown to be an effective way to evaluate the risk and uncertainty of CAVs on transportation planning analysis and project-level traffic forecasts. NCDOT should move forward with the consideration of CAVs in traffic forecasts and long-range transportation plans with a forecast year of 2050 and beyond. NCDOT should also adopt a regular practice of risk and uncertainty analysis for traffic forecasts.

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Executive Summary

NCDOT uses a data-driven process to inform the funding of transportation infrastructure, a process that includes a high degree of collaboration and cooperation with metropolitan and rural Planning Organizations (POs). The primary analytical tool supporting this data-driven process is the travel demand model (TDM) for the PO's region. The TDM is used to develop traffic forecasts that inform project decisions and millions of dollars of spending. The introduction and deployment of Connected and Automated Vehicles (CAVs) have the potential to significantly change traffic forecasts and may result in the Department having unnecessarily spent significant amounts of money–or on the other hand, being left unprepared for the disruption that CAVs may create in our transportation system.

This study focuses on advanced models for large POs and NCDOT's Regional Travel Demand Model (RTDM) for small and rural POs and aims to provide guidance to NCDOT on the consideration of CAVs in travel demand models developed by or for NCDOT in support of transportation planning analysis and traffic forecasts across the state.

Key findings from this research support the use of strategic scenario planning both within an existing model design (Tier 1) and design modifications (Tier 2) to evaluate the potential impact of CAVs on both system-level performance measures and project-level traffic forecasts. System-level performance measures for both the Tier 1 and Tier 2 analyses showed increases in daily vehicle miles traveled (VMT) but decreases in congested VMT and delay for both a high (95%) and medium-high (70%) CAV adoption level. The project-level analysis showed improvements in the demand-to-capacity ratio (D/C) and delay cost savings, but did not always indicate that project construction would no longer be necessary given increased CAV adoption. The evaluation of NCDOT's RTDM in Tier 3 suggests that CAV results may not be as intuitive in a small area with little congestion, but also that a deeper dive into the functionality and assumptions of this model is needed.

The study concludes that applying travel models in a scenario planning context is an effective way to understand the potential risks and benefits of CAVs on traffic forecasts. While model design (Tier 2) is the preferred method, this approach is more time and resource-intensive and requires a certain level of model development expertise. On the other hand, using an existing model (Tier 1) is an approach that could be implemented without delay on most, if not all, upcoming traffic forecasts. While not as realistic a representation of travel behavior, the results are shown to be an effective way to evaluate the risk and uncertainty of CAVs on transportation planning analysis and project-level traffic forecasts.

Based on the findings from this research, the team recommends that NCDOT immediately move forward with the consideration of CAVs in traffic forecasts and long-range transportation plans with a forecast year of 2050 and beyond. For existing models, the Tier 1 approach should be implemented for existing project analysis. For future model updates, the model design should incorporate the recommended methods for evaluating CAVs. It is also recommended that NCDOT incorporate a regular practice of risk and uncertainty analysis not just in consideration of CAVs, but to capture the variety of unknowns about the future.

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Introduction

NCDOT makes major investment decisions related to the development of transportation infrastructure across the state every year. Following the guidance outlined in the Strategic Transportation Investments law, the Department endeavors to use funding efficiently and effectively through a data-driven process that includes high levels of collaboration and cooperation with both metropolitan and rural Planning Organizations (POs). This data-driven process uses various tools, but the primary tool used by the POs is the travel demand model (TDM) for their region. Once projects are prioritized and advanced to implementation, the travel demand model is again used as the primary analytical tool for developing traffic forecasts. These forecasts then inform project decisions that influence the spending of tens of millions of dollars. While there are always points of dispute when envisioning the details around specific projects, the technical process is generally well-accepted, robust, and technically sound and has served the Department and its constituents well for years. The introduction and deployment of Connected and Automated Vehicles (CAVs) have the potential to significantly disrupt this well-established decision-making process and may result in the Department unnecessarily spending significant amounts of money–or on the other hand, being left unprepared for the disruption that CAVs may create in our transportation system.

There are three key factors at play in understanding the impact that CAVs will have on traffic forecasts: 1) supply side impacts, 2) demand side impacts, and 3) CAV deployment predictions. From extensive research around supply side impacts, there is a commendable understanding of supply side benefits. This is not the case on the demand side of the equation, in large part because it is related to travel behavior and how people will respond to the vast array of new choices that CAVs will provide and how these choices will impact travel demand and project-level traffic forecasts. The third factor is related to the timeline and intensity of CAV deployment, especially within the context of future year traffic forecasts, and how the number of CAVs impacts not only the proportion of CAVs in the travel stream but also the size of the travel stream.

While the impacts of CAVs will not be fully understood until more observable data is available, it is not prudent for NCDOT to wait until that time. There is an urgent need to provide guidance on how CAVs will impact travel in future years, and how travel demand models can be adjusted to capture these potential impacts. Some Metropolitan Transportation Plans (MTPs) have a future year of 2045, but most already have a future year of 2050, and some POs are currently working on MTPs with a future year of 2055. The North Carolina Long Range Multimodal Transportation Plan has a horizon year of 2050, and most, if not all, project-level traffic forecasts will soon have a design year of 2050. Some CAV forecasts suggest that by 2050 nearly 60% of new vehicle sales will be autonomous vehicles (AVs), and close to 40% of all vehicle travel will be made by AVs (Litman, 2021)–and these forecasts are thought by many to be too low.

When it comes to investing in North Carolina's transportation future, there are enormous implications if NCDOT does not plan and invest appropriately in infrastructure. It would take many years for a high-growth region to recover from under-investment in infrastructure due to overly optimistic assumptions about the benefits gained from CAVs. On the other hand, there are also consequences if NCDOT overbuilds, including unnecessary spending, environmental impacts, and community consequences. By their very nature, traffic forecasts have always included a certain level of uncertainty, but continuing to advance traffic forecasts that fail to consider CAVs will almost certainly lead to NCDOT making poor decisions given the very high likelihood that the vehicle fleet in 2050 will include a large percentage of CAVs. This research is urgently needed to better understand how CAVs impact transportation systems analysis and project forecasts so North Carolina can invest wisely in our future.

To address this need, NCDOT funded this study to better understand the potential implications of CAVs on travel demand and project-level traffic forecasts. The results of this study inform the conversation around CAV deployment and adoption and provide guidance on how best to capture the supply and demand side changes that will likely result from different levels of CAVs in the travel stream.

Overall, the research objectives of this research project are:

1. Provide guidance to NCDOT on possible updates to the RTDM Development Guidelines and to regional POs on how they should update and exercise their TDMs to include CAVs and their effects.
2. Develop guidelines for the modification and applications of TDMs using a realistic set of CAV scenarios.

The detailed results of this study are outlined in this report and the accompanying appendices, including guidelines for implementation within both an existing model and model design change context. For the purposes of this research, automated vehicles (AVs) are vehicles that rely on onboard sensors for driving tasks. AVs are a disruptive technology that can potentially enhance safety, capacity, and travel time reliability. There is a significant effort from the automotive industry to produce fully autonomous vehicles (SAE levels 4 and 5). However, lower-level applications of this technology such as adaptive cruise control are already in use with the goals of driver convenience, congestion relief, safety, and capacity enhancements.

Connected vehicles have the potential to gather information on their surroundings by communicating with other equipped vehicles and the infrastructure in their vicinity. Access to this information in real-time impacts drivers' response and decision making which can lead to potential improvements in safety and capacity. It is worth noting that the human driver is in control and makes all the operational, tactical, and driving decisions based on the information received through the vehicle's communication capabilities.

Vehicles that have both connectivity and automation are classified as connected and automated vehicles (CAVs). These vehicles not only rely on their onboard sensors but also their communication capabilities to make decisions and execute driving tasks. Equipped with both technologies these vehicles have access to real-time information about other vehicles' behavior and whereabouts in their vicinity along with the environmental and driving conditions downstream of their locations.

This study focused exclusively on CAVs, assuming Level 4 or 5 automation.

Literature Review Summary

A detailed literature review is provided in **Appendix A**. In summary, the literature review for this project focused first on establishing basic definitions for automated vehicles (AVs) and CAVs. The literature was then used to frame a possible understanding of CAV market penetration and ownership patterns. Changes in travel behavior and transportation system performance associated with CAV adoption were explored, as were methods for implementing these changes into travel demand models. These findings helped inform the development of an index of predictions and factors (**Appendix B**) and a conceptual framework for updating a travel demand model to include CAVs (**Appendix C**).

The review of literature also included a scan of peer agencies, summarized below.

The consulting firm Resource Systems Group (RSG) and Caliper Corporation collaborated with the Michigan Department of Transportation (MDOT) on the development of a new statewide transportation model emphasizing a data-driven approach and utilizing big data to accurately represent travel patterns. A significant aspect of this project was the integration of CAVs into the modeling framework. This addition aims to facilitate the examination of various scenarios that CAVs might present, despite the current inability to generate CAV-informed forecasts. The model's adaptability allows for exploring assumptions around the impact of CAVs on travel behavior, including changes in trip frequency, mode, duration, and timing, as well as considering the implications of zero-occupant vehicle trips (RSG et al., 2019).

In Virginia, VDOT publishes Travel Demand Modeling Policies and Procedures that guide public agencies in the development and application of travel models in Virginia (Cambridge, 2020). Version 3.00, released in August 2020, provides a section on model enhancement options for trip-based models to incorporate the effects of CAVs. In addition to covering model enhancement options, they also encourage the use of scenario planning for modeling CAV impacts.

While no specific guidance could be located, several MPOs in Ohio have coordinated with ODOT on the consideration of CAVs in their travel models (CDM, 2022).

Finally, project NCHRP 20-102(29), led by the University of Central Florida, aims to incorporate new mobility options (NMOs) including CAVs into travel demand forecasting and modeling. It addresses challenges such as data acquisition, model structure adaptation, calibration, and validation for emerging transportation technologies. The objective is to develop a guide for implementing the best practices in incorporating NMOs into travel demand models, focusing on understanding travel behavior changes, adoption rates, and benefits of NMOs to inform decision-making and investment in transportation planning (National Academies, 2024).

Definition of Terms

Average Trip Length: The average length calculated for all trips made in the region as a measure of either time or distance. The calculated value typically varies by trip purpose.

CAV: Connected and automated vehicle.

CAVihvi: CAV household classified as income high and vehicle insufficient, where vehicle insufficient refers to fewer vehicles than workers in the household.

CAVihvs: CAV household classified as income high and vehicle sufficient, where vehicle sufficient refers to vehicles equal to, or greater than workers in the household.

CAVilvi: CAV household classified as income low and vehicle insufficient.

CAVilvs: CAV household classified as income low and vehicle sufficient.

CAVvi: CAV household classified as vehicle insufficient.

CAVvs: CAV household classified as vehicle sufficient.

Congested VMT: Vehicle miles traveled under congestion conditions as defined by conditions where the roadway link demand exceeds capacity at a level of service (LOS) D. This is calculated as demand/capacity greater than one for LOS D.

Delay: Delay is calculated as the difference between the roadway link congested travel time and the roadway link free flow travel time multiplied by roadway link demand. The free flow speed is determined using the area type, facility type, and posted speed. The unit of delay is minutes.

System Delay: Calculated using all the roadway links in the travel model.

Project Delay: Calculated using only the roadway links for the identified project.

EE: External to external trips defined as vehicle trips that travel completing through the region.

HOV2: High-occupancy vehicle (HOV) trips defined as a trip with two people per vehicle.

HOV3: High-occupancy vehicle (HOV) trips defined as a trip with 3 or more people per vehicle.

HV: Vehicles classified as a human-driven vehicle.

IE/EI: Internal to external or external to internal trips defined as vehicle trips that have one end of the trip internal to the region and one end of the trip external to the region.

IVTT: The In-vehicle travel time for the transit mode.

KNR: A kiss and ride lot serving transit.

K12: Trips defined as trips from home to a k12 school.

MPR: Market penetration rate.

MUT: Multi-unit truck.

OD_Long: Trips defined as long duration discretionary trips made with one trip end at home.

OME: Trips defined as shopping, dining out or other maintenance trips with one trip end at home.

pCAV: Privately owned connected and automated vehicle.

PCE: Passenger car equivalent.

Peak Period Congested VMT or PM Peak Period Congested VMT: Refers to vehicle miles traveled under congestion conditions, as previously defined, during the 3-hour PM peak period from 3:30pm to 6:30pm

Peak Period VMT or PM Peak Period VMT: Vehicle miles traveled during the 3-hour PM peak period from 3:30pm to 6:30pm.

PNR: A park and ride lot serving transit.

sCAV: Shared connected and automated vehicle.

SOV: Single occupant vehicle trips defined as a trip with one person per vehicle.

SUT: Single unit truck.

Trip Length: The calculated length of an individual trip from the production (or origin) end of the trip to the attraction (or destination) end of the trip as a measure of either time or distance.

VMT: Vehicle miles traveled.

VOT: Value of time.

W_HB_O: Trips defined as work tours with one trip end at home and an interim stop along the tour.

W_HB_W: Trips defined as work tours with one trip end at home and no stops along the tour.

ZOV: Zero occupancy vehicle.

Linkages to Long-Range Planning

Long-range transportation planning is the process of planning, evaluating, and developing strategies for operating, managing, maintaining, and financing a region's transportation system in such a way as to advance the area's long-term goals. The planning process follows a well-established process of:

- Establishing a community vision,
- Understanding the types of decisions needed to achieve this vision,
- Assessing the opportunities and limitations of the future in relationship to goals and desired system performance measures,
- Identifying short- and long-term consequences of choices,
- Relating alternative decisions to goals, objectives, and performance measures, and
- Presenting information to decision-makers to help them make informed decisions.

A simplified version of this process along with travel modeling touchpoints is shown in **Figure 1**. The dashed line between the first step (goal setting) and travel modeling indicates that outputs from travel models can be used to inform targets related to goals, but it is not common practice to do so.

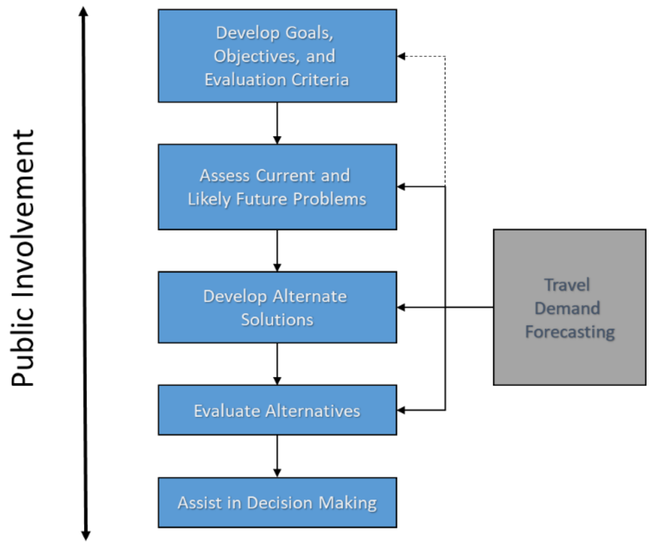

FIGURE 1 TRANSPORTATION PLANNING PROCESS WITH TRAVEL MODELING TOUCHPOINTS

The transportation plans developed through this process typically have a horizon year of 20- to 30-years. As such, these plans should consider potential disruptors to travel behavior and transportation systems in addition to past and future trends. Given predictions for CAV adoption rates, transportation plans being developed today for a horizon year of 2050 or 2055 should be considering CAVs as a part of plan development, even if nothing more than through scenario planning via modifying existing model parameters to better understand project priorities and risk and uncertainty.

Since travel demand models are the principal analytical tool supporting the transportation planning process, models designed with CAVs in mind, or models applied in scenario planning context that simply modify existing model parameters, will provide a better context for assessing likely future problems where CAVs are a part of that future. Likewise, alternative solutions can be evaluated through the lens of both the benefits and impacts of a CAV future. This analysis could inform the development of long-range transportation plans that consider the need for and prioritization of projects that may shift to a later horizon year, or may no longer be needed in a CAV future.

Scenario Development

Scenario planning is a well-regarded approach to understanding the risk and uncertainty inherent in any systems or project-level forecast. By defining specific scenarios to assess the impact of CAVs on travel demand models, scenario planning allows for a comprehensive evaluation of potential outcomes. The findings from the literature were used to develop scenarios for testing and evaluation through the application of case studies. These case studies are discussed in detail in the case studies section. This section focuses on the development of scenarios that will be tested and evaluated through the application of case studies. The case studies include analysis using a travel model from a large urbanized region and a travel model from a small urban region. The developed scenarios consider various model parameters related to both supply and demand and the potential for change in these parameters based on a medium-high (70%) and high (95%) CAV adoption rate. Scenario testing also considers the degree of uncertainty about the value of the different parameters informed by whether these parameter modifications are cited in the literature, and the process by which they were developed. For example, did previous researchers assert the documented parameters, or were they informed by data or modeling efforts? The development of scenarios informed the procedures for model design changes discussed in detail in the section on model adjustments.

Index of Predictions and Factors

Rather than associate a specific forecast year with a specific CAV adoption rate, this research informed the development of an index of predictions and factors for CAVs–see **Appendix B**. The index synthesizes findings from literature, conversations with experts, and the research team's knowledge. It provides a timeline of possible CAV adoption based on influencing factors, subsequent changes in travel behavior, and how to incorporate these changes in travel demand models. The primary purpose of the index is to inform the conversation around model adjustments to support scenario planning and model design changes needed to evaluate CAVs (assuming fully automated CAVs). Instead of using forecast years, a scale of low (0-30%), medium (30-70%), and high (70-100%) adoption was considered. The low scale captures early adopters, the medium represents majority adoption, and the high includes late adopters. The influencing factors towards CAV adoption were identified as cost, technology, driver experience, and policies. Each of these factors was evaluated within the context of the changes that might move the adoption rate from low, to medium, to high.

CAV adoption at various rates is likely to influence how people travel including the number of trips made, mode of travel, distance traveled, time of day traveled, and lifestyle. While some behavioral changes are initially likely, other changes may not occur until higher adoption levels. Having insight into these possible behavioral changes at various adoption rates informs the development of scenarios for evaluation. In total, six scenarios are evaluated, one at a Medium-High (MH) (70%) CAV adoption level, and one at a High (H) (95%) CAV adoption level for each of the three tiers of analysis. This research did not consider adoption levels below 70% given the focus of this research on planning horizon years of 2050 or later. The goal was to try and balance CAV adoption levels with the travel forecasts and associated infrastructure decisions for that time frame.

The first tier focuses on the modification of parameters in a regional model without any existing accommodations for CAVs. The advantage of this approach is that it can be quickly and easily implemented. The second tier focuses on a model redesign. This approach is more resource-intensive and may not be implemented by MPOs until the next update of their model which could be 5-10 years away. The third tier is the evaluation of an existing model that already includes a CAV component as a part of the original design.

The first and second tiers are implemented using the Triangle Regional Model Generation 2 (TRMG2) and the third tier is implemented using NCDOT's Regional Travel Demand Model (RTDM). The RTDM is the standardized model platform developed by NCDOT to meet the modeling needs of small MPOs and RPOs. All scenarios are based on a 2050 forecast year.

For each of the scenarios, the literature informed the assertion of parameter values, or parameter adjustments, for the different stages of the demand model. Sensitivity testing was used to evaluate the level of uncertainty for key parameter values for the Tier 1 and Tier 2 analyses.

See **Appendix B** for details on the index and parameter changes. These values were used to inform the development of scenarios for all three tiers.

Tier 1: Existing Model Design

The application of the travel demand model under the Tier 1 approach does not involve any model design changes but rather allows the user to modify existing rates and coefficients to reflect expected changes in travel behavior or transportation system operating characteristics. This approach is easier to apply than the Tier 2 approach and requires less modeling expertise and resource investment.

The scenarios developed for Tier 1 included both a MH and a H scenario. For each scenario, model parameter adjustments were made to account for changes in mode choice value of time, trip rates, and highway capacity. Adjusting the time coefficient (or friction factors) for trip distribution requires an iterative approach of adjusting the model coefficients, applying the model, and reviewing the modified trip lengths. This process repeats until the desired average trip length is achieved. To simplify the application of the Tier 1 approach, the time coefficient for the trip distribution models was not adjusted.

Table 1 summarizes the parameter adjustments for each scenario. These adjustments were informed by the literature, both with respect to which parameters to adjust and the amount. These values are directly transferable to all models with respect to trip rates and highway capacity. The value of time adjustment is also directly transferable to other models. As noted above, the user would simply adjust the shape of the impedance function until the desired reductions in average trip length are achieved.

TABLE 1 MODEL PARAMETER ADJUSTMENTS FOR TIER 1 SCENARIOS

Parameter Adjustment	Sub-category	Scenarios	
		Medium-High (70%)	High (95%)
Value of Time	All people[1]	-60%	-65%
Trip rates	All purposes[2]	9%	15%
Highway Capacity	Signalized arterial	40%	70%
	Control access facility	47%	77%

[1] The reduction applied in the model reflects the recommended reduction multiplied by the expected CAV adoption rate for the scenario. For medium-high scenario, VOT should be reduced by 42% (60%*70%).

[2]The adjustment captures additional trips as a result of ease of travel with CAVs, increased accessibility for elderly and disabled people, and empty trips from car sharing among household members.

Tier 2: Model Design Changes

Unlike the Tier 1 approach which is largely constrained by the existing construct of the model, the model design approach provides greater flexibility to reflect the change when CAVs become prevalent. Modifications to eight aspects of TRMG2, a four-step travel demand model, are proposed, and two CAV scenarios are developed to reflect the MH (70%) and H (95%) CAV adoption rate. The model design approach is preferred as it provides more realism but must be balanced against the available time and expertise of the analyst. The modified values for all parameters and coefficients were informed by the literature as documented in **Table 2**.

TABLE 2 RECOMMENDED PARAMETER MODIFICATIONS

Model Steps	Model Adjustments		Medium High (70%)	High (95%)
	Category	Sub-category		
Initial Processing				
	Higher capacity	Signalized arterial	40%	70%
		Controlled access	47%	77%
	Add CAV ownership	Apply cross-classification model	MPR = 70%	MPR = 95%
Trip Generation				
	Increased trip rates (because of ease of travel, ZOV trips from car sharing among household members, and enhanced mobility for elderly and disabled)	All purposes	9%	15%
*Time of Day (*see note 1)*				
	More through trips (EE) in night period	EE - SUT/MUT	30%	50%
		EE - Auto	15%	25%
	More external <--> internal (IE/EI) in night period	IE/EI	2%	8%
ZOV Trips				
	CAV parking avoidance trips (CAV users send CAV back to home to park. However, since at this step market segmentation is no longer preserved, a lower probability is picked to reflect the fact that not all trips can use this option) (*see note 1)	Trip distance > 20 miles	0%	0%
		Trip distance 15 -20 miles	10%	10%
		Trip distance 10 - 15 miles	20%	20%
		Trip distance 5 - 10 miles	35%	35%
		Trip distance <= 5 miles	50%	50%
	sCAV empty miles (*see note 2)	Apply growth factor to sCAV trip table	67%	50%
Mode Choice				
	Change auto pay mode to sCAV	Discount fare coefficient	fare coef -40%	fare coef -60%
	Add sCAV as an access mode to transit for the work tour	Treat as KNR but w/ lower drive access time	coef -60%	coef -65%
	Decrease value of time for all auto modes (except k12)	Discount VOT coefficient except for N_K12	coef -60%	coef -65%
Trip Distribution				
	Longer trip distance	Discount travel time for work purposes (both w_hb_w and w_hb_o)	31% for w_hb_o and 11% for w_hb_w	same adjustment but results a 14% longer w_hb_w and 40% longer in w_hb_o
		Discount travel time for social/recreational purposes (only ome and od_long)	27% *see note 3	44% *see note 3
Airport				
	Add CAV return home parking trips	Assume MPR% of airport trips will use CAV and those will go back home to park	70% of trips	95% of trips

[1]These numbers were developed based on professional experience due to a lack of relevant literature
[2]Only two papers were found related to this topic, suggesting empty miles are 50%-67% of sCAV miles. Under higher MPR scenario, the assumption is sCAV is easier to pick up next passenger thus reducing empty miles
[3]OD_Short purpose is already longer after mode choice adjustment because it uses auto log sum instead of travel time, which is around 27% longer in MH and 44% longer in H. Remaining trip purposes are adjusted to match this change.

Tier 3: Evaluating NCDOT's RTDM

As a part of the base design, NCDOT's RTDM includes a user option for evaluating the presence of CAVs based on a user input CAV adoption level. This model is well documented with respect to the treatment of CAVs and that document can be referenced for details (Stantec, 2023). The application of the model requires the user to modify a CAV cost ratio that considers the cost of a CAV as compared to the cost of a human driven vehicle. This ratio varies by horizon year and in doing so, forms the shape of a negative exponential curve that informs the CAV adoption rate, the number of new vehicles sold, and old vehicles retired each year. The CAV adoption level influences other modeling components as summarized in **Table 3**. The only parameter not tied to the cost ratio is the trip length parameter. This parameter requires independent adjustment by the user and is capped at 15%. This value is lower than the change in trip length suggested in the literature, and that applied for both the MH and H scenarios in the Tier 1 and Tier 2 analysis.

Scenario development for the RTDM focused on adjusting the cost ratio to achieve the MH and H scenario that matched the CAV adoption rates targeted in the TRMG2 to the extent possible. A trip length adjustment is capped at 15%, so this value was applied to the social/recreational trips for both the MH and H scenarios.

TABLE 3 SUMMARY OF MODEL COMPONENT ADJUSTMENTS BY SCENARIO

Parameter Adjustment	**Sub-category**		**Scenarios**	
			Medium-High (70%) **Cost ratio: 2030=1.5, 2040=1.2, 2050=1.1**	**High (90%)** **Cost ratio: 2030=1.5, 2040=1.1, 2050=1.1**
Trip rates	Trip rate adjustments informed by the cost ratio are applied to CAV households only. A factor is applied by trip purpose and household characteristics such as income, lifecycle, worker, and household size. These factors are used to boost trip rates. For details, see the model development documentation. (Stantec, 2023)			
Trip length	Manual adjustment that gets applied to all trip purposes (capped at 15%)	Work	11%	14%
		Social/Recreational	15%	15%
Time of day	Different time-of-day factors are applied for CAV autos owned by residents, CAV through trips, and CAV internal/external trips. The adjustment is informed by the cost ratio.			
Highway Capacity	Limited Access	CBD	1.175	1.363
		All other area types	1.21	1.388
	Multilane Hwy	CBD	1.175	1.363
		All other area types	1.21	1.388
	Two-lane Hwy	CBD and Urban	NA	NA
		All other area types	1.256	1.427
	Principal Arterial	All area types	1.256	1.427
	Minor Arterial	All area types	1.264	1.437
	Collector	Rural	1.264	1.437
		All other area types	NA	NA

Model Design Changes

Findings from the literature along with the development of scenarios informed the development of a broad conceptual framework that aligns with the proposed scenarios. This framework was used to guide design changes to the TRMG2 and to inform scenario development and case study analysis for the RTDM. Based on the current design of the RTDM, design modifications were not required. Individual elements of the conceptual framework elements are included in the model design discussion below. The full conceptual framework is provided in **Appendix C**.

Model Design Framework

This section documents both the recommended conceptual design changes for most trip-based models and the specific structural changes made to TRMG2 to capture the presence of CAVs.

Initial Processing

The first step in the TRMG2 model is initial processing. **Figure 2** shows the first step of the recommended conceptual design framework for this step.

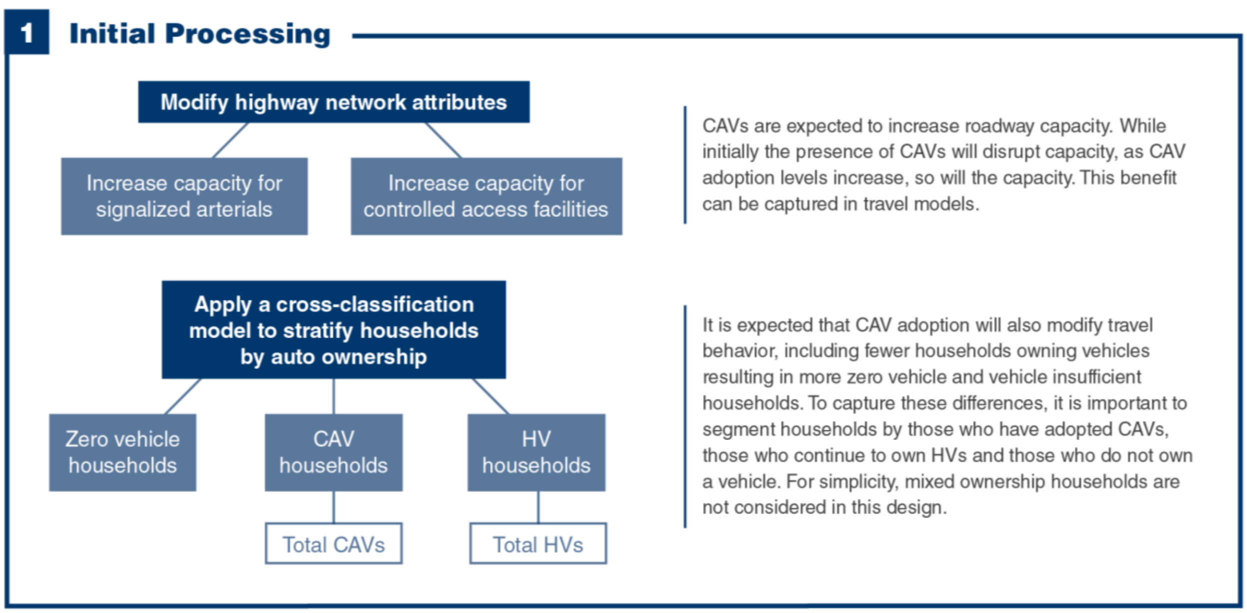

FIGURE 2 INITIAL PROCESSING CONCEPTUAL DESIGN CHANGES

The implementation of this step in TRMG2 required modifications to the auto ownership model to support the forecasting of both CAV households and human vehicle (HV) households. This approach assumed that households would be designated as one or the other and did not allow for mixed ownership households. As such, households designated as CAV households will have only CAV, while HV households will only have HV. Allowing mixed ownership households has been identified as a desirable future enhancement.

The TRMG2 model uses a logit-based auto ownership model that forecasts auto ownership based on household and person level variables such as income, household size, worker status, transit access, and walkability. After the TRMG2 auto ownership model is run, those results are stratified by household members into CAV and HV households using a cross-classification model based on age and income. The cross-classification table by age and income is shown in **Table 4**. The probabilities in the model were developed through an iterative process of selecting a probability for the age and income combinations to achieve the desired target CAV market penetration rate (MPR) for the MH scenario (70%) and H scenario (95%). Age and income were selected as the variables in the cross-classification model based on findings from the literature that suggest these variables will be strong predictors of CAV adoption (Bansal, 2018; Harb, 2022; Lavieri, 2017). The output from this model step is a data file with a record for each household in the region flagged as either a CAV or HV household.

TABLE 4 CAV OWNERSHIP CROSS-CLASSIFICATION TABLE

Max Adult Age Category	Income Category	Probability (MH)	Probability (H)
Age < 18	$0 - $25,000	0.46	0.87
Age < 18	$25,000 - $75,000	0.49	0.88
Age < 18	$75,000 - $150,000	0.52	0.89
Age < 18	$150,000 +	0.55	0.9
Age > 45	$0 - $25,000	0.58	0.91
Age > 45	$25,000 - $75,000	0.61	0.92
Age > 45	$75,000 - $150,000	0.64	0.93
Age > 45	$150,000 +	0.67	0.94
18 <= Age <= 45	$0 - $25,000	0.7	0.95
18 <= Age <= 45	$25,000 - $75,000	0.73	0.96
18 <= Age <= 45	$75,000 - $150,000	0.76	0.97
18 <= Age <= 45	$150,000 +	0.79	0.98

In addition to classifying households as either CAV or HV, the initial processing step also creates the highway network data structure and associated data values required for subsequent model steps. The most important highway network data attribute related to CAVs is the value of the highway capacity. As discussed in the literature review, it is commonly accepted that CAVs are expected to increase highway capacity. While initially the presence of CAVs will disrupt capacity, as CAV adoption levels increase so will the benefits to capacity. As noted previously, this research project assumes a medium-high and high CAV MPR at 70% and 95%, respectively. Based on these assumptions, the capacity lookup table for TRMG2 was modified to increase capacity for signalized arterials and controlled access facilities by the percentages in **Table 5** for the MH and H scenarios. These ranges are more optimistic than those included in the HCM manual but were developed by fellow researchers on this project using rigorous simulation methods as documented in (Hajbabaie, et al., 2024; Bardaka, et al., 2021).

TABLE 5 CAPACITY ADJUSTMENT FACTORS

Facility type	MH (70%)	H (95%)
Signalized arterial	40%	70%
Controlled access facility	47%	77%

Trip Generation

The next step in the process is trip generation where trips for different trip purposes are estimated for each person in the model region. **Figure 3** shows the second step of the recommended conceptual design framework for trip generation.

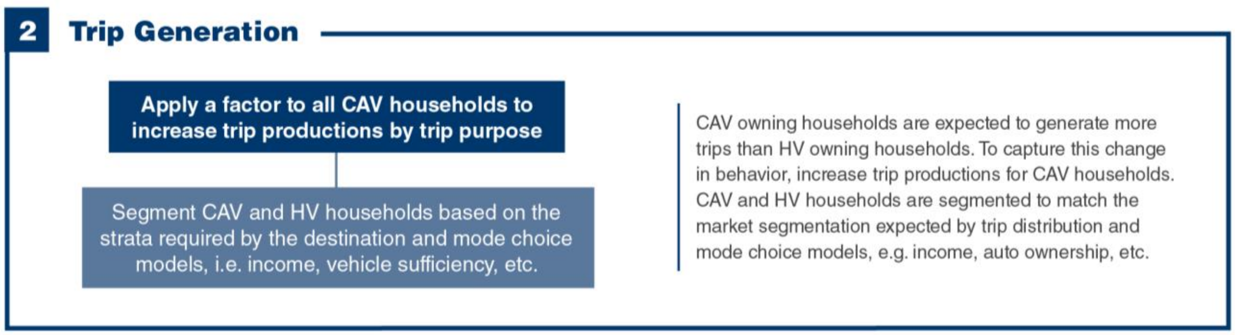

FIGURE 3 TRIP GENERATION CONCEPTUAL DESIGN CHANGES

To account for increases in trip-making by CAV households, modifications were made to the output trip productions for persons living in CAV-owning households. In this manner, the original trip production rates are not modified, but rather adjustments are made to the trip records for CAV-owning households after the model is applied. The rates estimated from the travel behavior survey are applied to individuals in both CAV and HV households. The output from this step is a record of trips by home-based trip purpose for each person and household in the model region. For trips made by CAV-owning households, an adjustment factor is applied to increase the number of home-based trips. This adjustment factor is coded in the model script. The initial modification of the model assumed the same adjustment factor for all trip purposes. The factors were set to both capture the increase in trip-making by CAV-owning households and to account for zero occupant vehicle (ZOV) trips resulting from car sharing among household members. The model design decision to apply a factor after the initial estimation of trip productions, rather than to redesign the structure of the production model and modify trip rates, was made to facilitate a simpler design modification.

Trip Distribution

Trip distribution, also referred to as destination choice, is the process of linking the trips produced by mode for each trip purpose to the destination. This process is heavily informed by the activities at the destination zone, distance to the destination zone, logsums from the mode choice model, and various accessibility measures. Capturing the influence of CAVs on destination choice focuses on the influence of CAVs on the value of time as discussed in the section on mode choice. **Figure 4** shows the third step of the recommended conceptual design framework for trip distribution.

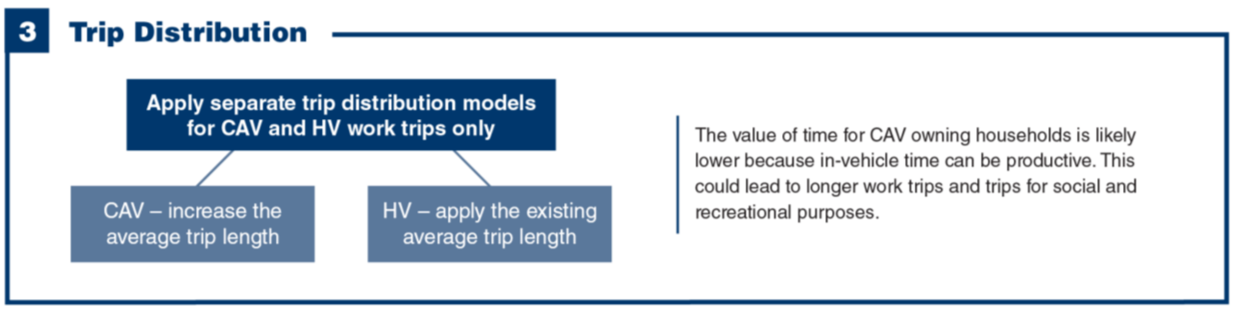

FIGURE 4 TRIP DISTRIBUTION CONCEPTUAL DESIGN CHANGES

The destination choice design changes implemented in TRMG2 required adjusting the coefficient on the congested travel time. No adjustments were made to the coefficient on free flow time as this variable is not used in the destination choice utility equation; it is the congested travel time that influences choice. Adjusting the coefficient on congested travel time has the effect of either shortening or lengthening the average trip length, depending on the direction of the change. Because the coefficient on travel time is very much influenced by the individual region, the literature did not make recommendations for directly adjusting the coefficient but rather suggested that the average trip length would increase for work trips and social/recreational trips (He, 2022). TRMG2 has two work-related trip purposes and three social/recreational trip purposes. The literature was used to inform the increased trip length for work trip purposes for the MH scenario as documented in **Table 6**. Achieving the suggested increase in average travel length as outlined in **Table 6** was an iterative process of adjusting the congested travel time coefficient, running the model, assessing the new trip length, and repeating the process until the desired increase in average travel time was achieved. Once achieved, the same coefficient adjustments are applied in the H scenario, resulting in an even longer trip length given less occurrence of congestion. The final adjustments by trip purpose and market segment are shown in **Table 7**. Regarding the social and recreational trip types, the trip length increases in short-duration discretionary trips drive the remaining two purposes. Unlike the other trip purposes, the short-duration discretionary trips use the logsum value from the mode choice model. The adjustments to the value of time in the mode choice model result in logsum values that capture the longer trip length. These logsum values result in longer trip lengths for the short-duration discretionary trips without the need to directly modify the congested travel time coefficient in the destination choice model. This is why the coefficient adjustment for short-duration discretionary trips in **Table 7** is blank, even though trip length adjustments are reflected in **Table 6**.

TABLE 6 TRIP LENGTH DISTRIBUTION ADJUSTMENT BY TRIP PURPOSE AND SCENARIO

Trip Type	**Trip Purpose**	**MH (70%)**	**H (95%)**
Work Trips	Work tour	11%	25%
	Work tour - interim stop	31%	45%
Social/Recreational Trips	Short-duration discretionary trips	29%	42%
	Long-duration discretionary trips and shop, dine, other trips	29%	42%

[1] Trip length adjustments captured through the mode choice model

TABLE 7 MODEL DESIGN FINAL ADJUSTMENTS TO THE DESTINATION CHOICE UTILITY EQUATIONS

Purpose	Market Segment	Coefficient	Adjustment
Work tour	CAVihvi, CAVihvs, CAVilvi, CAVilvs[2]	-0.0965	*0.79
Work tour – interim stop	CAVvi, CAVvs	-0.193	*0.79
Short duration discretionary trips[1]	--	--	--
Long duration discretionary trips	CAVvi, CAVvs	-0.171	*0.8
Shop, dine and other trips	CAVvi, CAVvs	-0.208	*0.79

[1] Trip length adjustments captured through the mode choice model
[2] ih: income high; il: income low; vs: vehicle sufficient; vi: vehicle insufficient.

Mode Choice

Most trip-based models in the United States execute the trip distribution step before the mode choice step. Intuitively, this sequencing does not best reflect reality because someone's choice of destination is influenced by their choice of mode. For example, a person from a zero-car household is unlikely to select a destination that cannot be accessed by a travel mode other than the automobile. In the TRMG2 model, the mode choice step and destination choice step are nested within each other such that the choice of mode influences the choice of destination. This section covers mode choice, and **Figure 5** shows the recommended conceptual design framework for mode choice, the fourth step in the framework.

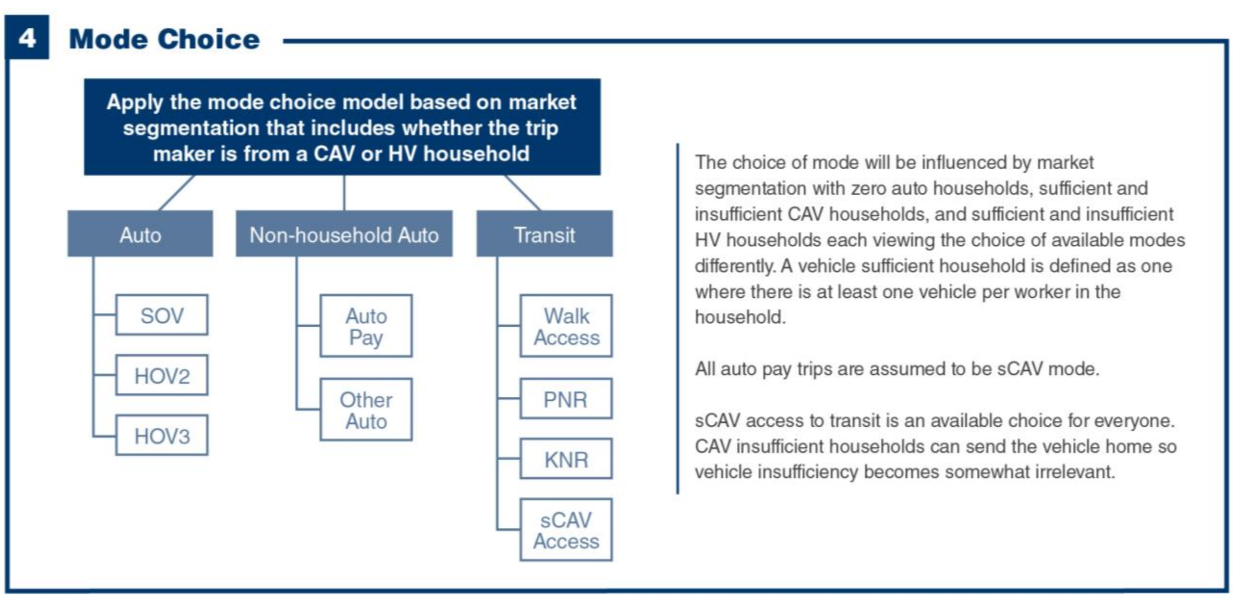

FIGURE 5 MODE CHOICE CONCEPTUAL DESIGN CHANGES

The mode choice model design changes implemented to account for CAVs focus on the mode choice utility equation variables, and the application of a factor for specific variables to account for differences in the utility coefficient for CAV households by different market strata. The household market strata are:

- Vehicle insufficient, high income;
- Vehicle insufficient, low income;
- Vehicle sufficient, high income;
- Vehicle sufficient, low income; and
- Zero vehicle households.

Vehicle insufficiency captures households where the number of adults is greater than the number of vehicles, and high income is defined as income greater than or equal to $70,000. **Table 2** provides a summary of modified coefficients by mode and trip purpose. These adjustments were informed by the literature. The auto modes include single occupant vehicles (SOV), high occupant vehicles with 2 persons (HOV2), high-occupant vehicles with 3 or more persons (HOV3), and auto pay (e.g. Uber or Lyft). Transit modes include local bus, express bus, bus rapid transit, light rail transit, and commuter rail. Transit access includes walking to transit and driving to transit, with the drive access being further stratified as park and ride, kiss and ride, and shared CAV (sCAV) access.

Coefficient adjustments include adjustments to capture changes in the value of time, auto-pay fare, and access mode. The adjustment to the value of time coefficient is not intended to imply that CAVs will change someone's value of time, but rather is intended to approximate the in-vehicle time productivity experienced by someone who has access to a CAV. This increased productivity may influence the likelihood of choosing an auto mode and may induce some people to live further away from their jobs. The reduction in the fare for auto pay modes is intended to capture an increase in usage and ease of use for subscription services as the auto pay mode becomes dominated by CAVs and the direct out-of-pocket cost goes down. For transit access, a new drive access mode for work trips was added to the model structure to cover access to transit by CAV.

For all modes, the coefficients on congested travel time are reduced by 60% in the MH scenario and 65% in the H scenario. This applies to all modes in the auto nest and sCAV access in the transit nest. For the auto modes, this is applied to all purposes except K12. For transit, the sCAV adjustment only exists in the work trip.

Time of Day

Figure 6 shows the recommended conceptual design framework for modifying the time-of-day factors for external trips, which is defined as trips that pass through the region, trips that start in the region but have a destination outside the region, or trips that start outside the region but have a destination inside the region. This is step six in the framework.

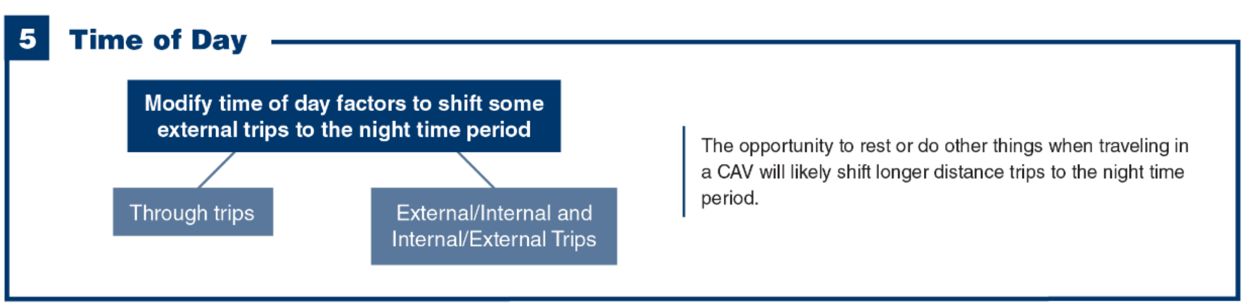

FIGURE 6 TIME OF DAY CONCEPTUAL DESIGN CHANGES

The design modification for implementing time-of-day changes for external trips was straightforward given the design of the external trip model. Time of day factors, estimated from travel surveys, are applied to the “through trip,” external/internal, and internal/external trip tables. These factors were modified to shift more trips to the night period, thereby reducing the number of external trips during the AM, midday, and PM time periods. **Table 8** summarizes the percent change applied to the existing nighttime factors by trip type and vehicle type.

TABLE 8 TIME OF DAY FACTOR ADJUSTMENTS TO THE NIGHT PERIOD

Trip Type	Vehicle Type	MH (70%)	H (95%)
Through trips	Autos	15%	25%
	Single-unit trucks		
	Multi-unit trucks	30%	50%
External/Internal and Internal/External	All	2%	8%

Zero Occupancy Vehicle (ZOV) Trips

One of the potential negative impacts of increased CAV adoption is the number of new trips that will be generated by zero occupant vehicles (ZOV). **Figure 7** provides a conceptual framework for addressing ZOVs in a travel demand model. The concept focuses on ZOV trips that will occur because of car sharing among household members, trips that will occur as a result of parking avoidance, and empty trips that result from shared sCAVs traveling between passenger drop off and pick up.

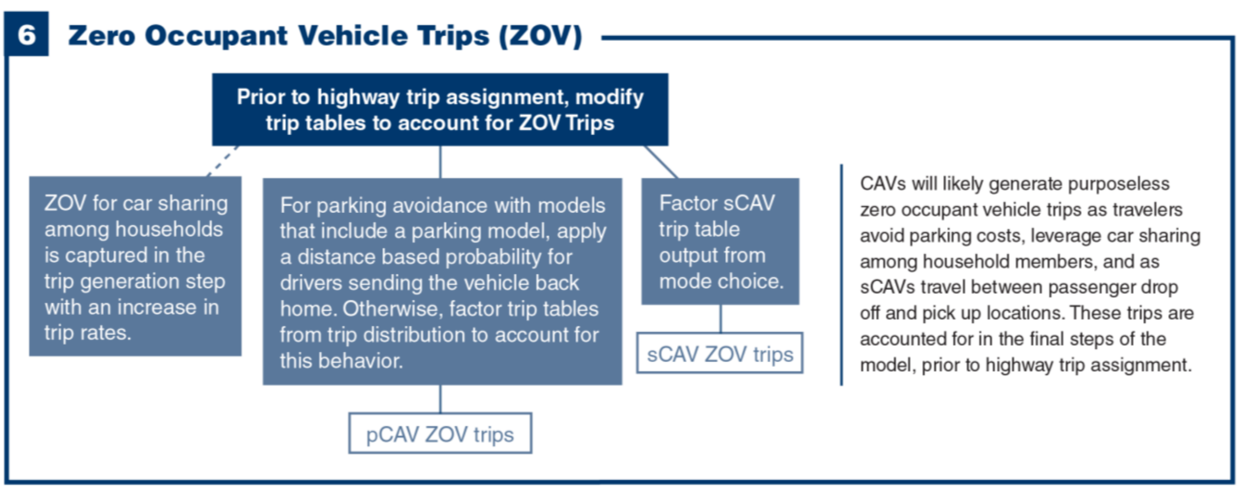

FIGURE 7 ZERO OCCUPANT VEHICLE TRIPS CONCEPTUAL DESIGN CHANGES

The TRMG2 design changes to account for ZOV trips related to CAV sharing among household members are accounted for in the design changes for the trip generation model. Design changes to account for ZOV trips resulting from parking avoidance were accounted for in the parking model. The TRMG2 model identifies specific zones in the region where parking is restricted either by supply or by cost. The ZOV calculation focused on all home-based trips using these parking zones. The trips going to these zones were stratified by the distance traveled from home to the parking location. Any trips traveling less than 20 miles from the home location to the parking location are candidates for avoiding parking and sending the CAV back to the home location. For these trips, a reverse trip back home was added, as was an additional trip from home back to the destination to pick the traveler up. Market segmentation, i.e. the ability to identify specific CAV travelers, is no longer preserved. To account for the fact that some of the trips going to the parking zones would be HV trips, a lower probability was applied to the total number of trips.

To account for sCAV empty miles, a growth factor was applied to the sCAV trip table output from the mode and destination choice step. This has the effect of growing the background traffic associated with sCAVs.

NHB

The handling of non-home-based trips in traditional trip-based models poses many problems stemming from the fact that the trips are disconnected from the original home-based trip. The TRMG2 model includes an advanced approach for handling these trips with a simple design change to the structure of the model, where the NHB trip model is run after, and conditional upon, the home-based model components instead of in parallel and independently of them in the traditional four-step model. Because of this unique design, no additional design changes are required for TRMG2 to account for CAV trips. The increase in NHB trips by CAV owners will happen as a function of the increased home-based trips by CAV owners.

Figure 8 shows the advanced design for NHB trips in the TRMG2 model. While identified as step seven in the framework, for traditional four-step models, the increase in NHB trips by CAV owners will be handled in design modifications for the trip production model.

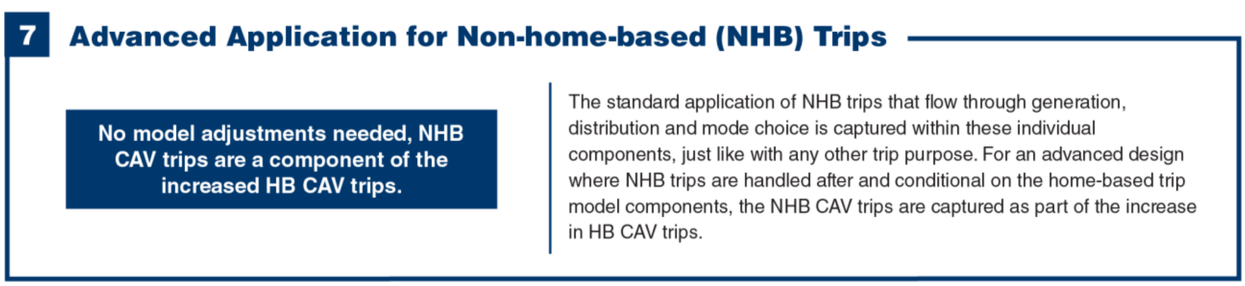

FIGURE 8 ADVANCED DESIGN CHANGES TO CAPTURE NHB TRIPS

Special Market - Airport

Travel to and from regional airports represents an important travel market that requires special attention in travel demand models. If the existing design of the travel model includes an airport sub-model to capture these unique travel patterns, then that design should be modified to account for CAV owners who travel to the airport but choose to send their vehicles back home to avoid parking costs. Most special market airport models do not include detailed level market segmentation in the airport sub-model. As such, the adjustment for CAVs is applied to all airport travelers assumed to have CAVs. For the MH scenario, the factor was applied to 70% of the airport trips, and for the H scenario to 95% of the airport trips. For each scenario, the appropriate proportion of the trip table is factored to generate an additional trip going back to the trip origin.

NCDOT RTDM Framework

The recently released NCDOT RTDM includes a CAV component, and no model design changes were required. Details on the design of the CAV model are found in the model development documentation (Stantec, 2023). The design of this model includes key elements captured in the literature. The Tier 3 case study analysis evaluates this model using the set of performance measures and evaluation criteria and presents findings and recommendations specific to this model design.

Case Study Evaluation and Findings

To support this research, the research team conducted case study evaluations using two different travel demand models, the Triangle Regional Model Generation 2 (TRMG2) and the NCDOT Regional Travel Demand Model (RTDM) for the Albemarle Rural Planning Organization. The case studies for each model are informed by the scenarios documented in the Scenario Development section.

For the *Existing Model Design* and *NCDOT RTDM* applications, only the input parameters were modified prior to running the model. In the *Model Design Change* application, the model was redesigned and input parameters were modified prior to running the model.

For each application, system-level performance measures were captured and reported. After confirming that the model was performing in a logical and expected way, project-level performance measures were captured and a project-level evaluation was conducted. These results are presented and summarized in the following sections. In addition to evaluating each case study for a medium-high and high CAV adoption level, the sensitivity of asserted parameters was evaluated independently and in combination with the other variables for the TRMG2 model.

System-level performance measures include:

- Average trip length by trip purpose,
- Vehicle miles traveled,
- Congested vehicle miles traveled, and
- Delay.

Project-level performance measures include:

- Demand,
- Capacity,
- Demand-to-capacity ratio,
- Daily delay, and
- Daily delay per mile.

The calculation of delay considers the difference between the free flow link travel time and congested link travel time multiplied by the demand on the link. While it is reasonable to assume that the presence of CAVs in the travel stream may impact the free flow travel time in addition to the congested travel time, a simplifying assumption in this analysis is that the free flow time is based on the posted speed limit and facility type and does not change between the CAV and no CAV scenarios.

A sensitivity analysis was conducted for the Tier 1 and Tier 2 case studies. This effort helped inform the development of a cone of uncertainty around model outputs informed by the CAV adoption level and the influence on model coefficients.

Triangle Region

Model Overview

ITRE and Caliper recently completed development on a new generation model for the Triangle region that reflects a best practice approach to both travel modeling and code development, with many advanced components designed to best capture travel behavior choices and an agile code base that makes model adjustments more streamlined and intuitive. This model was selected as the platform for evaluating various parameter changes designed to capture supply and demand uncertainty related to CAV deployment. Additionally, the Triangle region has a highly educated and affluent population and an economy that is largely driven by technology industries. Given these factors, it is likely that the Triangle region will be an early adopter of CAV technologies.

Selection of Projects

The research team coordinated with NCDOT to identify several project locations across the Triangle region to be used for evaluation purposes.

These selected projects were identified using NCDOT's online Traffic Forecasting Data Maps. These maps display NCDOT projects geographically and provide additional information on the progress of the project within the traffic forecast portion of the project development phase. The selected projects were cross-checked in the latest State Transportation Improvement Program (STIP) and the Metropolitan Transportation Plan (MTP), also available online. Finally, the shortlisted projects were submitted to the NCDOT project champion for review and approval. Regional significance, travel demand, and whether the project is programmed within the STIP and MTP were all considered in project selection. The case study projects for the Triangle region are listed in **Table 9** and mapped in **Figure 9**. The table also lists the county where the project is located and the average hourly wage rate for the county. This information is used in later analysis to calculate the cost of delay.

TABLE 9 CASE PROJECTS IN THE TRIANGLE REGION

P#	Facility Type	STIP Number	Project Type	Roadway Name	Project Extent	County	Hourly Wage Rate
1	Interstate	I-3306	Widening (from 4 to 6 lanes)	I-40	I-85 to US 15-501	Orange	$43.62
2	Interstate	R-2829	New Location	I-540	I-40 to I-87/ US 64 /US 264	Wake	$35.99
3	Freeway	U-6066	Widening (from 2 to 3 lanes)	US 1	US 64 to NC 55	Wake	
4	Freeway	U-5307A	Widening (upgrade to freeway)	US 1	I-540 to Thornton Rd	Wake	
5	Arterial	U-5891	Widening (upgrade to divided highway)	NC 50	I-540 to NC 98	Wake	
6	Arterial	R-3410B	Widening (from 2 to 4 lanes)	NC 42	Son-Lan Parkway/Cleveland Crossings Drive to US 70 Bus	Johnson	
7	Rural Roadway	R-5930 / R-5963	New Location	Chatham Parkway	US 15-501 N to US 15-501 S	Chatham	$23.28

https://www.commerce.nc.gov/north-carolina-county-average-wages

NOTE: While STIP projects were used to support case study analysis, the actual project extent, details, and results do NOT reflect actual projects. These projects were selected as guidance only and the traffic forecast data comes directly from the travel model. It has not been post-processed and analyzed, as is best practice for actual traffic forecasts.

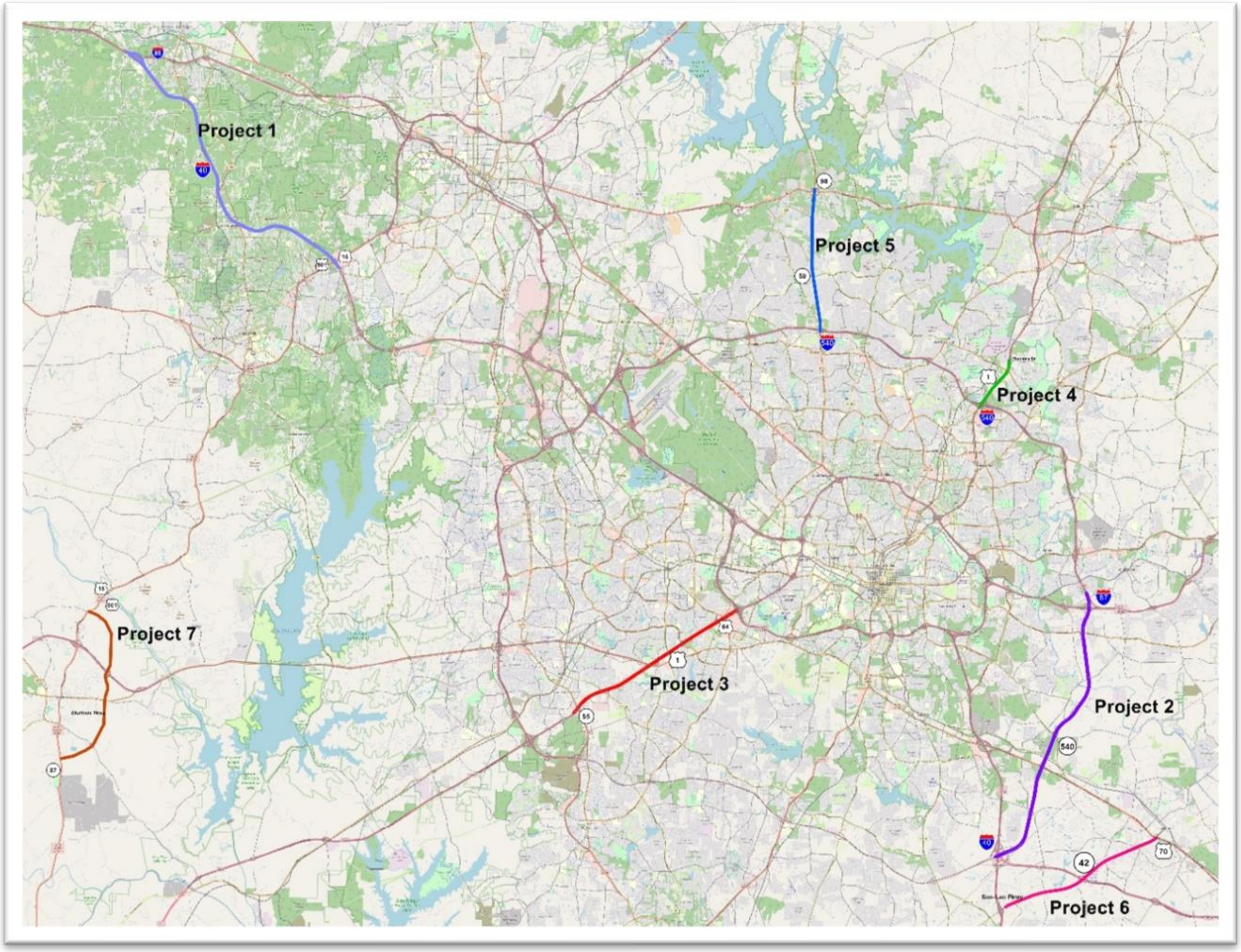

FIGURE 9 LOCATION OF PROJECTS IN THE TRIANGLE REGION

Existing Model Design Approach (Tier 1)

Overview

For the existing model design approach, model parameters were adjusted as documented in the Scenario Development section.

Approach

For each application, system-level performance measures were captured and reported. These results were reviewed for reasonableness. Project-level performance measures were also captured, and a project-level evaluation was conducted. These results are detailed and summarized in the following sections. In addition to evaluating each case study for medium-high and high levels of CAV adoption, the contribution of asserted parameters was evaluated independently and in combination with one another. The results of this sensitivity analysis help to identify the most uncertain parameter which requires further analysis. Identifying this parameter is crucial, as it highlights the areas where the model is most sensitive and where additional study is required to ensure robustness and reliability.

For further analysis on the identified parameter, a new sensitivity analysis was conducted to make sure that model outputs exist for all possible outcomes within the uncertainty cone of the model. This comprehensive approach ensures that the model is extensively tested across a broad range of possible scenarios, thereby validating its predictive capability and ensuring its resilience to variations in key parameters. Through this iterative process, we can refine our understanding, improve the accuracy of the model's forecasts, and ultimately support more informed decision-making.

Summary of Results

This section provides a high-level overview of the findings from the Tier 1 case study. A more detailed and comprehensive analysis is provided in **Appendix D**.

At the systems level, the introduction of CAVs results in notable changes across key performance measures. There was a modest increase in the average trip length, accompanied by an overall rise in daily VMT. However, this increase in VMT was balanced by a significant reduction in congested VMT, indicating that while vehicles traveled more, the presence of CAVs helped alleviate the congestion. Furthermore, delay showed substantial improvements. Specifically, delays on freeways were reduced by 60% under the medium-high (MH) CAV adoption scenario and by 74% under the high (H) CAV adoption scenario. These improvements highlight the potential of CAVs to enhance traffic flow and reduce the burden of congestion. However, not all facility types experienced the same level of benefit. For example, major collectors showed only marginal reductions in delay, suggesting that the positive effects of CAVs may vary based on roadway characteristics.

At the project level, performance measures were computed for each individual project analyzed earlier in the "Triangle Region" section. These results indicate that demand generally increases across all projects under the MH and H scenarios. Despite this increased demand, the demand-to-capacity (D/C) ratios decreased, suggesting that CAVs improved the efficiency of roadway capacity utilization.

The case study projects were further evaluated under a build condition with and without CAVs, and a no-build condition with CAVs considering medium-high CAV adoption level. The focus of this analysis was on trying to determine whether the presence of CAVs changes both the supply and demand side of transportation enough to reconsider whether the project should be built, built differently, or delayed due to the changes brought about by CAV adoption. Despite the advantages brought by CAVs, the analysis revealed that the improvements under the medium-high CAV adoption scenario were not sufficient to eliminate the need for all of the planned projects. In other words, while CAVs contribute to better system performance, they do not fully replace the necessity for infrastructure investments, at least under the medium-high adoption scenarios. Accordingly, although CAVs offer measurable benefits, they should complement rather than replace traditional infrastructure improvements to achieve optimal system performance.

Sensitivity Analysis

The Tier 1 (existing model design) approach included two types of sensitivity testing. The first focused on the interaction of the different variables that were adjusted during the Tier 1 approach (variables are presented in **Table 1**). The results of the variable interaction showed that the capacity variable emerged as the pivotal factor driving the results of the analysis. Capacity increases due to CAVs resulted in at least 84% reduction in congested VMT during the peak hour and 43% reduction in daily delay of mobility-oriented facilities. Therefore, capacity deserves further sensitivity analysis due to its foundational position at the base of the uncertainty cone in the scenario evaluations.

This effort informed the second sensitivity test that focused on evaluating different values for the capacity variable. So far, we examined the effect of increases in capacity variables by two scenario types of medium-high and high levels of CAV adoption. Therefore, we are interested to see how the performance measures will change if the increases in capacity variables are not high as expected. **Figure 10** shows the range of uncertainty in variable values as measured by changes in daily delay, peak period VMT, and peak period congested VMT for the two scenarios, reducing medium-high CAV adoption capacity by 25% (C1) and 50% (C2). **Figure 10** indicates a higher level of uncertainty in the C2 scenario, where the change in daily delay reaches more than 40% compared to C1, which demonstrates a more moderate capacity increase. This analysis highlights how lower CAV capacity scenarios significantly impact the level of uncertainty in system performance in terms of daily delays. Again, the findings emphasize the critical role of capacity values in influencing the reliability of system-level outcomes.

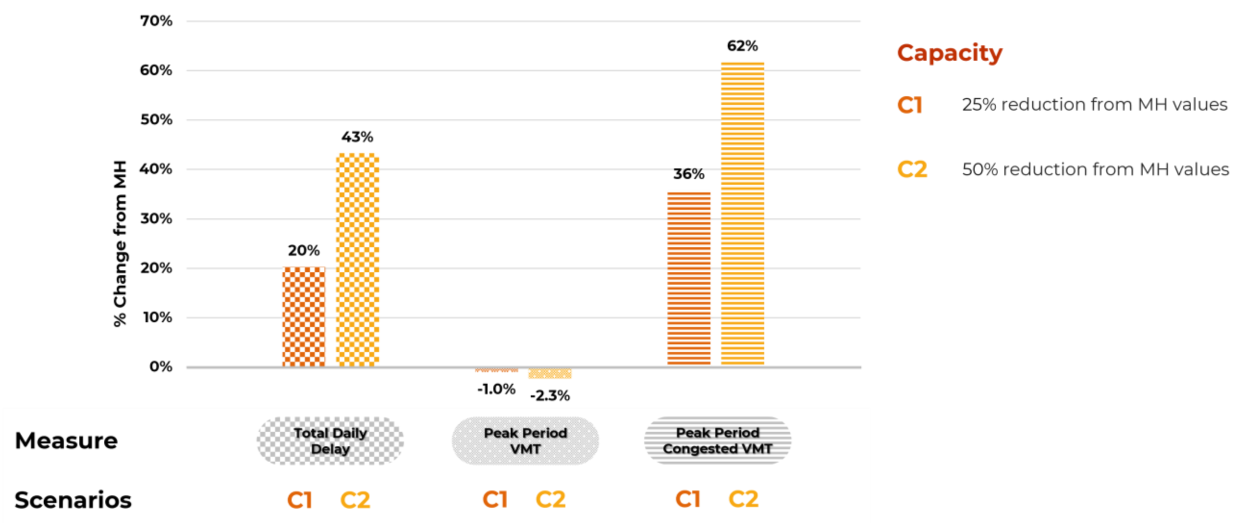

FIGURE 10 RANGE OF UNCERTAINTY AS MEASURED BY DAILY DELAY (MIN), PEAK PERIOD VMT, AND PEAK PERIOD CONGESTED VMT

According to **Figure 10**, moving from the MH scenario to C1 and then C2 results in a small reduction in peak period VMT values. These changes are less than 3% in the most critical scenario (C2) which means that VMT is not sensitive to changes in capacity values. Similar to the delay, congested VMT experiences a high risk when capacity values drop to level 1.

Figure 11 presents the comparison of peak hour D/C ratios for Project 1 under various scenarios projected for the year 2050. These scenarios include a build project without CAVs, a build project with MH CAV adoption, a no-build project with MH CAV adoption, and a build project with different levels of CAV capacity benefits, specifically C1 and C2.

In the 2050 baseline scenario without any CAV implementation, the D/C ratio is recorded at 0.69. With the introduction of CAVs under the MH adoption level, the D/C ratio improves to 0.56. In a scenario with CAVs only, the D/C ratio goes up to 0.72 which is higher than the build scenario without CAVs but is still in good condition. This implies that according to the Tier 1 method, this project can be deferred. When considering more cautious capacity adjustments with CAVs as seen in C2, the D/C ratio slightly increases to 0.60, while a less cautious adjustment in C1 shows a D/C ratio of 0.56. Intuitively, the capacity benefits for CAVs can be enough to defer this project based on CAV benefits alone, considering even the most cautious capacity benefit in the C2 scenario.

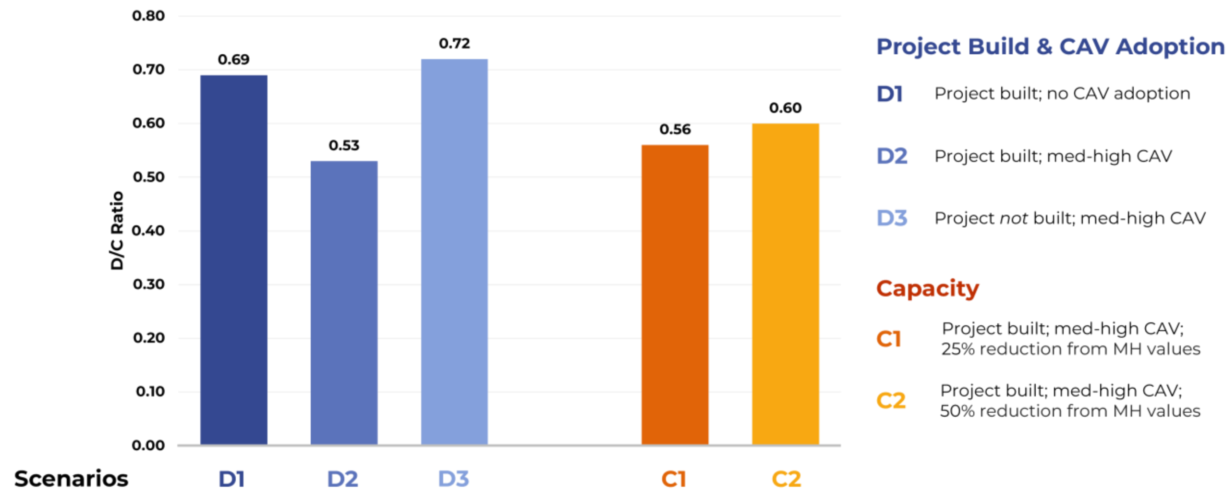

FIGURE 11 COMPARISON OF PEAK HOUR D/C RATIO FOR PROJECT 1 BY SCENARIO

Tier 1 Summary and Findings

The results of this analysis show that a strategic modification of parameters, informed by literature, in an existing model design is an effective and efficient approach for considering the potential impact of CAVs on project-level traffic forecast. Given the fact that no model design changes are required, this approach could be quickly deployed for most, if not all, traffic forecasts to improve the level of risk and uncertainty in the forecast traffic which can lead to better-informed decision-making. The results are shown to be effective as the model responds in the expected direction and the performance measures track with expectations documented in the literature. Model performance measures also trend in the same direction as the measures from the more advanced Tier 2 analysis described in the next section.

Model Design Changes (Tier 2)

Overview

For the Tier 2 analysis, model parameter adjustments were made as outlined in the Scenario Development section.

Approach

For each application, system-level performance measures were captured and reported, and system-wide performance measures were reviewed. Project-level performance measures were then captured, and a project-level evaluation was conducted. These results are captured and summarized in the following sections. In addition to evaluating each case study for a medium-high and high CAV adoption level, the contribution of asserted parameters was evaluated independently and in combination with each other.

Summary Results

This section provides a high-level summary of the Tier 2 case study. Detailed analysis is provided in **Appendix E**.

In the Tier 2 analysis, CAVs also lead to increased average trip lengths. Total VMT increases for both the MH and H scenarios, but the congested VMT is reduced by 34% under the MH scenario and 48% under the H scenario. Delay is also reduced in both the MH and H scenarios with the biggest reduction in delay for the mobility-focused facilities.

The Tier 2 project-level analysis included the same projects evaluated for the Tier 1 analysis. Project-level demand increases for all projects, but the D/C ratio decreases reflecting the capacity benefits of the CAV scenarios.

The build and no-build analysis showed improvements in D/C and daily delay for all projects under the build MH CAV scenario, leading to delay cost savings for the project with CAVs as compared to the project with no CAVs. For the no-build MH CAV scenario, both the D/C and daily delay increased, leading to increased costs. These results suggest CAV benefits, but not enough to negate the need for the project under the MH CAV adoption rate scenario.

Risk and Uncertainty

The emergence of CAVs presents a transformative potential for transportation systems, but their exact impact remains uncertain as they are not yet widely deployed. In this study, we have made various assumptions to forecast the future with CAVs. To evaluate the risk and uncertainty associated with the modified variables, a sensitivity analysis was conducted to better capture the contribution of the original asserted values for key variables in the model, including capacity, trip rates, and land use. The MH scenario was selected for the sensitivity analysis as it is more likely than the H scenario for CAV adoption in 2050. This analysis focused on both system and project-level outputs.

Six scenarios were evaluated–two cases for each key variable. The scenarios evaluated are described below. For each, the baseline is the MH CAV adoption scenario reflecting the originally asserted values based on the literature.

Capacity

- Baseline Scenario: optimistic benefits in capacity improvements (40-47% increase, depending on the facility type)
- C1: moderate benefits in capacity improvements (25% less capacity from baseline)
- C2: cautious benefits in capacity improvements (50% less capacity from baseline)

Land Use

- Baseline Scenario: 2050 land use forecasts from the 2050 Metropolitan Transportation Plan
- A1: Increased downtown and urban core density while maintaining regional control totals
- A2: Increased development in suburban and rural areas while maintaining regional control totals

Trip Rates

- Baseline Scenario: trips for all trip purposes increased by 9%
- B1: 33% more recreational trips, 55% fewer work trips from baseline (yields 9% increase in total trips)
- B2: 55% more recreational trips, 89% fewer work trips from MH values (yields 9% increase in total trips)

Figures 12 – 14 show the range of uncertainty in delay, VMT, and congested VMT at the systems-level for the different variable values. The effect on system-level delay to changes in land use patterns and trip making is very small, suggesting lower levels of risk in the asserted values of these variables. On the other hand, the capacity variable shows a higher degree of risk with a 40% higher measure of systems delay for the cautious capacity values. In other words, delay increases as the capacity improvements do not offset increases in demand.

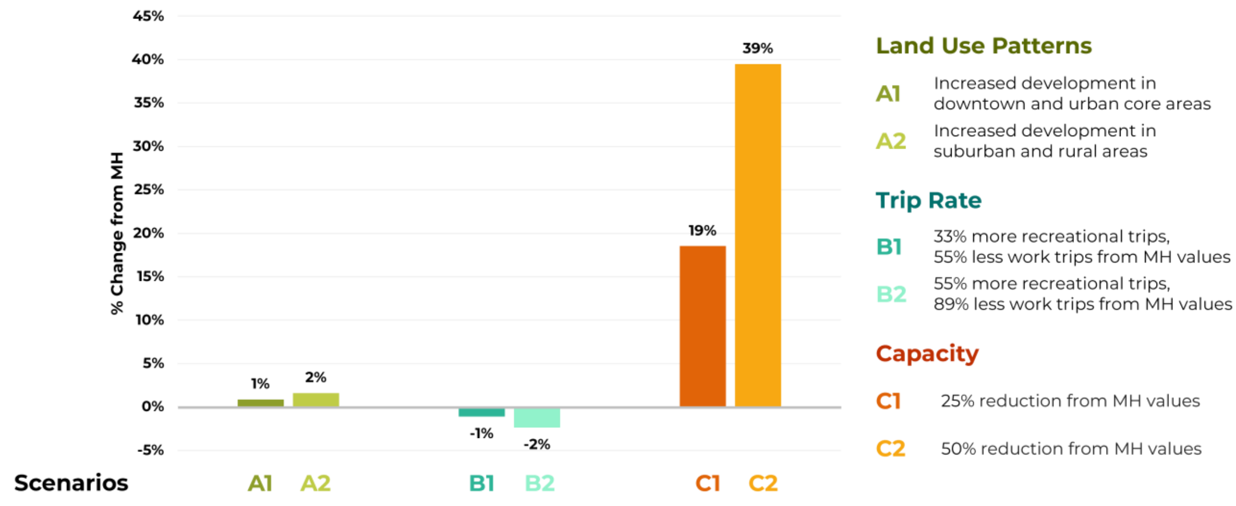

FIGURE 12 RANGE OF UNCERTAINTY AS MEASURED BY DELAY

The effect on system-level peak period VMT to changes in all variables is very small, suggesting lower levels of risk in the asserted values of these variables through the lens of systems-level VMT.

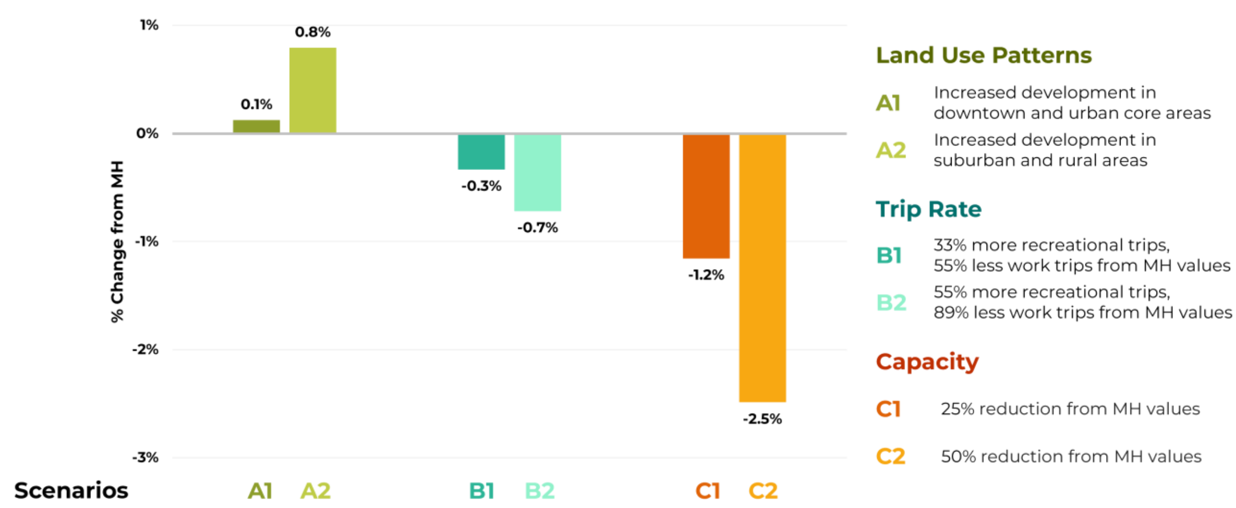

FIGURE 13 RANGE OF UNCERTAINTY AS MEASURED BY PEAK PERIOD VMT

The effect on system-level peak period congested VMT shows a similar pattern as the daily delay measure with changes in land use patterns and trip making having a very small impact on congested VMT indicating a low risk for these variables. The degree of risk for the capacity variable is much higher, especially for the capacity adjustment reflecting more cautious benefits.

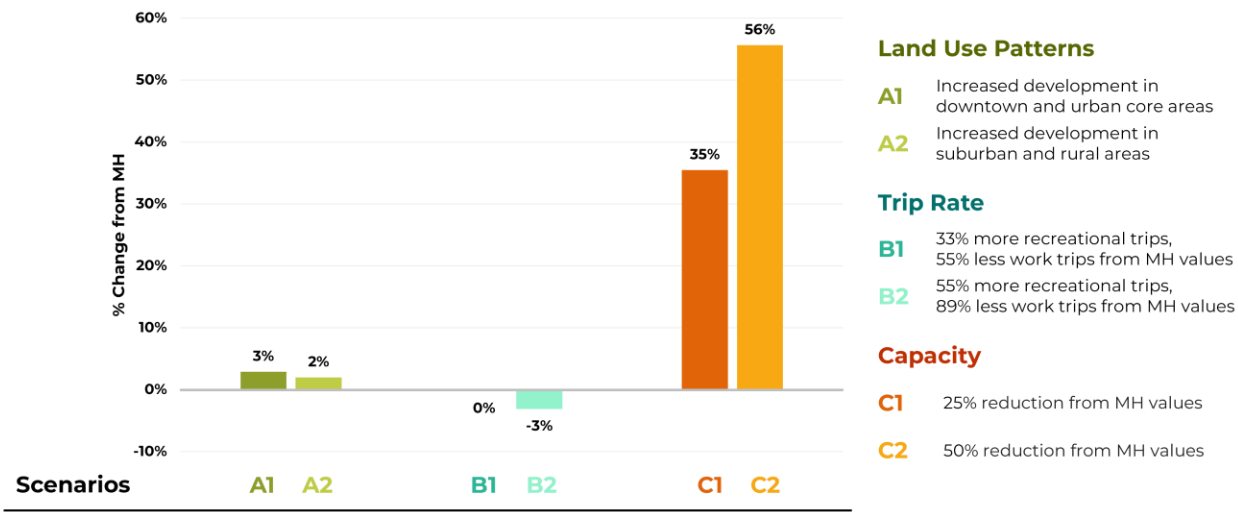

FIGURE 14 RANGE OF UNCERTAINTY AS MEASURED BY CONGESTED VMT

Systems-level performance measures are useful for understanding overall patterns, but the project-level analysis is needed to help answer the question of whether project improvements are still necessary with the presence of CAVs, or whether these project investments can be deferred to a later time frame allowing for a redistribution of project funds. Given that changes in land use and trip rates were identified as having low risk in the systems-level analysis, the project-level analysis focuses on how more cautious changes in capacity benefits might affect project-level decision-making. Project 1 is used as the case study example documented in the main body of the report. Details on additional projects are provided in **Appendix E**.

In **Figure 15** below, we see that in 2050 the D/C ratio with the project is 0.69 during the PM peak hour using a level-of-service (LOS) D capacity. With CAVs in the travel stream at the MH adoption level, the D/C improves to 0.56 reflecting the added capacity benefits of CAVs. An important question then becomes whether the capacity benefits from CAVs are high enough to suggest that the project can be deferred to a future date. In this case, the capacity benefits of the MH scenario without the project yield a PM peak hour D/C ratio of 0.82 which may suggest that the project could be deferred, and the money invested in another project that has greater needs. A D/C ratio of 0.82 during peak conditions suggests that the facility is operating below capacity during heavy demand, even with no investment in infrastructure.

Given the potential negative impacts of deferring important transportation investments to a later time frame, understanding the level of uncertainty around that decision is key. We know from the earlier analysis that there is a high degree of risk if the capacity benefits from CAVs are in the cautious to moderate range. In the Project 1 example, **Figure 15** shows a 0.08 higher D/C ratio than the MH CAV scenario for the cautious scenario. This result suggests that the capacity benefits for CAVs may not be enough to defer this project based on CAV benefits alone. **In application, this strongly supports risk and uncertainty analysis on the asserted capacity values for any traffic forecast that includes CAVs as a part of the forecast scenario**. While risk and uncertainty analysis is not conducted on traffic forecasts as a matter of practice, this would be good practice for NCDOT to adopt.

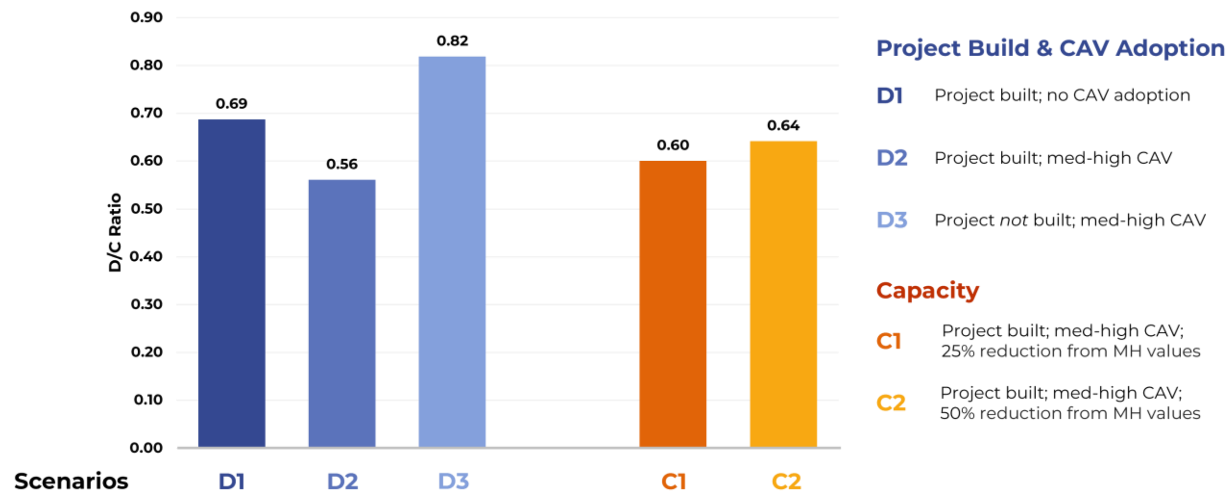

Figure 15 Comparison of Peak Hour D/C Ratio for Project 1 by Scenario

Model Design Summary and Findings

The results of this analysis support model design changes that can improve the utility of travel forecasting for considering a future that includes CAVs. The consideration of CAVs in travel models and the associated traffic forecast at different levels of CAV adoption can help NCDOT understand the level of risk and uncertainty in the traffic forecast which can lead to better-informed decision-making.

Comparative Analysis between Tier 1 and Tier 2

The Existing Model Design (Tier 1) and Model Design Changes (Tier 2) both used the Triangle Regional Model for implementation and analysis. This provides an opportunity to compare the two methods. The Tier 1 method focused on the modification of parameters within the existing model design and an approach that was quickly and easily implemented. The redesign of the model (Tier 2) was more time- and resource-intensive and required a certain level of model development expertise. In many ways, the implementation of a Tier 1 approach could lead to the development and evaluation of traffic forecasts that consider CAVs sooner than what a model redesign might require. This section evaluates the difference between key outputs between the two approaches. Comparison Tables are provided in **Appendix G**.

Tier 2 (Model Design Changes), on the other hand, was a more involved process requiring significant model redesign and testing. This resulted in a more realistic representation of travel behaviors, particularly with respect to travel time, trip lengths, and congestion factors. The model incorporated additional demand elements like empty CAV parking trips and sCAV trips, which significantly impacted the network performance. These adjustments led to higher VMT and increased congestion and delay, as the model was better able to simulate the real-world complexities introduced by automated vehicle technologies. Ultimately, the differences in the results between the two tiers stem from the contrasting methodologies; see **Table 10**. While Tier 1 allowed for faster evaluations with fewer resource demands, Tier 2 provided a more nuanced and precise understanding of traffic and demand dynamics due to the more robust behavioral design changes and inclusion of additional factors. The key driver of the differences in outputs is the increased demand captured in Tier 2, which translates into higher VMT, longer trip lengths, and increased delays, offering a more comprehensive picture of potential traffic scenarios. This difference does not suggest that the Tier 1 analysis has limited usefulness, but rather that a more detailed approach offers more behavioral realism. When time and resources allow, the Tier 2 approach is preferred, but the Tier 1 approach is much better than nothing.

TABLE 10 TOTAL DAILY VMT, CONGESTED VMT, AND DAILY DELAY BY TIER

Performance Measure	Tier 1	Tier 2	% Diff
Daily VMT (veh.mi)	98,622,106	103,506,007	4.9%
Cong. VMT (veh.mi)	2,796,820	4,499,830	60.9%
Daily Delay (min)	137,650	170,702	24.0%

At a project level, the results presented in **Table 11** suggest that the Tier 1 and Tier 2 approaches are comparable, especially when considering the D/C ratios across projects and segments. While there are minor differences in D/C ratios between Tier 1 and Tier 2 these variations are not significant, as most differences remain small across all projects, including the three segments of P7. This indicates that Tier 1 can provide reasonable estimates of network performance without requiring the additional time and resources needed for the more complex Tier 2 approach. For scenarios where quick and efficient evaluations are prioritized, Tier 1 proves to be a practical and effective option while still delivering results close to those of Tier 2.

TABLE 11 PROJECT LEVEL PEAK HOUR DEMAND AND DEMAND-TO-CAPACITY RATIO (D/C) BY TIER

Project	Peak Hour Demand (veh/h)			D/C		
	Tier 1	Tier 2	% Diff	Tier 1	Tier 2	% Diff
P1	9,519	10,165	6.36%	0.53	0.56	5.36%
P2	2,636	2,844	7.31%	0.14	0.15	6.67%
P3	14,845	15,333	3.18%	0.82	0.85	3.53%
P4	13,105	13,786	4.94%	0.68	0.71	4.23%
P5	3,710	4,199	11.65%	0.48	0.55	12.73%
P6	2,683	2,675	-0.30%	0.37	0.37	0.00%
P7	1,085	1,078	-0.65%	0.29	0.29	0.00%
	449	460	2.39%	0.06	0.06	0.00%
	1,227	1,225	-0.16%	0.33	0.33	0.00%

NCDOT RTDM (Tier 3)

Model Overview

Given that North Carolina is still largely a rural state, and the fact that CAV deployment will likely be different for these regions of the state, a second case study focusing on a more rural part of the state was conducted. NCDOT develops and maintains all travel demand models outside of the three regional models and has developed guidelines for the newly created Regional Travel Demand Models (RTDMs) that will, region by region, eventually provide model coverage for the entire state. The new RTDM platform has a built-in process for considering CAVs. The first model developed using the RTDM is the Region 17 RTDM covering the Albemarle Rural Planning Organization (RPO) in the far northeast of the state. The model provides a framework for using scenario planning to evaluate the existing CAV guidance.

Selection of Projects

The same approach for project selection applied in the Triangle was followed for the Albemarle RPO region. The case study projects for the Albemarle RPO region are listed in **Table 12** and displayed in **Figure 16**.

TABLE 12 PROJECTS IN THE ALBEMARLE REGION

P#	Facility Type	TIP Number	Project Type	Roadway Name	Project Extent	STIP #
1	Arterial	R-2574	Widening	US 158 (Shortcut Rd)	NC 34 to NC 168 / US 158 (Caratoke Highway)	R-2574
2	Arterial	NA	Widening	US 17	US 17/US 158 North of Elizabeth City to Virginia State line	

NOTE: While STIP projects were used to support case study analysis, the actual project extent, details, and results do <u>NOT</u> reflect actual projects. These projects were selected as guidance only and the traffic forecast data comes directly from the travel model. It has not been post-processed and analyzed, as is best practice for actual traffic forecasts.

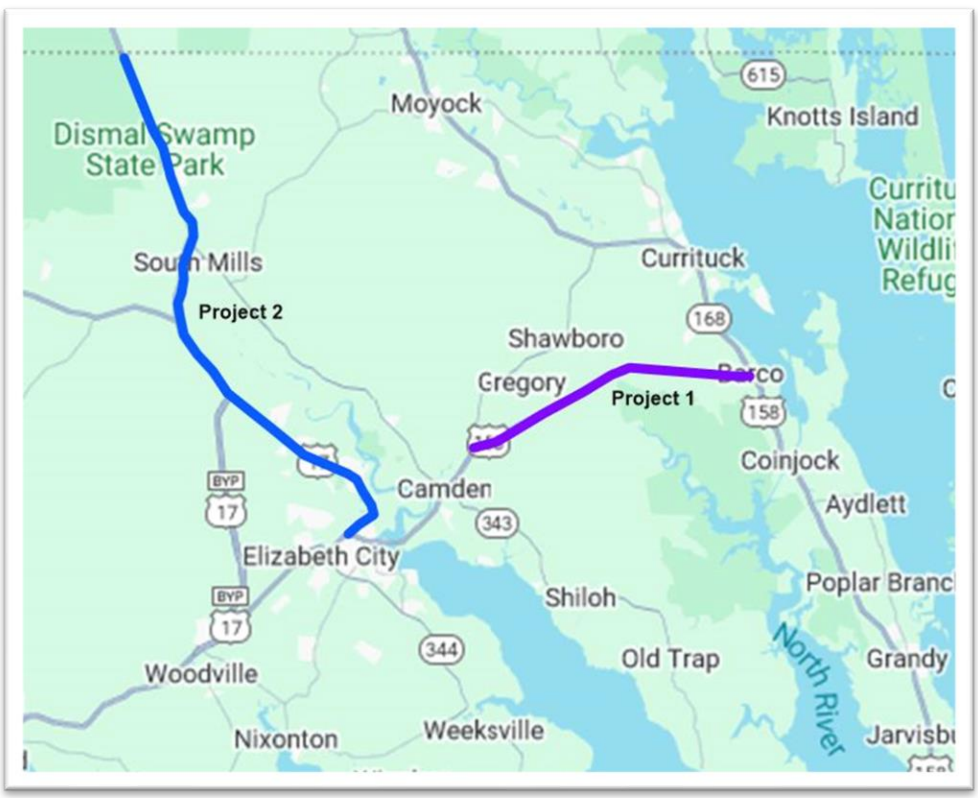

FIGURE 16 LOCATION OF PROJECTS IN THE ALBEMARLE REGION

RTDM Evaluation

Overview

For the RTDM evaluation, the cost ratio was modified and the trip length was adjusted as outlined in the Scenario Development section.

Approach

For each application, system-level performance measures were captured and reported. Project-level performance measures were captured, and a project-level evaluation was conducted. These results are captured and summarized in the following sections.

Summary Results

This section provides a high-level summary of the Tier 3 case study. Detailed analysis is provided in **Appendix F**.

Unlike the previous two case studies, trip purposes are modeled separately for HV and CAV households. As with the Tier 1 and 2 case studies, the average trip length increases for the home-to-work trip for the CAV households. However, the average trip length decreases for all other trip purposes, and for all trip purposes made by the HV households. A case can be made that CAVs may only impact work trips, but it is unclear why HV trip lengths would decrease with the presence of CAVs.

Unlike the Triangle region, the Albemarle region does not experience significant congestion. For both the MH and H scenarios, the total VMT decreases while the congested VMT increases slightly. The decrease in total VMT presumably results from the reduced average trip lengths, but the increase in congested VMT is unexpected. Most facilities in the Albemarle region experience little to no delay. The presence of CAVs leads to a slight increase in delay for multilane and two-lane highways which seems to suggest that the CAV-associated capacity improvements are not sufficient to offset the increased travel demand resulting from CAVs under both the MH and H scenarios. These results seem counterintuitive and cannot be explained without an in-depth review of the model specification and assumed values. It is possible that the slight increase in delay simply shows that there are still large uncertainties in rural area predictions.

To evaluate changes at a project-level, performance measures were summarized for the individual projects described previously.

The project-level analysis shows a small decrease in forecast demand from 2,354 vehicles in the peak hour to 2,308 vehicles for Project 1 under the MH scenario, but an increase of 490 vehicles for the H scenario. The base level forecast demand for Project 2 is 10,763 vehicles in the peak hour. Project 2 shows small increases in demand for both MH and H, 715 and 524 vehicles respectively. The demand is so low compared to the roadway capacity for both projects that the D/C is 0.1, and therefore inconsequential to the analysis.

The build CAV alternative showed slight improvements to both D/C and delay for Project 1, resulting in very small delay cost savings; see **Table 13**. While the reported performance measures do not strongly indicate a need for the project under any scenario, the CAV benefits alone do not perform better than the build CAV scenario, which is expected.

TABLE 13 PROJECT 1 (US 158) PROJECT LEVEL PERFORMANCE MEASURES – PM PEAK HOUR

	Build No CAV	Build CAV	No Build CAV
D/C	0.14	0.10	0.24
Delay (min)	0.70	0.67	2.8
Cost of delay per mile	$6.10	$5.86	$24.51

The results of the build MH CAV alternative for Project 2 do not show improvement in either the D/C or delay as compared to the build no CAV alternative; see **Table 14**. As expected under this situation, the no-build CAV alternative performs much worse than the build no CAV for both D/C and delay. It should be noted that there is very little congestion, and this may very well impact the results.

TABLE 14 PROJECT 2 (US 17) PROJECT LEVEL PERFORMANCE MEASURES – PM PEAK HOUR

	Build No CAV	Build CAV	No Build CAV
D/C	0.1	0.1	0.1
Delay (min)	0.06-0.57[1]	0.08-0.58[1]	0.12-0.99[1]
Cost of delay per mile	$22.62	$26.17	$45.65

[1]Varies by segment.

The research project did not include a sensitivity analysis of the NCDOT RTDM, but it is clear from these results that additional investigation into the CAV assumptions and functionality of this model is needed to better understand the unexpected results.

Research Limitations and Assumptions

As with any analytical approach, especially one developed with fully asserted parameters, there are several limitations and assumptions that bear mentioning.

Focus on CAVs

This research project concentrated exclusively on Connected and Autonomous Vehicles (CAVs) and did not examine Automated Vehicles (AVs). The likelihood of AVs operating on roadways in the near future is high; for instance, many vehicles currently function with low levels of automation within our transportation networks. In contrast, the widespread implementation of CAVs is expected to occur over a longer time horizon. The coexistence of AVs, CAVs, and human-driven vehicles (HVs) in the traffic stream is anticipated to be highly disruptive. However, this potential future scenario involving the mixed presence of AVs, CAVs, and HVs was not evaluated in this study.

Roadway Capacity

The biggest benefit of CAVs captured in the travel model is the positive influence on roadway capacity at high levels of CAV adoption. At lower levels of CAV adoption, the impact may be disruptive to roadway capacity and may create higher levels of congestion and delay. This research focused on medium-high (70% adoption) and high (95% adoption) CAV levels. Based on these levels, capacity improvements for mobility-focused corridors were increased. The increase applied was based on results documented in the literature, largely informed by microsimulation. These are all hypothesized results based on sound analysis but are not directly informed by actual observations. The sensitivity testing showed that the degree of capacity gain has a large impact on the measured benefit and how this influences the decision around project build versus no-build. The other limitation of a travel demand model that bears mentioning is that aggregate traffic assignment, as opposed to microsimulation, requires broad assumptions such as all facilities of a certain type receiving the same broad percent increase in capacity. In actuality, the capacity changes are likely to be much more nuanced than that.

ZOV Trips

There is a great deal of uncertainty around the impact of ZOVs in the future with CAVs. Perhaps the best paper on this topic was by Harb et al. (2022) where chauffeured cars were used to simulate the way people would use AVs. The findings from this paper suggest a 60% increase in VMT, half of which can be attributed to ZOV trips. To account for these changes, the Tier 2 model design captured ZOV trips in three different model steps based on how ZOV trips are expected to be generated. ZOV trips related to CAV sharing among household members are accounted for in the trip generation model. The parking model was redesigned to account for ZOV trips resulting from parking avoidance. A growth factor was applied to the sCAV trip table output from the mode and destination choice model to account for sCAV empty trip miles and to increase the background traffic associated with sCAVs. Sensitivity analysis was performed on the trip rates, and that captures some uncertainty in ZOV trips related to car sharing among household members. Given the potential impact of ZOVs and the uncertainty associated with these new trip types, additional research into this area would be beneficial.

Land Use Assumptions

In general, it is not expected that CAVs will increase trip lengths while everyone continues to live in the same location that they live in today. Increased trip lengths will likely result because people move farther away from their jobs or the more developed region for reasons that may be motivated by affordability or a more rural lifestyle. For all models in North Carolina and most across the country, future land use is a model input. As a fixed input, the location of jobs and households will not dynamically be informed by the changes in travel impedance and accessibility expected to result from higher levels of CAV adoption. An integrated land use transportation model would capture this effect–but in lieu of that, an increase in trip length was asserted. Leaving land use the same but increasing trip lengths creates an incorrect picture of which roads will be impacted from land use shifts brought about from higher levels of CAV adoption.

Fleet versus Ownership

There is a high degree of uncertainty around whether the majority of CAVs will be owned by individual drivers or operated by fleet companies. If CAVs are very expensive, it is more likely that companies will own them and will use sophisticated control software to maximize revenue miles per vehicle. The travel future may look completely different if companies like Uber own CAVs rather than most individual households in the current auto ownership paradigm. If this is the case, then the current construct and logic represented by travel demand models may no longer apply when CAV penetration reaches 70% or greater. In this case, shopping and dining trips may be substituted with freight trips, and most households may no longer choose to own vehicles. Shared CAVs may choose the path of travel to minimize cost rather than travel time, as the current path builder assumes. On the other hand, studies have shown that CAVs could still be the least costly option in most cases, which would make private ownership more attractive (Wadud and Mattioli, 2021; Galich and Stark, 2021).

Black Swans

The term "black swan" is often used to describe an event that is unexpected, but that could have positive or negative impacts on the future. A recent example of this is the impact of COVID on teleworking. An earlier example is women entering the workforce. Both events stress the previous models because the observed behavior and associated model parameters no longer represent the expected future. Well-specified and estimated travel models rely heavily on travel behavior survey data that captures revealed decision-making about travel under today's conditions. Until CAVs become more commonplace, we cannot estimate models based on revealed travel behavior but rather must assert parameters informed by literature or expert opinion. As such, these assumptions and asserted parameters should be revisited on a regular basis to make sure they reflect the best information we have at the time, until such time that models can be estimated using observed data.

Conclusions and Recommendations

CAVs have the potential to significantly change travel demand across North Carolina by the year 2050, and NCDOT is currently planning the infrastructure that will service travel needs in 2050 and beyond. There is an urgent need for NCDOT to better understand the potential effects of CAVs on travel demand and traffic forecasts, as a failure to do so could lead to significant implications for NCDOT and the citizens of North Carolina.

This research effort explored the use of travel demand models to better understand the possible impacts of a future with a 70% or greater adoption rate of CAVs. Work focused on the modification of parameters and assumptions within a scenario planning context for an existing model design (Tier 1), a redesigned model (Tier 2), and a model that already includes some accommodation of CAVs (Tier 3). Case studies were used to evaluate the potential effects of CAVs on regional and project-specific performance measures. The results of the case studies for the medium-high (MH) scenario, reflecting a 70% CAV adoption, show an increase in peak period VMT of 13% (Tier 1) and 16% (Tier 2). While peak period VMT increased, the peak period congested VMT declined by 50% (Tier 1) and 34% (Tier 2), and freeway delay declined by 60% (Tier 1) and 44% (Tier 2). The results for the Tier 3 model analysis showed unexpected results with a slight decrease (0.3%) in peak period VMT and a slight increase (0.4%) in peak congested VMT. There are no freeway facilities in Tier 3 but delays on multilane and two-lane showed small increases with MH CAV adoption.

At the project-level, the analysis for the Tier 1 and Tier 2 models shows an increase in demand across all projects evaluated, while demand over capacity (D/C) improves. The benefits of CAVs did not, however, remove the need for the projects under the MH scenario. The Tier 3 model showed no project-level benefit at either the MH or H CAV adoption level, primarily due to very low demand on the projects for the base, MH, and H scenarios. A sensitivity analysis of the key variables shows that the uncertainty in capacity improvements associated with CAVs has the highest level of risk and uncertainty when considering the effects of CAVs on key performance measures.

Given the level of risk and uncertainty associated with the adjustment of the capacity values, this work would benefit from additional research into additional scenarios that vary both adoption, capacity, and ZOVs. The analysis presented in this research included the CAV adoption level as a scenario analysis and separately conducted sensitivity analysis on the parameters. In practice, analysts should conduct a risk and uncertainty analysis using a best case and worst-case scenario. The best-case scenario would assume high adoption, optimistic capacity improvements, and low ZOV generation. The worst-case scenario would assume medium adoption, HCM recommended capacity improvements, and high ZOV generation. Additionally, all changes to model parameters were asserted based on knowledge gleaned from the literature and professional experience. It is impossible to estimate these parameters that reflect actual behavior until we have observed travel behavior for households who own a CAV. In lieu of that, stated preference surveys could be used to better understand how people might behave if they owned a CAV, and that data could then be used to estimate, rather than assert, the coefficients. NCDOT should consider investing in such a survey.

Given the level of uncertainty in the asserted parameters, additional sensitivity analysis is also recommended, especially with respect to the varied components of ZOV trips. This effort would help to tighten the range of recommended asserted values for each parameter in conjunction with the level of uncertainty associated with each. In addition to the additional testing recommended for the capacity values at different levels of CAV adoption, this should be undertaken for all parameters.

Finally, the results from the NCDOT RTDM were unexpected. For instance, the literature suggests that CAVs will result in longer trip distances, resulting in increased VMT. The RTDM does show increased average trip length for work trips made by CAV households, but a decreased trip length for non-work trips made by CAV households and decreased trip lengths for all trips made by non-CAV households. Additionally, VMT decreases slightly while congested VMT increases slightly. Delay is insignificant in the rural region covered by the RTDM; even so, the delay on most facilities increases with the presence of CAVs, counterintuitive to what experts say will be a benefit of CAVs at the adoption rates evaluated. While this research was not designed to delve deeply into the functionality and assumptions of the model, further examination is warranted if this model is to become the standard for small urban and rural POs.

This research has provided a significant contribution to the use of travel models in a scenario planning context to better understand the potential effects of CAVs on key transportation system performance measures and traffic forecasts. The tiered approach lays a solid groundwork for changes that could be implemented immediately as well as those that require more time and effort but offer more behavioral realism. Additionally, this work informed the development of guidelines that can be used to incorporate these findings into the models that NCDOT funds or develops to better capture the effects of CAVs on long range transportation plans, project prioritization, and project-level traffic forecasts.

Most Metropolitan Transportation Plans (MTPs) have a future year of 2050 and some MPOs are initiating work on MTPs with a 2055 future year. While a handful of traffic forecasts are using a forecast year of 2045, the majority are using a 2050 forecast year. The time to start considering CAVs in future planning and infrastructure development is now. At a minimum, MTPs and traffic forecasts currently underway should incorporate a Tier 1 approach on the selection and prioritization of projects, and to better understand the risk and uncertainty around traffic forecasts and the decisions they inform. For planned model development projects, the recommended guidelines should be followed such that future travel demand models incorporate a robust and behaviorally-realistic approach to evaluating CAVs. NCDOT should conduct additional analysis on the RTDM to better determine if the counterintuitive results capture the uncertainties of CAV deployment in rural areas with little to no congestion, or if design modifications are required. Following this investigation, NCDOT should continue to move forward with the development of RTDMs with a CAV component for small MPOs and RPOs so these regions can consider the influence of CAVs in the development of their transportation plans.

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Appendix A – Literature Review

Guidance on Considering CAVs in Travel Demand Models

Literature Review

Leta Huntsinger, Ph.D., P.E.
Nita Bhave
Si Shi
M. Shoaib Samandar, Ph.D.

Institute for Transportation Research and Education

North Carolina State University

Ali Hajbabaie, Ph.D.
Fahim Kafashan
Ramin Niroumand

Department Civil, Construction, and Environmental Engineering

North Carolina State University

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1. Introduction

The emergence of connected and autonomous vehicle (CAV) technology is expected to significantly alter transportation systems from various aspects. CAVs have the potential to improve safety, reduce congestion, and increase efficiency (Mondal et al. 2022). In addition, the widespread adoption of CAVs will also have a significant impact on current travel demand models (He, Jiang, and Ma 2022). Travel demand models are a crucial component as they assist in the planning and management of transportation infrastructure.

The advent of CAVs has the potential to change many aspects of travel demand models. These may include trip generation, trip distribution, mode choice, travel behavior coefficients, transportation system performance, highway capacity, parking pricing, and travelers' value of time. These factors can be modified to capture changes in travel behavior for CAV users, thereby reflecting possible shifts in forecast travel demand.

For instance, CAVs can lead to changes in land use patterns as they will impact the way people travel and how land is used for transportation (Bansal and Kockelman 2018). Additionally, CAVs can impact trip generation and distribution as they can change the way people travel including how often they travel, their destination, and the route selected (Bridgelall and Stubbing 2021). The use of CAVs can also influence mode choice, leading to a decrease in traditional modes of transportation (Malokin, Circella, and Mokhtarian 2015). Moreover, CAV adoption can lead to significant changes in the performance of transportation systems, including intersection and highway capacity (Hajbabaie, Tajalli, and Bardaka 2022).

Overall, the emergence of CAVs has the potential to transform the transportation system and therefore, travel demand models will need to transform as well. Examining travel demand model elements that can be changed because of CAVs, will lead to a better understanding of the potential needed adjustments in existing models.

The remaining sections will cover topics related to incorporating the impact of CAVs into travel demand models. First, basic definitions for both Autonomous Vehicles (AV) and CAVs are provided. The market penetration rate of CAVs and how CAV ownership patterns may change in the future is then discussed. Next, the relationship between land use and transportation planning, with a focus on the four-step modeling approach is discussed. Then, how CAVs could impact travel behavior and the potential effects on transportation system performance and capacity is explored. Additionally, parking pricing as a tool for managing demand for parking spaces in a future with CAVs is discussed. Finally, the methodology and scenario development used in the literature to analyze the potential impacts of CAVs on travel demand models is described.

2. Definitions and Classification of Vehicle Types

Over the past decade, there has been significant interest and research in two emerging technologies, connectivity and automation, as a means to enhance the efficiency, reliability, and safety of vehicles and transportation systems. By leveraging these technologies, there is a growing expectation that the benefits of enhanced connectivity and automation will provide promising outcomes.

This research classifies vehicles into four categories based on the existence and integration of automation and connectivity technologies, as demonstrated in Figure 1. These categories include autonomous vehicles (AVs), connected vehicles (CVs), connected-autonomous vehicles (CAVs), and human-driven vehicles (HVs).

		Automation	
		+	-
Connectivity	+	CAV	CV
	-	AV	HV

FIGURE A-1: VEHICLE CLASSIFICATION BASED ON CONNECTED/AUTONOMOUS TECHNOLOGIES EXISTENCE AND INTEGRATION
[Source: (Samandar 2019)]

AVs, according to the United States Department of Transportation (USDOT), refer to vehicles where some aspects of safety-critical control functions, such as steering, braking, or throttle, occur without direct input from the driver (Administration 2013). The Society of Automotive Engineers (2021) has established six levels of autonomous driving, which vary from no autonomous intervention to full vehicle autonomy. Table 1 outlines the different levels of automation identified by the Society of Automotive Engineers (SAE) J3016 standard.

TABLE A-1: SAE J3016 LEVELS OF AUTOMATION

SAE INTERNATIONAL

SAE J3016™ LEVELS OF DRIVING AUTOMATION

	SAE LEVEL 0	SAE LEVEL 1	SAE LEVEL 2	SAE LEVEL 3	SAE LEVEL 4	SAE LEVEL 5
What does the human in the driver's seat have to do?	You are driving whenever these driver support features are engaged – even if your feet are off the pedals and you are not steering			You are not driving when these automated driving features are engaged – even if you are seated in "the driver's seat"		
	You must constantly supervise these support features; you must steer, brake or accelerate as needed to maintain safety			When the feature requests, you must drive	These automated driving features will not require you to take over driving	
	These are driver support features			These are automated driving features		
What do these features do?	These features are limited to providing warnings and momentary assistance	These features provide steering OR brake/ acceleration support to the driver	These features provide steering AND brake/ acceleration support to the driver	These features can drive the vehicle under limited conditions and will not operate unless all required conditions are met		This feature can drive the vehicle under all conditions
Example Features	• automatic emergency braking • blind spot warning • lane departure warning	• lane centering OR • adaptive cruise control	• lane centering AND • adaptive cruise control at the same time	• traffic jam chauffeur	• local driverless taxi • pedals/ steering wheel may or may not be installed	• same as level 4, but feature can drive everywhere in all conditions

[Source (SAE Levels of Driving AutomationTM Refined for Clarity and International Audience, n.d.)]

2.1. Human-driven vehicles

HVs lack both connectivity and automation, and their operations solely rely on their human driver. The categorization of vehicles into these four categories highlights the potential for increased efficiency, reliability, and safety through the integration of connectivity and automation technologies, and underscores the need for further research and development in this area.

2.2. Autonomous vehicles

AVs utilize built-in sensors to monitor their surroundings and control driving functions. They are considered a game-changing technology with the capability to substantially improve safety, increase capacity, and ensure dependable travel times. The car manufacturing industry is putting considerable efforts into developing completely self-driving vehicles (as defined by SAE levels 4 and 5). Yet, simpler implementations of this groundbreaking technology, such as adaptive cruise control, have already been successfully deployed. These features aim to enhance driver comfort, alleviate traffic bottlenecks, bolster safety measures, and augment vehicular capacity.

2.3. Connected vehicles

CVs hold the potential to collect data about their environment through interaction with similarly equipped vehicles and local infrastructure. This real-time information access can significantly influence the driver's reactions and decision-making processes, potentially leading to considerable enhancements in safety and vehicle capacity. It is crucial to underscore that the human operator retains control and makes all the operational, tactical, and driving decisions, drawing upon the data obtained via the vehicle's communication features.

2.4. Connected and autonomous vehicles

CAVs incorporate both connectivity and automation technologies. These advanced vehicles utilize not only their integrated sensors but also their communication abilities to formulate decisions and perform driving tasks. They leverage real-time data about the actions and locations of other vehicles nearby, as well as environmental factors and driving conditions further along their path. This wealth of information enables these sophisticated vehicles to make educated and timely decisions, optimizing their performance and safety.

3. Market Penetration Rate (MPR)

Estimating the CAV penetration rate is crucial for strategic planning purposes. Several studies examined the factors that can influence changes in CAV penetration rate. One study by Lavasani, Jin, and Du (2016) used a market diffusion model to estimate the CAV penetration rate up to 2045, considering variables such as the price of vehicles and the economic status of households. Their results indicate that the AV market size could reach 8 million by 2035, if AVs are commercialized by 2025. Assuming a market saturation of 75%, it would take 35 years for the market to reach its maximum potential. In another study Johnson and Walker (2016) developed two scenarios of slow and fast CAV growth rates to predict the market penetration rate of CAVs, estimating that it could be 3% and 11%, respectively by 2024. In a more recent study, Litman (2020) predicted that Level 5 AVs may become commercially available by the 2020s, but the real benefits of this technology will be realized when self-driving cars become common and affordable, which may happen between 2040 and 2060. The study identified six factors that affect the growth rate of AVs, including technological advancements, evaluation standards, additional costs, lifestyle of users, predictable level of service, and social preference for new products.

4. CAV Ownership

Previous research focuses on predicting auto ownership, whether a household owns a vehicle and if that vehicle is a CAV or human driven vehicle (HV). Once the autonomous driving technology is widely adopted, people may choose to trade their HVs for private CAVs (pCAV) or solely rely on other modes like shared CAVs.

Multiple researches tried to simulate this by adding a CAV ownership scheme to household stratification (Bernardin Jr et al. 2019; Dias et al. 2020). Generally, two types of factors are suspected to have impact on CAV ownership – traveler level characteristics and trip level characteristics. Traveler characteristics can be further categorized into physical and psychological. Physical characteristics like age, income, household size, education, and especially life cycle are believed to have a strong impact (Pendyala et al. 2017; Tu et al. 2022). Psychological characteristics like CAV safety perception, technology savviness, and interests in using travel time productively also play an important role (Dannemiller et al. 2021; Lavieri et al. 2017). Parking cost, travel time, and built environment, as trip level characteristics, have less significant but measurable effects (Pendyala et al. 2017; Tu et al. 2022).

5. Land Use

The existing literature presents conflicting findings on the influence of CAVs on land use. A survey conducted in Texas by Bansal and Kockelman (2018) found that AVs and Shared-autonomous vehicles (SAVs) are less likely to impact relocation decisions, with a significant proportion of respondents expressing a desire to remain in their current location. In contrast, a study by Moore et al. (2020) predicts significant urban sprawl, as the ability to use travel time productively may lead to workers tolerating longer commutes. The NCHRP guidance (Zmud et al. 2018) on updating regional models to address the impacts of CAVs, suggests that adjustments to accessibility measures in land use models should be made based on the potential impact that CAVs will have on travel costs. Since higher accessibilities make regions more attractive for development, the reduced travel costs from CAVs may lead to greater development in suburban and rural areas.

6. Travel Behavior

Several studies in the literature have analyzed the potential effects of CAV technology on travel behavior. In one of the first articles published, Childress et al. (2015) defined four scenarios using an activity-based travel model from Seattle WA. They assumed changes in MPR, capacity, and travel cost. The results show that vehicle-miles traveled (VMT) will increase continuously with an increasing MPR. Eventually, a 100% MPR yields a 20% increase in VMT. This increasing trend was also observed in the number of daily trips per person. In addition, the average distance traveled for work and school trips also increased by about 16%.

In a study from Southern California, He et al. (2022) evaluated the effects of CAVs on the transportation system using an activity-based model. The changes in people's travel behavior were investigated based on survey results. The model predicted that in the presence of CAVs, total trips will increase by 9% and the total distance traveled will increase by 13%.

Harb et al. (2022a) have used chauffeured cars to simulate the way people would use AVs. A total of 43 households from Sacramento CA were selected to participate in this study. They presented the results of the experiment to investigate AVs-related changes in travel behaviors. Of the selected households, 34 households benefited from the chauffeur service for 1 week and the remaining 9 households had this service for 2 weeks. Moreover, smartphones were used to collect travel data. This research had 5 main findings, 3 of which are related to changes in passenger travel behavior: 1) in the presence of AVs, VMT increased by 60% (half of which were zero occupancy vehicle or ZOV trips) and vehicle trips increased by 39%, 2) households decreased their use of non-autonomous household vehicles by 53%, 3) the share of transit, ride-hailing, biking, and walking trips in the weeks of using AV respectively decreased by 71%, 58%, 37%, and 13%.

6.1. Long Distance Trips

CAVs are also speculated to significantly impact long distance travel. Dannemiller et al. (2021) examined potential CAV impact on travel behaviors using survey-based modeling approach based on data collected in the Austin, Texas area. Results suggested that over 50% of people would make more long distance trips. Huang, Kockelman, and Quarles (2020) used the Texas statewide model to forecast travel changes across the megaregion and predicted that 82% of within-region airline passenger travel will be replaced by CAVs.

6.2. Value of Time

Travelers' perception of travel time would change once they are released from the task of driving. Instead of being a disutility, travel time could be productive and relaxing. Studies using stated preference surveys or revealed preference surveys indicate that the value of time reduction varies. Moore et al. concludes that individuals who are young and have more interest in productively using travel time can tolerate longer commute times. They suggests a modest decrease of 30% in value of time (VOT) (Moore et al. 2020). Harb et al. (2022a) did a simulation experiment by offering selected households free chauffer services to estimate CAVs effect on VOT and found a 60% reduction in VOT. Researchers also implemented changes in various travel demand models by reducing VOT by 25% - 50% (Cohn et al. 2019; Gucwa 2014; Kim et al. 2015; Sonnleitner, Friedrich, and Richter 2022; Vyas et al. 2019).

6.3. Truck Trips

As AVs continue to gain attention in the transportation industry, it is crucial for transportation planners to understand their potential impact on truck trips. Recent studies have examined the effects of AVs on truck trip efficiency, employment, and freight transportation.

Efficiency is a major concern for the trucking industry, and AVs have the potential to increase efficiency (Rad et al. 2020) through optimized routing, reduced fuel consumption, and constant speed travel. In addition to efficiency, employment in the trucking industry may also be impacted by AVs (Clements and Kockelman 2017). Research suggests that the increased efficiency and automation brought about by AVs could lead to a reduction in the need for human truck drivers, which could have significant implications for the labor market.

Freight transportation is another area that may be affected by AVs. Huang et al. (2020) examine shippers' choice between autonomous trucks and conventional or human-driven trucks using a random-utility-based multi-region input–output model, driven by foreign export demands. They simulated the impacts to freight traffic among 3109 U.S. counties and 117 export zones via a nested logit model for shipment or input origin and mode. They found that the adoption of autonomous trucks works in favor of longer truck trips, but rail's competitive prices hamper autonomous truck trips for trade distances over 3000 miles. Human driven trucks dominate in shorter-distance freight movements, while autonomous trucks dominate at distances of over 500 miles. In another study, Huang et al. (2020) used a four-step model structure with nested logit models to reflect future availability of AVs across Texas. They found that the truck trips in all of the commodity classes are predicted to increase. Cantarella and Di Febbraro (2017) reviewed the existing methods for predicting truck trips and conclude that modeling user mode choice behavior with autonomous vehicles might require a hierarchically structured model.

7. Parking

One of the most discussed advantages of CAVs is that travelers no longer need to park their cars close to their destinations, nor do they need to go to the parking lot to pick up their car. After getting dropped off, CAVs can either find a cheaper parking lot somewhere else, cruising at a low speed, or return to home to park and then pick up the passenger at the destination.

To simulate CAV's impact on parking, previous research primarily considered two approaches - reducing parking costs and relaxing parking constraints. The first approach reflects CAV's behavior in parking at cheaper locations. Kim et al. (2015) set parking costs at the primary destination to zero together with other modifications using Atlanta's activity-based model and found an increase of 2.6% in daily vehicle trips and 12.2% in total VMT. Similarly, Childress et al. (2015) and Cohn et al. (2019) assumed a 50% reduction in modeled parking costs. The second approach, relaxing parking constraints, is used in models which parking lot choice is modeled in the trip distribution or mode choice model (Kang, Hu, and Levin 2022). It is commonly implemented in tour-based models as the tour mode choice rules are based on car status and mode cannot be switched (for instance, a commuter that takes transit to work cannot drive a traditional vehicle back home) (Vyas et al. 2019).

8. Four-Step Modeling

8.1. Trip Generation Process

Many researchers attempt to predict how trip generation will change as CAVs become more prevalent. The predictions are fairly broad. Bridgelall and Stubbing (2021) state that CAVs may increase trip rates by 50% and the demand for shopping, dining and entertainment may increase by a factor of 2.24. However, Dannemiller et al. (2021) state that AVs may not have a substantial impact on overall trip-making levels, although local area trips are likely to become longer. Cohn et al. (2019) suggest that non-work trips may increase by 25% accounting for more discretionary vehicle trips including those by unlicensed drivers. Bernardin Jr et al. (2019) suggest that these populations, including disabled persons, seniors, and/or children, may increase trip rates more moderately at 5%. NCHRP (Zmud et al. 2018) suggests the consideration of trip rate adjustments to account for expanded mobile populations, though no specific rate adjustments were specified.

Cohn et al. (2019) offer nuances to potential changes in trip making behavior. Up to 50% of single-occupancy vehicles (SOV) trips may shift to high-occupancy vehicles (HOV) trips. And, there is no significant difference in the number of days people choose to travel; in other words, having access to a CAV is unlikely to change whether people choose to stay home or engage in non-home activities (Harb et al. 2022a). The difference in trip generation rates between AV and non-AV households is fairly minimal; Dias et al. (2020) suggest a 5% increase to rates for AV households.

Overall trips could increase by CAVs introducing an entirely new trip – zero-occupant vehicle trips (ZOV) – where a driver- and passenger-less vehicle independently makes a trip. Many researchers offer rates for ZOV trips (Bernardin Jr et al. 2019). Areas with constrained parking may see more ZOV trips where the vehicle parks itself in a neighboring area with available parking and then returns to pick up its owner (Bernardin Jr et al. 2019). Mondal et al. (2022) segmented CAV owners into those who have access to free parking at their destination and those who use alternative parking locations; it was assumed that 40% of CAV owners have access to onsite parking and do not generate empty trips. CAV empty trip generation, parking costs, and empty trip timings are also considered. NCHRP also suggests rate modifications to account for zero-occupant trips, though no specific adjustments were recommended. (Zmud et al. 2018).

Researchers also offer potential adjustments to trip generation components of travel demand models. Vyas et al. (2019) modifies the Columbus, Ohio activity-based model to account for AVs and they evaluate the potential impacts on accessibility measures, activity participation, tour formation and mode choice. Dannemiller et al. (2021) suggested adjustments to modeling coefficients and t-stats. Mondal et al. (2022) offers a framework that incorporates empty trips for CAVs. And Harb et al. (2022b) model personal tours in activity-based models.

8.2. Trip Distribution Process

Researchers attempt to predict how trip distribution will change as CAVs become more prevalent, specifically where people will travel to, how long they will travel, and how far they will travel. The predictions are fairly broad. Many agree that travelers will have a reduced sensitivity to travel time (Bernardin Jr et al. 2019). In their study, Dannemiller et al. (2021) found that over 60% are willing to accept between 5 and 15 minutes of additional commute travel time. This goes hand in hand with willingness to travel farther distances. There is some propensity for CAV users to travel farther for work, to shop, pursue leisure, and in general, make more long-distance trips (Dannemiller et al. 2021; He et al. 2022).

Some researchers have studied how CAVs may change people's willingness to relocate their residence and therefore cause even more changes in trip distribution. There are three main decisions of interest: binary choice of moving (or not) home location, binary choice of moving (or not) work location, and the amount of additional travel time people are willing to tolerate (Moore et al. 2020). Individuals who significantly value productively using travel time are more willing to relocate their home and office locations and travel further for commuting (Moore et al. 2020). Young adults (18-34 years old) and suburban dwellers show a strong tendency for both home and work relocations as well as commute time increases; women are on the opposite end of that spectrum. The magnitude of impact or trickle-down effects of CAV ownership plus potential home and office relocation may be very significant for trip distribution (Moore et al. 2020).

Modeling trip distribution impacts by CAVs has also been investigated. Dias et al. (2020) used a unique trip distribution value of time variable of 0.75, obtaining impedances for AV trips by multiplying the non-AV impedances by this variable. Harb et al. (2022b) modeled the decrease in disutility of traveling to farther locations through the mode choice log-sum that captures the value of time reduction. CAV parking is also related; Kang et al. (2022) modeled parking lot choice as a trip distribution problem. And lastly, NCHRP offers trip distribution factors including network cost matrices reflecting CAVs and new friction factor matrices if CAVs affect trip lengths (Zmud et al. 2018).

8.3. Mode Choice

Many researchers attempt to predict how people's choice of transportation mode will change as CAVs become more prevalent. As with other transportation variables, it is often dependent on demographic characteristics. Lavieri et al. (2017) estimated a heterogeneous data model system with data from Puget Sound, Washington and determined that lifestyle factors play an important role in shaping AV usage. Younger, educated, tech-savvy, urban residents are more likely to be early adopters of CAVs than are older, suburban or rural individuals. Malokin, Circella, and Mokhtarian (2015) created and administered a survey to determine who would be more likely to use CAVs. They determined that those who prioritize engaging in productive activities while driving could significantly increase their utility by using CAVs and could account for a small but non-trivial portion of the current mode shares. A study in southern California had other mode choice related findings: more than half the population are willing to use CAVs, many HOV trips shift to CAVs and transit trips increased (He et al. 2022). Cohn et al. (2019) also found that transit frequency increased especially for services with dedicated right-of-way.

Researchers also investigated willingness to use shared CAVs and how that would both introduce a new mode and impact selection of existing modes. Eluru and Choudhury (2019) explored preferences towards personal AVs, shared AV and existing ride-sharing options. In another study Gurumurthy and Kockelman (2020) investigated willingness to pay to ride with a stranger in a shared AV on various trip types using a stated-preference survey; it provided insight on privacy concerns and safety. Moreno et al. (2018) applied a logit model for willingness to use shared CAVs and its impact to mode choice. Hardman, Chakraborty, and Tal (2022) and Dias et al. (2020) both offer mode choice specific coefficient modifications. These impacts on people's value of time were one of the main aspects of Harb et al. (2022a)'s study and this adjustment can be made directly within the model.

Some researchers have studied how to incorporate CAV impacts to mode choice components of travel demand models. Lavieri et al. (2017) provides alternative coefficients, t-stats and model elasticities based on education level, age, income, employment status and household composition. Bernardin Jr et al. (2019) and NCHRP suggest model adjustments to add CAVs and shared CAVs as separate modes and transit access modes, introducing a new nesting structure. NCHRP also recommends new routing routines to model dynamic ridesharing and coordinated multimodal mobility services (Zmud et al. 2018).

9. Transportation System Performance

CAVs can transform the transportation system from both supply and demand perspectives. To investigate these alternations, Vyas et al. (2019) conducted a study in Columbus, OH. They used different scenarios related to AV deployment to enhance the regional activity-based travel demand model. Based on the results, AV deployment yielded two fundamental changes in system performance: 1) reduced highway headway and 2) increased roadway capacity.

In another study, Bernardin Jr et al. (2019) investigated the effects of CAVs on system performance. They defined two scenarios to predict the potential effects of CAVs. In scenario 1, they assumed 80% CAV market share for 2050, and a fully CAV fleet in scenario 2. Their results show that the total system delay for the first and second scenarios increased by 40% and decreased by 15%, respectively. Also, the average delay of each user increased by 45% and decreased by 20% for these scenarios, respectively.

Dias et al. (2020) considered a general framework to extend the four-step model to observe AV-related changes in the system. The methodology defined different scenarios to capture the system response to different AV MPRs. Five scenarios were generated based on different assumptions. In the first scenario, no AVs are used. In the second, AV use is high. For the next three scenarios, they considered some changes in the share of travel generation for vehicle types, time value, and capacity. By examining link speeds, a direct relationship between average speeds and MPR was observed. In addition, as the capacity decreases, the speed also decreases.

The important point in examining the changes caused by CAVs is that without the CAV-related observed data, the integration of CAVs in travel demand models requires basic assumptions.

9.1. Highway Capacity Change Due to Use of AVs

Among the various autonomous vehicle technologies, adaptive cruise control (ACC) stands out. This system uses onboard sensors to automatically adjust vehicle speed and prevent collisions (Bishop 2000). The performance of ACC relies heavily on its sensor systems, leading to driving behaviors similar to fully autonomous vehicles.

Chang and Lai (1997) previously studied the impact of autopiloted vehicles on the capacity of a one-lane freeway. They found a 33% increase in the number of vehicles that can safely merge onto the highway when all vehicles were autopiloted. Meanwhile, Vander Werf et al. (2002) showed that the introduction of autonomous adaptive cruise control (AACC) had a modest but significant 7% impact on freeway capacity.

Minderhoud and Bovy (1999) explored the effect of autonomous intelligent cruise control (AICC) on freeway capacity using simulations. They discovered that the time gap between vehicles significantly influenced capacity when more than 20 percent of vehicles used AICC.

Tientrakool, Ho, and Maxemchuk (2011) used equations of motion instead of simulations to analyze the impact of sensor-equipped autonomous vehicles on highway capacity. They found a 43% increase in freeway capacity when all vehicles were autonomous.

Le Vine et al. (2019) created a model of autonomous vehicles driving to estimate freeway capacity. They also conducted a simulation-based study to examine the effect of ACC on freeway capacity, revealing that conservative ACC increased travel time and delay, while aggressive ACC reduced them.

Another study examined the effects of dedicated lanes for AVs on congestion and travel time (Talebpour, Mahmassani, and Elfar 2017). They found that AVs using dedicated lanes resulted in better travel time.

While there is a lot of research on how AVs affect capacity and travel time reliability, less research exists on their safety impact. However, Carbaugh, Godbole, and Sengupta (1998) found that AVs are safer than manually driven ones, and the transition to CAVs further improved safety.

9.2. Highway Capacity Change Due to Use of CAVs

Cooperative adaptive cruise control (CACC) is a notable technology among various CAV innovations due to its potential to greatly enhance roadway traffic conditions by increasing capacity and stabilizing flow (Milanés et al. 2013). The integration of vehicle-to-vehicle communication with onboard sensors allows CACC to maintain shorter following distances and respond more quickly to changes in traffic conditions.

Vander Werf et al. (2002) developed one of the first models of CACC. Their model and subsequent simulations showed that with a 0.5 seconds time gap between CACC equipped vehicles, road capacity could more than double. Later studies by the same team confirmed these findings in mixed traffic scenarios.

Shladover et al. (2012) conducted a study to understand the effect of different levels of CACC adoption on highway capacity. Their findings showed that once a moderate level of CACC adoption was reached, the potential for a substantial increase in highway capacity was very high, with increases of up to 4000 vehicles per hour per lane in a fully saturated CACC environment.

Recent field experiments also validate the potential of CACC to enhance roadway capacity and flow stability (Bu, Tan, and Huang 2010; Milanés et al. 2013; Ploeg et al. 2011). Particularly, experiments conducted by Milanés et al. (2013) and Shladover et al. (2012) demonstrated the ability of CACC equipped vehicles to maintain a time gap as small as 0.6 seconds, significantly lower than the typical gap maintained by traditional vehicles, thus indicating a significant potential for freeway capacity enhancement.

Vander Werf et al. (2002) also studied the impact of varying CACC adoption levels on traffic flow using Monte Carlo simulations. Their findings suggest that CACC has the potential to substantially enhance highway capacity, with the degree of increase being quadratically related to the level of CACC adoption.

Several studies, such as those conducted by Ni et al. (2010), Tientrakool et al. (2011), and Van Arem, Van Driel, and Visser (2006), also demonstrate the potential of CACC and other CAV technologies to significantly improve highway capacity, with increases of up to 270% under certain conditions.

However, the majority of existing research on AVs and CAVs has predominantly focused on the longitudinal control dynamics of these technologies, with very little attention given to their lateral dynamics. A notable exception is the work of Liu et al. (2017), which explores the impact of lateral control algorithms on freeway capacity and traffic flow dynamics. Their findings suggest that the potential benefits of CAVs, particularly in terms of freeway capacity and safety, are most pronounced at high levels of adoption.

9.3. Intersection Capacity Change Due to Use of CAVs

The integration of wireless communication and autonomous driving in CAVs bears the potential to revolutionize intelligent transportation systems by reducing accidents, improving mobility, and reducing emissions (Deng et al. 2023; Mirheli et al. 2019; Tajalli, Mehrabipour, and Hajbabaie 2020; Wu, Wang, and Zhu 2022; Zong 2019). Since intersections are critical components of transportation networks, utilizing CAVs for controlling them would be beneficial. CAVs have two main benefits for intersection control. Firstly, CAVs facilitate joint optimization between signal timing and motion trajectories at fully- or partially-autonomous traffic intersections (Niroumand et al. 2020a). In other words, vehicles will operate with predetermined trajectories within assigned timeslots to improve traffic efficiency by circumventing unnecessary speed changes and stops at stop bars. Secondly, CAVs allow for vehicle platooning, which can further increase the capacity by reducing inter-vehicular headway and improving energy efficiency by mitigating aerodynamic drag and unnecessary speed variations (Deng et al. 2023; Niroumand et al. 2020b; Wu et al. 2022). As a result, CAVs in traffic streams can have significant effects on intersection capacity.

Sun, Zheng, and Liu (2017) proposed a new intersection operation scheme called MCross that maximizes intersection capacity by utilizing all lanes of a road simultaneously through dynamically optimized lane assignments and green durations. The motivation behind this research was to utilize the controllability of

CAVs in order to maximize intersection capacity. The proposed scheme is formulated as a multi-objective, mixed-integer, non-linear programming model (MO-MINLP), and its demand conditions for achieving full capacity are derived analytically. They used theoretical analysis and problem decomposition to mitigate the complexity and solve the MO-MINLP problem. The results showed that MCross can nearly double intersection capacity compared to conventional signal operation schemes, with an increase of up to 99.51%. The authors acknowledged that implementing MCross in the real world is limited to theoretical analysis until a sufficient amount of CAVs are available. Furthermore, the authors acknowledged the importance of investigating the scalability of MCross to larger control areas.

Ding et al. (2022) have proposed a method to optimize the management and control of signalized intersections by taking advantage of the real-time traffic information that can be collected from CAVs. The authors developed a mixed integer quadratic programming (MIQP) model that jointly optimizes signal timings and variable guiding lane (VGL) settings at a typical four-legged intersection. The proposed method overcomes the restrictions of a conventional signal cycle and assigns phase sequences, green start, and duration for each CAV platoon based on movement-based signal timing. The allocation of lane resources is also optimized to consider the dynamic traffic demand distribution. The proposed method integrates vehicle trajectory control into the collaborative control framework to reduce or eliminate wasted green time. The simulation results show that the proposed collaborative control method (signal timing and VGL) outperforms the fixed-time and signal optimization control modes in terms of travel time and intersection capacity, particularly when traffic demand is under-saturated with strong uncertainty. Intersection capacity can increase up to 17.7% by considering the signal timing optimization and VGL simultaneously in comparison to fixed-time traffic signal. The study provides a framework for the collaborative control of traffic signal, VGL, and vehicle trajectory in a fully connected and autonomous driving environment. However, the uncertainties of human driving behaviors under mixed traffic conditions are not considered.

Adebisi et al. (2022) estimated the capacity benefits of CAVs at signalized intersections and developed capacity adjustment factors (CAFs) that can be integrated into the Highway Capacity Manual (HCM). Microscopic traffic simulation was used to model CAVs, and variations in CAV gap/headway settings, platoon lengths, turning movement types, and left-turn phasing modes were considered. The results showed that CAVs could lead to a 40% capacity increase for protected movements and a 45% capacity increase for permitted left turns at 100% MPR. The CAF tables consider factors such as CAV market penetration rate, opposing traffic demand, and the type of vehicle automation in the traffic stream. The lookup tables can be used directly as multipliers for existing HCM equations to account for CAV impacts, giving HCM users more flexibility.

Mohammadi, Roncoli, and Mladenović (2021) have proposed a user-based signal timing optimization (UBSTO) strategy for optimizing user throughput at signalized intersections using connected vehicle data. The strategy comprises three main components: user throughput prediction, signal timing optimization, and cycle dynamic adaptation. The inputs of the proposed algorithm include the position, speed, and the number of passengers traveling in each vehicle, while the output is the optimal green time duration for each signal phase. The proposed strategy was tested against a fully actuated controller in microscopic simulation for various scenarios, including different CV penetration rates. Results show that UBSTO can significantly increase user throughput, decrease average user delay, and reduce the number of stops per vehicle, while also prioritizing vehicles with higher numbers of passengers on-board. In a fully-connected environment, UBSTO is able to increase user throughput 40% to 100%, depending on the demand level. However, their strategy lacked consideration of the automation aspect of future vehicles.

Wu, Wang, and Zhu (2022) explored the impact of CAVs on intersection capacity in a mixed traffic environment where conventional human-driven vehicles also share the road space. The study considers the penetration rate and platooning behavior of CAVs as major concerns and investigates individual willingness of CAVs to form platoons. Intersection capacity is modeled as an objective function of a linear program problem that maximizes the sum of throughput of each stream crossing the intersection under collision-free constraints, and the average occupation time of conflict points is used to determine the constraints. The results show that higher platooning willingness and lower platoon gaps are associated with higher intersection capacity, and that higher CAV penetration rate does not necessarily correspond to higher intersection capacity. Based on the results of this study, CAV platooning can increase intersection capacity up to 250%, when platooning willingness and MPR are at the highest level.

Hajbabaie, Tajalli, and Bardaka (2022) investigated the potential effects of CAVs on saturation headway and capacity at signalized intersections. The authors used simulation and created a signalized intersection testbed in Vissim, where four vehicle types were modeled and tested: HVs, CVs, AVs, and CAVs. Various scenarios were defined based on different market penetration rates of these four vehicle types, and their effects in mixed traffic were investigated in terms of saturation headway, capacity, travel time, delay, and queue length in different lane groups of an intersection. The authors used a Python script code developed by Vissim to provide the communication between the signal controller and CVs and CAVs to adjust their speeds accordingly. The authors developed a model of saturation headway as a function of HV, CV, AV, and CAV market penetration rate, lane group configuration, and turning percentage. This model was used to determine capacity adjustment factors that could be used to calculate the saturation flow rate and capacity of various lane groups. The authors note that the study makes certain assumptions and changes in certain parameters of Vissim's car-following and lane-changing models, which were originally designed to represent human driving behavior. The study found that increasing CV and CAV market penetration rates reduces saturation headway and increases capacity at signalized intersections. In contrast, increasing AV market penetration rate deteriorates traffic operations, as AVs drive more cautiously and yield longer saturation headways and delays. The study also found that the highest increase (80%) and decrease (20%) in lane group capacity were observed, respectively, in a traffic stream of 100% CAVs and 100% AVs.

Song and Fan (2023) have estimated both lane-level and intersection-level capacity to guide intersection planning and operations under different CAV market shares and traffic demands. The study investigates adjustment factors for saturation headway and saturation traffic flow rate for each lane under different MPRs and calibrates the maximum throughput function. The study utilizes a typical four-approach intersection with three lanes per approach and assumes a decentralized signal CAV control logic with no limitation on the platoon length within the intersection control range. The results of the study show that with 100% CAVs, the saturation headways for the exclusive through lane, exclusive left-turn lane, and shared-right-and-through lane decrease by 55.8%, 48.9%, and 42.4%, respectively. The maximum throughput of the intersection with 100% CAVs increases by 70% compared to the scenario with only HVs. Moreover, the maximum throughput increases rapidly after 60% MPRs of CAVs, as CAVs are more likely to follow a CAV and activate the cooperative adaptive cruise control mode under high MPRs of CAV scenarios.

10. Implementation Methodology

Many efforts have been made to estimate the impact of CAVs on travel patterns. Generally, these efforts can be categorized into two parts – with and without Travel Demand Model (TDM) approaches.

Non-TDM approaches include statistical models, micro simulation models, and computer programming simulation. Dannemiller et al. adopts a direct survey-based modeling approach to examine potential AV effects on short-term activity travel behavior patterns as opposed to the factor modification-based approach. Four latent constructs representing tech-savviness, safety concern, variety-seeking lifestyle, and interests in productive travel time are used in the statistical model system to explain the main outcomes of interest (Dannemiller et al. 2021). Similarly, Harb et al. (2022a), Hardman et al. (2022), and He et al. (2022) use survey-based approaches to capture people's behavior changes associated with CAV deployment. Microsimulation models are also commonly used to investigate the potential impact of CAVs (Auld, Sokolov, and Stephens 2017; Kumakoshi, Hanabusa, and Oguchi 2021). Tu et al. (2022) use computer programming to investigate the potential reduction of vehicle ownership under 100% CAV penetration rate using Atlanta travel profile.

The second approach – TDM – can be more systematic. NCHRP published a report on how to update modeling tools to address impacts of CAVs and recommended a list of TDM modifications (Zmud et al. 2018). Table 2 is built on that and summarized techniques recent researchers applied. None of the nine papers analyzed in this table take into account the crucial model components, sociodemographic factors and fleet composition.

Table A-2: Recent Research Categorized by Recommended TDM Modifications

Model Component	Model Improvement	Childress (2015)	Kim (2015)	Bernadin (2019)	Vyas (2019)	Dias (2020)	Huang (2020)	Mondal (2022)	Harb (2022b)	He (2022)
Auto Ownership										
Auto ownership model	Estimate and forecast CAV or manual vehicle ownership			x	x	x				x
Auto availability model	Estimate and forecast availability of SAVs and carsharing				x					
Trip Generation										
Trip rates	Estimate and forecast rates for expanded mobile populations			x	x		x	x		
Trip rates	Account for zero-occupant vehicle trip generation			x		x		x	x	
Trip Distribution										
Impedance to travel	Estimate network cost matrices reflecting CAVs			x				x		
Impedance to travel	Estimate new friction factor matrices if CAVs affect trip lengths (though IVTT)		x			x	x			x
Ease of parking	Adjust parking constrain for parking restricted area	x								
Mode Choice										
Mode choice model	Design new nesting structure including CAVs, SAVs, and SAV access to transit	x		x	x	x	x			x
Mode choice model	Account for MaaS impacts on multimodal tour plans			x			x			
Operating cost	Account for future auto operating cost		x				x			
Value of time	Account for improved value of time for CAV modes	x			x	x		x	x	
Options of parking			x				x			
Network Assignment										
Supply models	Estimate CAV-enhanced capacity on signalized arterial systems	x	x	x	x					
Network capacity	Estimate CAV-enhanced capacity on grade-separated facilities		x	x	x					
Path costs; pricing and tolling	Estimate value of time including discounts for CAV passengers		x			x		x		
Commercial Vehicle / Truck			x				x			

One other element is time of day (TOD). Harb et al. (2022a) suggests that there is no need to modify the parameters of a time-of-day model as AVs do not appear to significantly influence the TOD decision for individual activity participation at aggregate levels. Though Bernardin Jr et al. (2019) indicates a new, shifted diurnal distribution of long-distance passenger and freight travel.

10.1. Scenario Development

The development of behaviorally rich travel demand models relies on observed travel survey data for the estimation of coefficients and parameters that capture observed travel behavior. However, in cases where such data is not available, scenario generation with asserted coefficients and parameters can estimate changes in travel demand due to factors that are yet to be observed or are difficult to measure. This method has been used to understand the impact of CAVs on travel demand, as demonstrated in various studies. For instance, Cohn et al. (2019) evaluated eight different scenarios that considered various levels of AV adoption, auto occupancy rates, non-work trips, transit service, freeway capacity, terminal time, parking cost, and values of time to quantify the equity impacts of CAVs. In another study, an activity-based model was used by Childress et al. (2015) to evaluate the impact of AVs with scenarios focused on increased capacity for freeways and major arterials, reduced value of time, and reduced parking cost. Finally, Dias et al. (2020) utilized a traditional four-step model to assess the impact of AVs by developing scenarios that captured changes in auto ownership, trip generation, trip distribution, mode choice, and the value of time parameter in highway trip assignment.

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Appendix

Table A.1 includes all the information from Table 2 in a more comprehensive form. The table follows the same structure provided in NCHRP Report 896 and captures the current practice of modifying travel models to capture CAV impacts. The table suggests that models should be modified to account for several travel behavior impacts of CAVs. Table cells with an “x” notation represent papers where the particular model adjustment was addressed by the authors but sufficient detail was not provided on the implementation of such an adjustment. Additionally, NCHRP Report 896 recommends a modest increase to all trip production rates to reflect the improved accessibility.

TABLE A-A.1: COMPREHENSIVE INFORMATION OF RECENT RESEARCH CATEGORIZED BY RECOMMENDED TDM MODIFICATIONS

Model Component	Model Improvement	Literature								
		Harb et al (2022)	Vyas (2019)	Dias (2020)	Bernardin (2019)	Mondal (2022)	Huang et al (2020)	Childress et al (2015)	Kim et al (2015)	He et al (2022)
Auto Ownership										
Auto ownership model	Estimate and forecast CAV or conventional vehicle ownership		x	x	x					x
Auto availability model	Estimate and forecast availability of SAVs and carsharing		x							
Trip Generation										
Trip rates	Estimate and forecast rates for expanded mobile populations		Expand car availability to other population		5% more HBO	5%	15%			
	Account for zero-occupant vehicle trip generation			5%	50% HBW, HBO and NHB will generate 2 empty parking (applicable only for destinations where there is paid parking)	Matrices (35%-47% empty miles)				

Model Component	**Model Improvement**	**Literature**								
		Harb et al (2022)	Vyas (2019)	Dias (2020)	Bernardin (2019)	Mondal (2022)	Huang et al (2020)	Childress et al (2015)	Kim et al (2015)	He et al (2022)
Trip Distribution										
Impedance to travel	Estimate network cost matrices reflecting CAVs				x	x				
Impedance to travel	Estimate new friction factors			75%			-0.019 for IVTT coeff.		IVTT travel time coefficient decreased by -50%	Reduced β1 and β2 by 31% and 72% to reflect the 31% increase in work-home travel distance
Ease of parking	Adjust parking constrain for parking restricted area							-50%		

Model Component	Model Improvement	Literature								
		Harb et al (2022)	Vyas (2019)	Dias (2020)	Bernardin (2019)	Mondal (2022)	Huang et al (2020)	Childress et al (2015)	Kim et al (2015)	He et al (2022)
Mode Choice										
Mode choice model	Design new nesting structure including CAVs, SAVs, and SAV access to transit		x	x	x		x	SAV cost of $1.65/mi		SAV borrows taxi coefficients
Mode choice model	Account for MaaS impacts on multimodal tour plans				x		x			
Operating cost	Account for future changes in auto operating cost						$0.6 for HV, 0.8 for AV, $1 for SAV		-71%	
Value of time	Account for improved value of time for CAV modes	60%	25% - 50%	75%		25%		-65% (high income HH for low CAVs all HHs for high CAVs)		
Options of parking	Adjust parking cost						No parking cost for SAV		No cost for CAV	

Model Component	**Model Improvement**	**Literature**								
		Harb et al (2022)	Vyas (2019)	Dias (2020)	Bernardin (2019)	Mondal (2022)	Huang et al (2020)	Childress et al (2015)	Kim et al (2015)	He et al (2022)
Network Assignment										
Supply models	Estimate CAV-enhanced capacity on signalized arterial systems		15% - 60%		50%			30%	50%	
Network capacity	Estimate CAV-enhanced capacity on grade-separated facilities		20% - 80%		75%				50%	
Path costs; pricing and tolling	Estimate value of time including discounts for CAV passengers			PCE = 0.7		PCE = 0.7			Reduce operating cost	

Appendix B – Index of Predictions and Factors

Index of Predictions and Factors for Connected and Automated Vehicles (CAV)

Introduction

This document synthesizes findings from literature, conversations with experts, and the research team's own knowledge. It provides a timeline of possible CAV adoption based on influencing factors, subsequent changes in travel behavior, and how to incorporate these changes in travel demand models. The intended audience includes transportation planners, travel modelers and traffic forecasters. The primary purpose is to inform the conversation around model adjustments to support scenario planning, and possible model design changes needed to evaluate CAVs (assuming Level 5 automation). Instead of using forecast years, scale was considered: low captures early adopters, medium represents majority adopters, and high includes late adopters.

Influencing Factors towards CAV Adoption

The cause and effect relationship between various factors and CAV adoption.

	Low (0–30%)	Medium (30–70%)	High (70–100%)
Cost	CAV adoption is hindered by high costs	Costs begin to normalize	The cost of **not** owning a CAV increases
Technology	Technology is new making many reluctant to use CAVs	Implementation and more testing normalize the technology	Continued advances in technology and safety countered with less advances for regular vehicles
Driver Experience	Few are attracted to convenience features that are largely untested and less understood	Understanding and trust in CAV convenience features increases	Investment in convenience features for regular vehicles declines
Policies	Lack of supportive CAV policies	Supportive policies mature	Unfavorable policies towards regular vehicles arise

Anticipated Behavioral Changes Resulting from CAV Adoption

CAV adoption could influence how people travel including the number of trips made, mode of travel, distance traveled, time of day traveled, and their lifestyle. While some behavioral changes are initially likely, other changes may not occur until higher adoption levels. This section highlights how CAVs are likely to influence behavior.

Number of Trips
- Send an unoccupied CAV to run errands, return home or go elsewhere
- Shopping trips convert to e-shopping with deliveries by automated freight vehicles
- Productivity while traveling make traveling less cumbersome or 'time consuming'
- Sensitive populations (elderly, children, disabled) become mobile when the burden of driving is removed

Mode
- Shared CAVs used for all or some portions of a trip
- Improved access to transit increase the number of people using transit

Distance
- Eliminated driving burden supports if not encourages traveling longer distances

Time of Day
- Ability to sleep or do other activities in the vehicle shift some travel to overnight

Lifestyle
- Convenient and affordable shared CAVs encourage people to own fewer cars
- Eliminated driving burden encourages people to move to suburban or rural areas

Scenario Planning Model Adjustments

Scenario planning is a well-regarded approach to understanding the risk and uncertainty inherent in any systems or project level forecast. It can be implemented without modifying the travel demand model structure, providing a streamlined approach for evaluating CAVs. This section summarizes techniques found in the literature for adjusting model parameters or factors within the existing model specification.

Model Adjustment	Sub-Category	<70%	70–85%	>85%
Value of Time	All people	*Not modeled*	-60%	-65%
	High income only		-65%	-70%
Trip Rates	All purposes (captures ZOV trips)		9%	15%
	Shopping only		5%	5%
	ZOV trips only		50%[1]	50%[1]
Trip Distance	All trips			14%[2]
	Work trips			31%[3]
Capacity [4]	Signalized arterial		40%	70%
	Controlled access		47%	77%

Model Design Changes

While more resource intensive, the best approach for evaluating CAV impacts on systems and project level forecasts is to implement model design changes. This section summarizes model design changes from the literature findings. The design elements and adjustments are focused on trip based models.

Model Component	Design Changes	Adjustment
Auto Ownership		
Auto Ownership	Include both CAVs and human vehicles (HV)	Assert model coefficients based on the assumed level of CAV adoption
Trip Generation		
Trip Rates	Account for trip making for expanded mobile populations	5 – 15%
	Account for zero-occupant vehicle trips	5 – 50%
	Increase trip rates to account for improved accessibility	Recommended by NCHRP 896 but specific adjustments not found in the literature
Trip Distribution		
Impedance to Travel	Generate cost matrices for CAVs	Resulting CAV network demand will lead to different cost matrices
	Estimate new friction factors to account for increases in trip length	• 50% – 75% decrease in IVTT coefficients to increase trip length • 31% increase in home-work distance
Ease of Parking	Reduce the parking constraint for restricted parking areas	50%
Mode Choice		
Available Modes	Include CAVs and shared CAVs under the auto nest, and shared CAVs as an access mode under the transit nest	No specific ranges for asserted coefficients were cited in the literature
Operating Cost	Modify the coefficient on auto operating cost to account for CAV efficiencies and assert coefficients for shared CAVs	• Decrease by 71% • $1 operating cost for SAV and $0.8 for SAV or CAV
Value of Time	Modify the coefficient on value of time for CAVs modes to account for the reduced burden of travel using a CAV	25% – 75% decrease in VOT, especially for high income households
Parking	Decrease or eliminate parking cost	No cost for SAV or CAV
Network Assignment		
Network Assignment	Modify arterial roadway capacity values	15% – 60%
	Modify grade-separated facility capacity values	20% – 80%
	Modify PCE to account for reduced car following distances possible with CAVs	Decrease PCE to 0.7
Pricing and Tolling	When converting toll costs to travel time, include discounted value of time for CAV users	Use VOT adjustments cited in the literature to inform asserted values

This table summarizes content from NCHRP Report 896 and content from journal articles. It recommends how to adjust trip-based models to reflect CAV impacts. Successfully modeling CAVs will require several of these changes.

Footnotes:

1. *Assumes that 50% of the home-based-other and non-home based trips will generate two empty parking trips: one empty trip returning home and one picking up the occupant.*
2. *Adjust coefficient in destination choice model or gravity model so that it achieves 14% increase in trip distance.*
3. *Adjust work trip coefficient in destination choice model or gravity model so that it achieves 31% increase in trip distance to reflect relocated population.*
4. *The range on capacity adjustments was informed by microsimulation work.*

This reflects draft research. Concepts are subject to change before final publication.

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ITRE Institute for Transportation Research and Education

Appendix C – Conceptual Framework

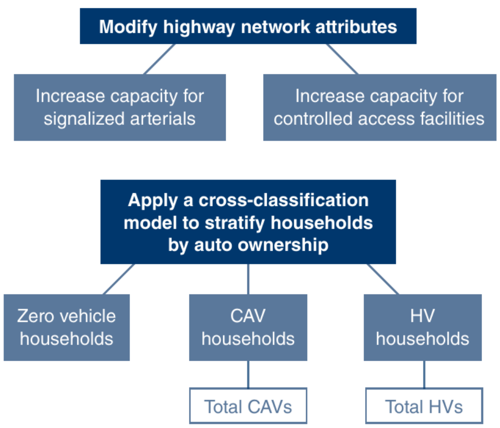
Conceptual Framework for Updating a Trip Based Travel Demand Model to Include Connected and Automated Vehicles

Most trip based travel demand models follow a 4-step process of trip generation, trip distribution, mode choice and trip assignment, though the order of these steps may vary for different model designs. Advanced models often include a step for initial processing and time of day. This conceptual design provides guidance on how each step can be modified to address connected and automated vehicles (CAVs). These recommendations are informed by literature and the research team's experience in designing and developing travel demand models.

Acronyms:

- **CAV** – connected and automated vehicle
- **pCAV** – private CAV
- **sCAV** – shared CAV
- **HV** – human driven vehicle
- **ZOV** – zero occupant vehicle
- **SOV** – single occupant vehicle
- **HOV2** – high occupant vehicle, 2 persons
- **HOV3** – high occupant vehicle, 3 or more persons
- **PNR** – park and ride access to transit
- **KNR** – kiss and ride access to transit
- **NHB** – non-home-based trip, or trips having neither end at home

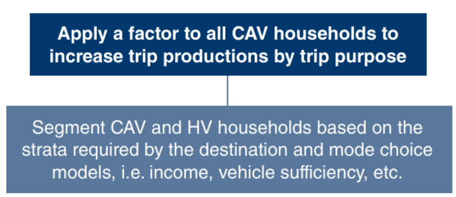
1 Initial Processing



CAVs are expected to increase roadway capacity. While initially the presence of CAVs will disrupt capacity, as CAV adoption levels increase, so will the capacity. This benefit can be captured in travel models.

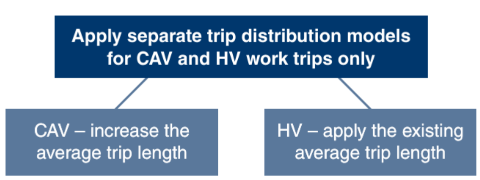
It is expected that CAV adoption will also modify travel behavior, including fewer households owning vehicles resulting in more zero vehicle and vehicle insufficient households. To capture these differences, it is important to segment households by those who have adopted CAVs, those who continue to own HVs and those who do not own a vehicle. For simplicity, mixed ownership households are not considered in this design.

2 Trip Generation

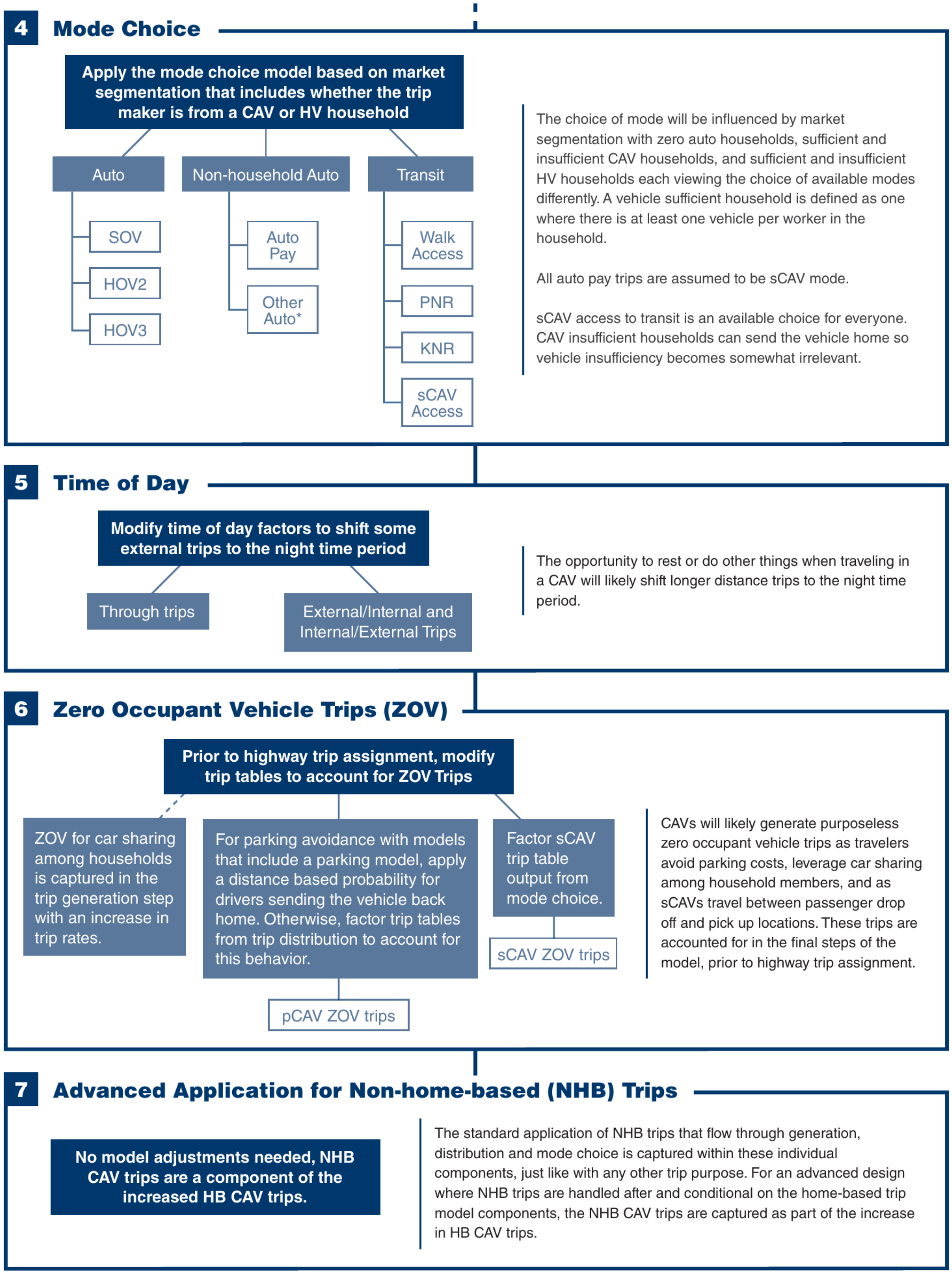


CAV owning households are expected to generate more trips than HV owning households. To capture this change in behavior, increase trip productions for CAV households. CAV and HV households are segmented to match the market segmentation expected by trip distribution and mode choice models, e.g. income, auto ownership, etc.

3 Trip Distribution



The value of time for CAV owning households is likely lower because in-vehicle time can be productive. This could lead to longer work trips and trips for social and recreational purposes.



*Friends car, work car, etc.

Appendix D –Tier 1 Existing Model Design

Systems Level Performance Measures

Average Trip Length by Trip Purpose

Table D-1 summarizes the average trip length for home-based trips by trip purpose for the scenario with no CAVs (base), scenario with medium-high CAV adoption, and scenario with high CAV adoption. All scenarios reflect a 2050 forecast year. The analysis shows a modest increase in trip length for most trip purposes with the presence of CAVs. The results are intuitive given the increase in capacity that in turn leads to less congestion and travelers being able to travel farther in less time, paired with lower values of time that result from the opportunity to be productive during the trip. The largest increase in trip distance is for short duration trips. Intuitively, people generally travel less distance for a trip with a short duration stay. However, as the "cost" of making that trip is reduced, travelers are willing to travel farther for trips that may only last 10 minutes or less.

Table D-1 Average Trip Length in Miles by Home-based Trip Purpose and Scenario

Trip Purpose	Base	Medium-High		High	
	Avg. Trip Length (mi)	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff
K12 trips	6.04	6.30	4%	6.40	6%
Long duration discretionary trips	8.96	9.39	5%	9.63	7%
Short duration discretionary trips	4.92	6.26	27%	7.07	44%
Medical trips	10.11	10.82	7%	11.14	10%
Shop, dine, other trips	6.58	6.88	5%	7.24	10%
Work tour – drop off kids K12	6.12	6.46	6%	6.62	8%
Work tour - interim stop	8.39	8.82	5%	9.03	8%
Work tour	13.29	13.61	2%	13.73	3%

Vehicle Miles Traveled

Table D-2 summarizes daily VMT by facility type. **Table D-3** reports the same information for the PM peak period VMT and the PM peak period congested VMT for each scenario for the entire region.

A review of daily VMT shows increased VMT for both the medium-high and high scenarios, but reduced congested VMT for all facilities except collectors and locals. The capacity values for these facilities were not adjusted as no supporting evidence for doing so was found in the literature. With the improved capacity and operating conditions for the higher-level facilities, trips are diverted to these facilities resulting in a slight reduction in VMT for collectors and locals in the medium-high scenario. For the high level of CAV adoption, the increase in overall trips overcomes any VMT benefits for these lower-level facilities.

Table D-2 Daily VMT and Congested VMT by Facility Type and Scenario

Facility Type	Base		Medium-High				High			
	VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
Freeway	36,868,915	6,256,314	42,825,329	16%	1,888,472	-70%	45,938,303	25%	696,366	-89%
ML Highway	3,194,051	371,833	3,618,003	13%	96,116	-74%	3,879,606	21%	0	-
TL Highway	601,669	18,035	614,287	2%	0	-	639,210	6%	0	-
Major Arterial	14,372,606	525,916	16,202,527	13%	299,152	-43%	17,403,832	21%	231,136	-56%
Arterial	22,643,077	515,891	24,417,203	8%	269,205	-48%	25,783,596	14%	186,480	-64%
Superstreet	999,943	84,795	1,231,226	23%	58,379	-31%	1,381,396	38%	28,269	-67%
Major Collector	2,284,146	77,622	2,245,386	-2%	57,763	-26%	2,278,342	0%	63,870	-18%
Collector	5,522,634	104,958	5,467,283	-1%	110,914	6%	5,563,039	1%	122,075	16%
Local	2,020,949	16,559	2,000,862	-1%	16,819	2%	2,033,907	1%	19,743	19%
Total	88,507,990	7,971,923	98,622,106	11%	2,796,820	-65%	104,901,231	19%	1,347,939	-83%

As with the daily VMT trends, total VMT increases for both scenarios, but congested VMT goes down by a significant amount indicating a strong benefit for CAVs in the travel stream.

Table D-3 VMT and Congested VMT by Scenario for the Peak Period

Base		Medium-High				High			
VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
19,951,727	3,023,255	22,575,659	13%	1,526,009	-50%	24,227,716	21%	574,981	-81%

Delay

The delay is a measure of congestion and how many people experience it. Delay results from increased demand that results in slower travel speed. It is the difference between the free flow and congested travel time for each link in the highway network, multiplied by the demand on that given link. **Table D-4** summarizes the daily delay by facility type and scenario. The capacity improvements resulting from CAV adoption led to reductions in delay, with the bigger benefits realized on the higher level facilities.

Table D-4 Daily Delay by Facility Type and Scenario

Facility Type	Base	Medium-High		High	
	Delay (min)	Delay (min)	% Diff	Delay (min)	% Diff
Freeway	110,423	43,676	-60%	28,795	-74%
ML Highway	10,921	4,626	-58%	3,229	-70%
TL Highway	1,088	352	-68%	236	-78%
Major Arterial	44,480	25,678	-42%	19,607	-56%
Arterial	46,324	28,382	-39%	22,455	-52%
Superstreet	3,669	2,960	-19%	2,526	-31%
Major Collector	7,070	6,170	-13%	6,448	-9%
Collector	18,594	18,151	-2%	19,252	4%
Local	7,690	7,655	0%	8,125	6%
Total	250,259	137,650	-45%	110,673	-56%

Figures D1-D-4 show maps comparing system performance measures including VMT and delay in the MH and H scenarios against the Base scenario. The maps reveal that in the MH scenario, as depicted in **Figure D-1**, mobility-oriented facilities see a greater rise in VMT due to increased capacity. Similarly, the H scenario, shown in **Figure D-2**, follows this trend and shows even higher VMT increases with additional capacity enhancements.

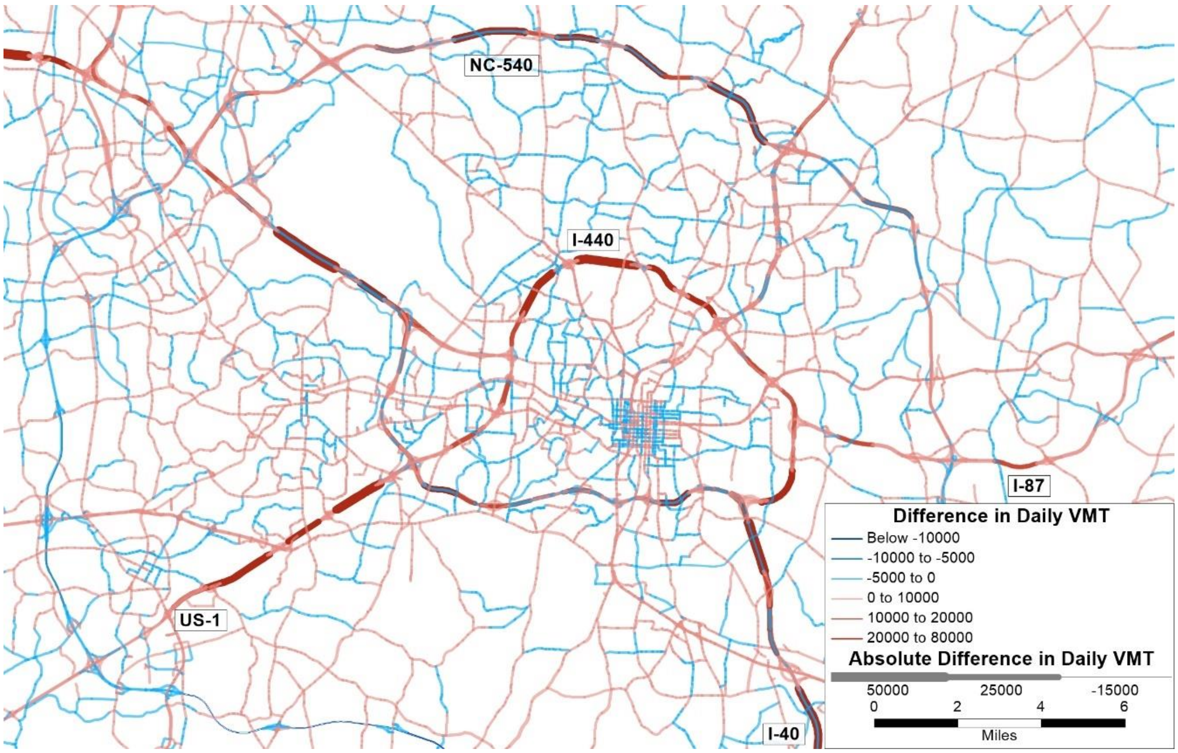


Figure D-1 Difference in Daily VMT between MH and Base Scenario

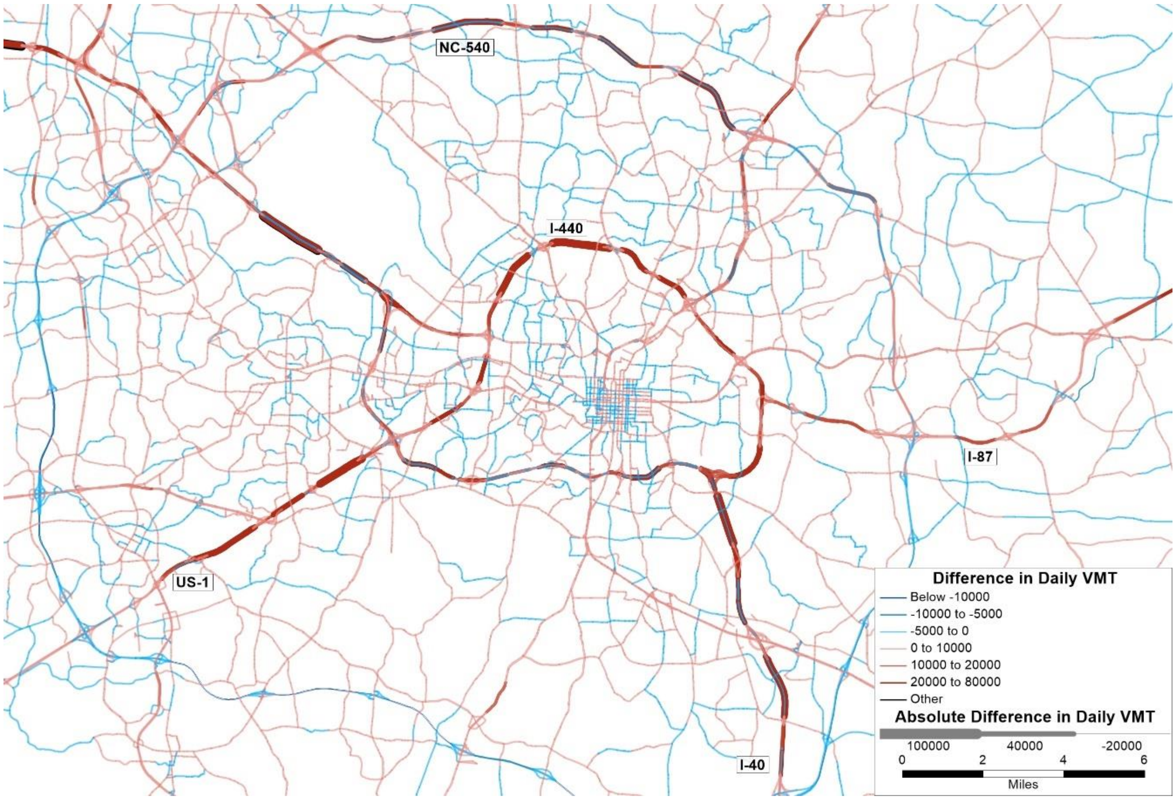


Figure D-2 Difference in Daily VMT between H and Base Scenario

Daily delay follows the same pattern. This means that mobility-oriented facilities experience a decrease in the delay value for both MH and H scenarios compared to the base scenario. By comparing MH and H scenarios it can be concluded that there is a larger delay drop in H scenario.

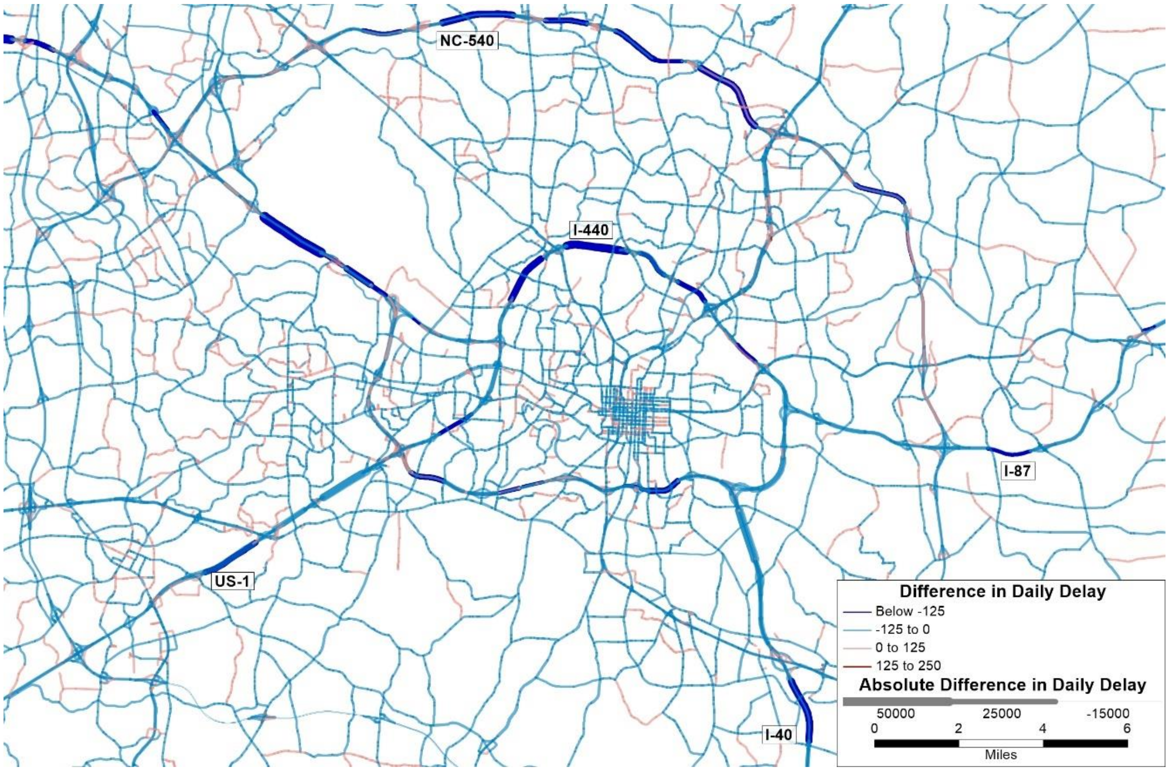


Figure D-3 Difference in Daily Delay between MH and Base Scenario

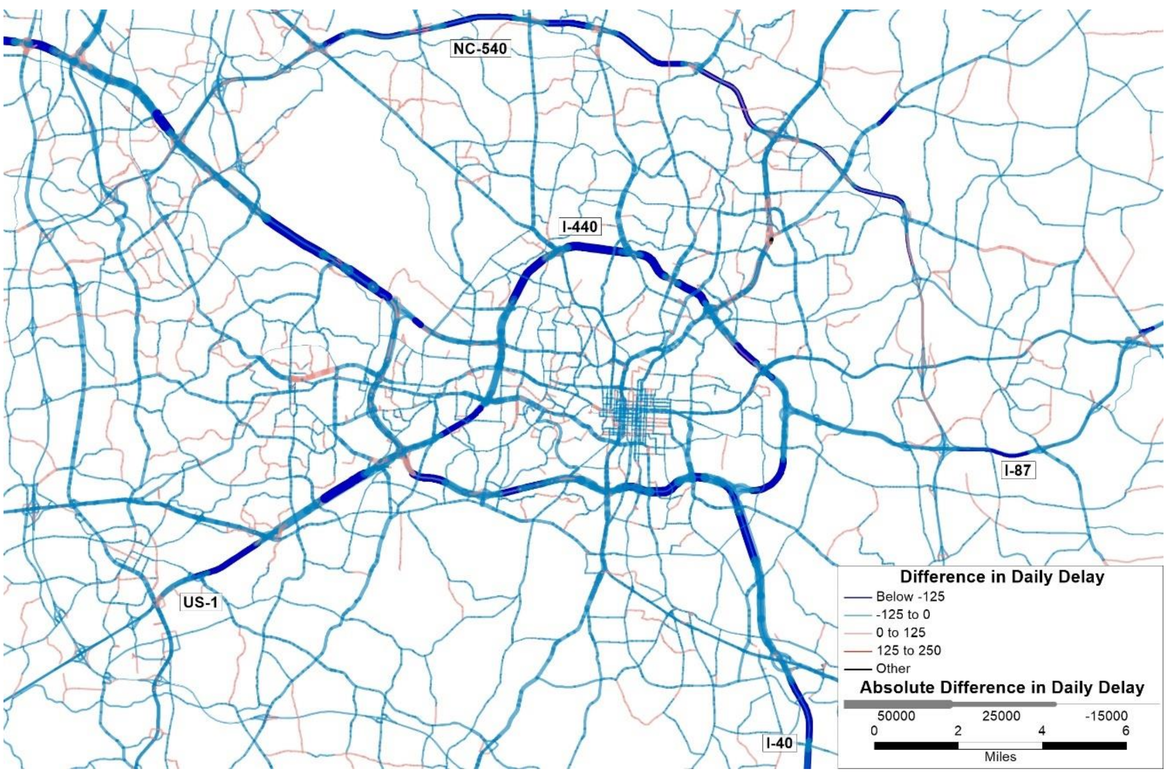


Figure D-4 Difference in Daily Delay between H and Base Scenario

Project Level Performance Measures

To evaluate changes at a project level, performance measures were summarized for the individual projects described previously. ***NOTE: these projects are for illustrative and case study purposes. Neither the projects nor the data presented reflect official projects and forecasts.***

Table D-5 summarizes the projects' peak hour demands and demand/capacity (D/C) for the base 2050 scenario with no CAVs, 2050 with MH CAV adoption, and 2050 H CAV adoption. The project level performance measures indicate that with MH and high H CAV adoption, demand generally increases across all projects while demand/capacity (D/C) ratios decrease, suggesting improved capacity utilization. For example, in Project P1, demand increases by 12% and 21% under MH and H CAV adoption respectively, while the D/C ratio drops from 0.69 to 0.53 and 0.47. Similar trends are observed in Projects P2 through P7. Across these projects, the increase in demand ranges from 4% to 18% with MH CAV adoption and 8% to 30% with H CAV adoption, while D/C ratios consistently decline, indicating enhanced capacity efficiency. This pattern highlights the potential for CAV adoption to significantly impact traffic demand and network performance.

Table D-5 Project Level Peak Hour Demand and Demand/Capacity (D/C) by Scenario

Project	Base		Medium-High			High		
	Demand	D/C	Demand	% Diff	D/C	Demand	% Diff	D/C
P1	8,473	0.69	9,519	12%	0.53	10,241	21%	0.47
P2	2,529	0.20	2,636	4%	0.14	2,742	8%	0.12
P3	12,555	1.02	14,845	18%	0.82	16,373	30%	0.75
P4	11,123	0.83	13,105	18%	0.68	14,472	30%	0.62
P5	3,420	0.63	3,710	8%	0.48	3,920	15%	0.42
P6	2,370	0.45	2,683	13%	0.37	2,875	21%	0.32
P7	1,018	0.38	1,085	7%	0.29	1,132	11%	0.25
	398	0.08	449	13%	0.06	479	20%	0.05
	1,087	0.41	1,227	13%	0.33	1,306	20%	0.29

Project Evaluation

The case study projects were further evaluated under a build condition with and without CAVs, and a no-build condition with CAVs. The focus of this analysis was on trying to determine whether the presence of CAVs changes both the supply and demand side of transportation enough to reconsider whether the project should be built, built differently, or delayed. This analysis considers capacity, demand, D/C, and delay. Instead of using the overall project length, we utilized "Miles of Travel," representing the total project distance, in both directions of travel, over which daily delays are measured. Delay is further evaluated using an average wage rate for the county where the project mostly resides. See **Table 9** for the wage rate by county and project.

I-40 (Project 1)

The analysis of this case study project under three scenarios—build with no CAV, build with medium-high CAV (MH CAV), and no-build with medium-high CAV—reveals critical differences in capacity, demand, D/C ratio, and daily delay. A summary of the build and no-build analysis for I-40 is shown in **Table D-6**. The build no CAV scenario has a LOS D capacity of 12,329, a demand of 8,473, a D/C ratio of 0.69, and a daily delay of 1,815 minutes. In contrast, the build MH CAV scenario shows substantial improvements with a capacity of 18,124, a demand of 9,519, a D/C ratio of 0.53, and a significantly reduced daily delay of 389 minutes. The no-build MH CAV scenario presents a capacity of 12,803, a demand of 9,270, a D/C ratio of 0.72, and a daily delay of 1,749 minutes.

The cost analysis shown in **Table D-7** further emphasizes the benefits of CAV integration. The savings from implementing the project with CAVs, calculated as the difference between the costs of delay per mile with the project but no CAVs ($56.94) and with CAVs ($12.20), amount to $44.74 per mile. Additionally, the loss when comparing the cost of delay per mile with CAVs but no project ($54.87) against the cost with the project but no CAVs results in a minimal savings of $2.07 per mile. These results suggest that building the project with medium-high CAVs not only enhances transportation efficiency but also offers significant economic benefits by reducing delays and associated costs. Almost similarly, postponing the project while there are MH CAVs on the road can improve the overall condition, but the improvement is not significant and needs to be evaluated through sensitivity analysis.

Table D-6 I-40 MH Build and No-Build Project Level Performance Measures – PM Peak Hour (Project 1)

	Build No CAV	Build MH CAV	No Build MH CAV
Miles of Travel	23.17		
Capacity	12,329	18,124	12,083
Demand (peak hour)	8,473	9,519	9,270
D/C	0.69	0.53	0.77
Daily Delay (min)	1,815	389	1,749

Table D-7 I-40 MH Build and No-Build Annual Cost of Delay

Cost of delay per minute per mile with project but no CAVs	$ 56.94
Cost of delay per minute per mile with project and CAVs	$ 12.20
Savings	$ 44.74
Cost of delay per minute per mile with CAVs but no project	$ 54.87
Loss	$ (2.07)

US 1 South of Cary (Project 3)

The analysis of the case study projects for US 1 South of Cary under three scenarios provides important insights into capacity, demand, D/C ratio, and daily delay. Results are summarized in **Table D-8**. In the build no CAV scenario, the capacity is 12,277, demand is 12,555, D/C ratio is 1.02, and delay is 833 minutes. For the build MH CAV scenario, the capacity increases to 18,048, demand rises to 14,845, D/C ratio improves to 0.82, and delay reduces significantly to 449 minutes. In the no-build MH CAV scenario, the capacity is 12,032, demand is 13,963, D/C ratio is 1.16, and delay is 1,712 minutes.

The cost analysis, summarized in **Table D-9**, highlights the economic impact of these scenarios. The savings, calculated as the difference between the cost of delay per mile with the project but no CAVs ($73.72) and the cost with the project and MH CAVs ($39.73), amounts to $34.00 per mile. The loss, calculated as the difference between the cost of delay per mile with CAVs but no project ($151.47) and the cost with the project but no CAVs, amounts to $77.75 per mile. These results indicate that building the project with medium-high CAVs significantly enhances transportation efficiency, reduces delays, and offers substantial economic benefits. Conversely, not building the project with CAVs results in significant losses due to increased delays and associated costs.

Table D-8 US 1 South MH Build and No-Build Project Level Performance Measures – PM Peak Hour

	Build No CAV	Build CAV	No Build CAV
Miles of Travel		6.78	
Capacity	12,277	18,048	12,032
Demand (peak hour)	12,555	14,845	13,963
D/C	1.02	0.82	1.16
Delay (min)	833	449	1,712

Table D-9 US 1 South MH Build and No-Build Annual Cost of Delay

Cost of delay per minute per mile with project but no CAVs	$ 73.72
Cost of delay per minute per mile with project and CAVs	$ 39.73
Savings	$ 34.00
Cost of delay per minute per mile with CAVs but no project	$ 151.47
Loss	$ (77.75)

US 1 North (Project 4)

The evaluation of the case study projects for US 1 North under three scenarios reveals critical insights into capacity, demand, D/C ratio, and delay, see **Table D-10**. In the build no CAV scenario, the capacity is 13,440, demand is 11,123, D/C ratio is 0.83, and delay is 506 minutes. In contrast, the build MH CAV scenario significantly improves the metrics with a capacity of 19,393, demand of 13,105, a D/C ratio of 0.68, and a reduced delay of 367 minutes. The no-build MH CAV scenario shows a capacity of 9,297, a demand of 9,692, a D/C ratio of 1.04, and a substantial delay of 1,492 minutes.

The cost analysis underscores the economic implications of these scenarios, see **Table D-11**. The savings, calculated as the difference between the cost of delay per mile with the project but no CAVs ($72.63) and the cost with the project and CAVs ($52.64), amount to $19.98 per mile. The loss, determined as the difference between the cost of delay per mile with CAVs but no project ($214.02) and the cost with the project but no CAVs, results in a significant loss of $141.39 per mile. These findings suggest that building the project with medium-high CAVs not only enhances transportation efficiency and reduces delays but also provides substantial economic benefits. Conversely, not building the project while having CAVs leads to considerable losses due to increased delays and associated costs.

Table D-10 US 1 North MH Build and No-Build Project Level Performance Measures – PM Peak Hour

	Build No CAV	Build CAV	No Build CAV
Miles of Travel		4.18	
Capacity	13,440	19,393	9,297
Demand (peak hour)	11,123	13,105	9,692
D/C	0.83	0.68	1.04
Delay (min)	506	367	1,492

Table D-11 US 1 North MH Build and No-Build Annual Cost of Delay

Cost of delay per minute per mile with project but no CAVs	$ 72.63
Cost of delay per minute per mile with project and CAVs	$ 52.64
Savings	$ 19.98
Cost of delay per minute per mile with CAVs but no project	$ 214.02
Loss	$ (141.39)

Sensitivity Analysis on Variable Interactions

This section summarizes the results and the rationale behind conducting sensitivity tests, which were primarily aimed at evaluating the impact of the individual variables asserted within the Tier 1 approach. Specifically, three critical variables were examined: Trip Rates, Value of Time (VOT), and Capacity. These analyses were conducted under the premise of a high CAV adoption rate to understand how each variable affects overall model performance. To comprehensively assess the potential interactions and independent effects of these variables, we considered six new scenarios: three involving individual changes to each variable and three involving pairwise combinations of these variable changes. This approach allows us to isolate the impact of each variable as well as understand how their interactions influence outcomes. Notably, altering all three variables simultaneously would result in a scenario identical to the high CAV adoption scenario, indicating that the model's high CAV scenario encompasses the combined effects of changes in Trip Rates, VOT, and Capacity. This approach ensures a thorough investigation into the model's sensitivity to variations in key parameters, thereby enhancing the robustness and reliability of Tier 1 outcomes and enabling more precise and informed decision-making.

Table D-12 presents the average trip length (in miles) by trip purpose across six scenarios, each compared to the base scenario. The scenarios are: VOT Only, Trip Rates Only, Capacity Only, VOT + Trip Rates, VOT + Capacity, and Trip Rates + Capacity. The measure of effectiveness is the average trip length for all trips within the study region.

In the VOT Only scenario, average trip lengths show minimal changes compared to the base, with the most significant difference being a 33% increase in short duration discretionary trips. The Trip Rates Only scenario generally results in slight reductions in average trip lengths, with the most notable decrease being 2% for work tour – drop off kids K12 trips. Conversely, the Capacity Only scenario sees increases across most trip purposes, with the largest being a 10% increase for work tour – drop off kids K12 trips. When combining VOT and Trip Rates, trip lengths generally remain close to the base values, with a notable 30% increase for short duration discretionary trips. The VOT + Capacity scenario results in significant increases in trip lengths across most purposes, especially for short duration discretionary trips (45%) and work tours (8%). The Trip Rates + Capacity scenario shows mixed results, with some trip lengths increasing and others decreasing, but generally aligning more closely with the Capacity Only scenario.

In general, scenarios involving changes to VOT or Capacity tend to increase trip lengths, particularly for short duration discretionary trips, while changes to Trip Rates tend to decrease trip lengths. Based on the results it can be assumed that among all three variables, capacity is the biggest driver of the increasing trends in average trip length values.

Table D-12 Average Trip Length in Miles by Trip Purpose and Sensitivity Test

Trip Purpose	Base	VOT Only		Trip Rates Only		Capacity Only		VOT + Trips Rates		VOT + Capacity		Trip Rates + Capacity	
	Avg. Trip Length (mi)	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff
K12 trips	6.04	6.00	-1%	5.92	-2%	6.48	7%	5.86	-3%	6.46	7%	6.43	6%
Long duration discretionary trips	8.96	9.10	2%	8.84	-1%	9.49	6%	8.97	0%	9.68	8%	9.45	5%
Short duration discretionary trips	4.92	6.53	33%	4.79	-2%	5.36	9%	6.38	30%	7.15	45%	5.30	8%
Medical trips	10.11	10.64	5%	10.00	-1%	10.66	5%	10.54	4%	11.20	11%	10.60	5%
Shop, dine, other trips	6.58	6.76	3%	6.48	-2%	7.02	7%	6.64	1%	7.30	11%	6.98	6%
Work tour – drop off kids K12	6.12	6.05	-1%	5.94	-3%	6.73	10%	5.87	-4%	6.71	10%	6.65	9%
Work tour - interim stop	8.39	8.41	0%	8.23	-2%	9.03	8%	8.24	-2%	9.10	8%	8.97	7%
Work tour	13.29	13.26	0%	13.22	0%	13.78	4%	13.18	-1%	13.77	4%	13.75	3%

Table D-13 shows the Peak Period VMT and Congested VMT across six scenarios compared to the base scenario. In the VOT Only scenario, there is a 2% increase in total VMT and an 8% increase in congested VMT. The Trip Rates Only scenario results in an 8% increase in total VMT and a 23% rise in congested VMT. The Capacity Only scenario demonstrates an 8% increase in total VMT but significantly reduces congested VMT by 90%, highlighting the effectiveness of capacity improvements in reducing congestion. The VOT + Trip Rates scenario sees a 10% increase in total VMT and a 34% increase in congested VMT. The VOT + Capacity scenario shows an 11% increase in total VMT, with an 88% reduction in congested VMT, again emphasizing the impact of capacity enhancements. Lastly, the Trip Rates + Capacity scenario experiences an 18% increase in total VMT, with an 84% drop in congested VMT. Overall, capacity changes consistently result in substantial reductions in congested VMT, while VOT and Trip Rates changes alone tend to increase both total and congested VMT. Combining these variables yields varied impacts, but the dominant influence of capacity improvements on reducing congestion is evident across scenarios.

Table D-13 Peak Period VMT and Congested VMT by Sensitivity Test

Base		VOT Only				Trip Rates Only				Capacity Only			
VMT	Cong. VMT	VMT		Cong. VMT		VMT		Cong. VMT		VMT		Cong. VMT	
19,951,727	3,023,255	20,438,861	2%	3,269,498	8%	21,474,886	8%	3,724,621	23%	21,525,452	8%	310,830	-90%
		VOT + Trip Rates				VOT + Capacity				Trip Rates + Capacity			
		VMT		Cong. VMT		VMT		Cong. VMT		VMT		Cong. VMT	
		22,022,246	10%	4,056,232	34%	22,178,140	11%	358,560	-88%	23,509,482	18%	494,201	-84%

Table D-14 presents the Daily VMT by facility type across six scenarios compared to the base scenario. For Freeways, VMT increases slightly by 1% in the VOT Only scenario, by 5% in the Trip Rates Only scenario, and significantly by 15% in the Capacity Only scenario. This trend continues with combined scenarios showing increases, particularly the Rates + Capacity scenario with a 22% rise. Similarly, major increases are observed for other mobility-oriented roads such as ML Highways and TL Highways across various scenarios, with Capacity Only and combined scenarios leading to notable rises. Conversely, accessibility-oriented roads like Major Collectors and Local roads exhibit a drop in VMT under Capacity Only (-10%) and VOT + Capacity scenarios (-8%), indicating improved capacity on higher-tier roads reduces usage on lower-tier roads. Arterials and Superstreets show mixed results with minor increases across most scenarios. This pattern suggests that capacity improvements on major roads effectively redistribute traffic, enhancing mobility and reducing congestion on less critical routes. Overall, while VOT and Trip Rates changes alone produce varied effects, capacity changes dominate in increasing VMT on primary roads and decreasing VMT on secondary, accessibility-oriented roads, underscoring the significant influence of capacity enhancements on traffic distribution.

Table D-14 Daily VMT by Facility Type and Sensitivity Test

Facility Type	Base	VOT Only		Trip Rates Only		Capacity Only		VOT + Rates		VOT + Capacity		Rates + Capacity	
Freeway	36,868,915	37,385,312	1%	38,695,055	5%	42,243,940	15%	39,253,615	6%	43,130,816	17%	44,993,217	22%
ML Highway	3,194,051	3,262,882	2%	3,368,895	5%	3,538,347	11%	3,440,999	8%	3,630,614	14%	3,777,038	18%
TL Highway	601,669	615,045	2%	632,264	5%	592,908	-1%	647,750	8%	605,656	1%	624,455	4%
Major Arterial	14,372,606	14,808,630	3%	15,631,419	9%	15,060,870	5%	16,099,897	12%	15,652,420	9%	16,748,835	17%
Arterial	22,643,077	23,405,272	3%	24,979,822	10%	22,353,693	-1%	25,842,144	14%	23,164,314	2%	24,856,557	10%
Superstreet	999,943	1,027,837	3%	1,057,337	6%	1,231,254	23%	1,086,812	9%	1,279,967	28%	1,330,662	33%
Major Collector	2,284,146	2,346,693	3%	2,483,245	9%	2,057,150	-10%	2,555,547	12%	2,105,625	-8%	2,223,753	-3%
Collector	5,522,634	5,689,999	3%	6,061,031	10%	4,978,901	-10%	6,249,882	13%	5,104,341	-8%	5,417,469	-2%
Local	2,020,949	2,082,423	3%	2,238,432	11%	1,815,674	-10%	2,313,145	14%	1,857,213	-8%	1,985,109	-2%

Like previous tables, **Table D-15** shows the dominant role of capacity to decrease the congested VMT for all types of facilities, except for collectors and locals. It is mainly due to keeping the same capacity values for these types in different scenarios. It should be noted that VOT and Trip Rates increase the congested VMT values for all facility types.

Table D-15 Daily Congested VMT by Facility Type and Sensitivity Test

Facility Type	Base Scenario	VOT Only		Trip Rates Only		Capacity Only		VOT + Rates		VOT + Capacity		Rates + Capacity	
Freeway	6,256,314	6,807,005	9%	7,854,411	26%	379,221	-94%	8,424,539	35%	429,321	-93%	577,683	-91%
ML Highway	371,833	383,346	3%	406,612	9%	0		469,090	26%	0		0	
TL Highway	18,035	30,959	72%	31,151	73%	0		36,268	101%	0		0	
Major Arterial	525,916	597,743	14%	769,830	46%	132,611	-75%	911,515	73%	154,826	-71%	201,679	-62%
Arterial	515,891	590,824	15%	780,840	51%	101,317	-80%	892,575	73%	114,650	-78%	153,674	-70%
Superstreet	84,795	110,558	30%	119,257	41%	6,754	-92%	171,966	103%	12,080	-86%	14,787	-83%
Major Collector	77,622	79,725	3%	104,057	34%	42,350	-45%	118,719	53%	44,580	-43%	57,629	-26%
Collector	104,958	110,798	6%	131,961	26%	85,832	-18%	148,073	41%	91,517	-13%	111,680	6%
Local	16,559	18,892	14%	21,775	31%	11,687	-29%	24,280	47%	13,781	-17%	17,672	7%

Table D-16 presents the results from sensitivity tests on daily delay across various facility types. Notably, increases in Capacity generally result in significant reductions in daily delay across all types of facilities. For example, on Freeways, an increase in Capacity alone reduces daily delays by 82%, highlighting its potent impact. When variables are combined, the effects on delay can vary. For instance, the combination of decreased VOT and increased Capacity on Freeways results in a smaller delay reduction compared to the impact of increased Capacity alone. This indicates that while increasing Capacity typically reduces delay, other factors like VOT can moderate this effect. Similarly, the combination of increased Rates and Capacity generally shows lesser reductions in delay compared to just increasing Capacity, but still significantly reduces delays compared to the base scenario. The sensitivity tests underscore that while individual changes to variables such as VOT, Trip Rates, and Capacity can influence delays, the interactions between these variables can sometimes diminish these impacts. Again, the Capacity is having the dominant role in delay changes.

Table D-16 Daily Delay (min) by Facility Type and Sensitivity Test

Facility Type	Base	VOT		Rates		Capacity		VOT + Rates		VOT + Capacity		Rates + Capacity	
Freeway	110,423	116,027	5%	128,618	16%	17,742	-84%	136,231	23%	20,162	-82%	25,438	-77%
ML Highway	10,921	11,350	4%	12,250	12%	2,444	-78%	12,868	18%	2,639	-76%	2,976	-73%
TL Highway	1,088	1,170	8%	1,218	12%	162	-85%	1,320	21%	185	-83%	204	-81%
Major Arterial	44,480	49,460	11%	59,213	33%	11,486	-74%	66,374	49%	13,305	-70%	16,857	-62%
Arterial	46,324	51,544	11%	62,805	36%	14,174	-69%	70,543	52%	15,953	-66%	19,834	-57%
Superstreet	3,669	4,185	14%	4,596	25%	1,488	-59%	5,257	43%	1,812	-51%	2,090	-43%
Major Collector	7,070	7,683	9%	9,112	29%	4,587	-35%	9,991	41%	4,971	-30%	5,924	-16%
Collector	18,594	20,107	8%	23,813	28%	14,288	-23%	26,001	40%	15,262	-18%	17,898	-4%
Local	7,690	8,250	7%	9,572	24%	6,331	-18%	10,404	35%	6,692	-13%	7,627	-1%

Table D-17 focuses on Project 3 for its sensitivity tests, targeting the worst D/C conditions among seven projects analyzed. The table presents changes in peak hour demand and D/C ratios under various scenarios involving modifications in three aforementioned variables.

In the base scenario, Project 3 starts with a D/C ratio of 1.02, slightly exceeding full capacity. When VOT alone is adjusted, the demand increases slightly, worsening congestion with a D/C ratio of 1.05. Altering Trip Rates results in a higher increase in both demand and D/C ratio to 1.09, indicating more severe congestion. A substantial improvement is seen when Capacity is increased: demand rises moderately, but the D/C ratio drops to 0.67, significantly alleviating congestion. The scenario combinations show varying effects; VOT + Rates increases the D/C ratio to 1.40, exacerbating congestion, whereas VOT + Capacity decreases it to 0.69, effectively managing congestion despite higher demand. The combination of Rates + Capacity also successfully reduces the D/C ratio to 0.73, improving traffic flow despite a significant rise in demand. This analysis highlights that while changes in VOT and Rates generally worsen congestion, increasing Capacity, either alone or in combination with other variables, effectively counteracts these effects. This demonstrates the importance of capacity enhancements resulted from high adoption rate of CAVs.

Table D-17 Project Level Peak Hour Demand and Demand/Capacity (D/C) by Scenario Test

Project	Base		VOT			Rates			Capacity			VOT + Rates			VOT + Capacity			Rates + Capacity		
	Demand	D/C	Demand		D/C	Demand		D/C	Demand		D/C	Demand		D/C	Demand		D/C	Demand		D/C
P3	12,555	1.02	12,847	2%	1.05	13,321	6%	1.09	14,450	15%	0.67	13,641	9%	1.40	15,032	20%	0.69	15,799	26%	0.73

In conclusion, Capacity emerges as the pivotal factor in driving the anticipated improvements from high CAV adoption rates, warranting further sensitivity analysis due to its foundational position at the base of the uncertainty cone in the scenario evaluations.

Sensitivity Analysis on Capacity Benefits

Given the dominant role that asserted capacity values play in the overall systems benefits of CAVs, the sensitivity analysis for the Tier 1 Case Study focused on modifications to the asserted capacity values. This analysis employed the medium-high adoption rate of CAVs as the reference point to anchor the evaluations in a more realistic framework rather than an overly optimistic one. The sensitivity assessment incorporated two distinct scenarios, each altering only the capacity metrics relative to the baseline medium-high (MH) scenario.

In the first scenario, capacity was posited to be approximately 50% of that in the established MH scenario. Conversely, the second scenario envisioned capacity at roughly 75% of the MH scenario's level. These scenarios are designed to elucidate the effects of varying capacity constraints on the overall efficacy and benefits of CAVs, highlighting critical thresholds and operational breakpoints.

Table D-18 presents an analysis of average trip lengths by home-based trip purpose across three scenarios compared to a Base, detailing variations under different capacity conditions. The scenarios include the MH CAV adoption rate, and two reduced capacity scenarios. Notably, the MH scenario generally exhibits an increase in trip lengths across most trip purposes, with the most substantial rise observed in short duration discretionary trips at 27%, suggesting higher capacities may facilitate longer trips. In contrast, Capacity 1 and Capacity 2 scenarios show more modest changes; for example, K12 trips increase by 2% and 3% respectively, illustrating a nearly linear relationship with capacity changes. However, other trip purposes such as short duration discretionary and medical trips display less predictability, with increases of 24% and 6% under Capacity 1, and 26% and 7% under Capacity 2, indicating a nonlinear relationship where even reduced capacities result in longer trips, likely due to factors like rerouting or altered traffic flows. This analysis underscores the varied impact of capacity on trip lengths, revealing both linear and nonlinear responses across different trip types.

Table D-18 Average Trip Length in Miles by Home-based Trip Purpose and Scenario

Trip Purpose	Base	Medium-High		Capacity 1		Capacity 2	
	Avg. Trip Length (mi)	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff
K12 trips	6.04	6.30	4%	6.17	2%	6.25	3%
Long duration discretionary trips	8.96	9.39	5%	9.24	3%	9.34	4%
Short duration discretionary trips	4.92	6.26	27%	6.11	24%	6.20	26%
Medical trips	10.11	10.82	7%	10.68	6%	10.77	7%
Shop, dine, other trips	6.58	6.88	5%	6.76	3%	6.84	4%
Work tour – drop off kids K12	6.12	6.46	6%	6.28	3%	6.39	4%
Work tour - interim stop	8.39	8.82	5%	8.64	3%	8.76	4%
Work tour	13.29	13.61	2%	13.48	1%	13.57	2%

Table D-19 analyzes Peak Period VMT and Congested VMT by comparing three scenarios against the base scenario, focusing on the PM peak period. In the base scenario, the total VMT is recorded at 19,951,727 with 3,023,255 of those being congested VMT. Transitioning to the MH scenario, total VMT increases by 13% and congested VMT experiences a substantial drop of 50%. This indicates that higher capacity under the MH scenario significantly reduces congestion levels. Conversely, under Capacity 1, where capacity is about 50% of the MH scenario, total VMT sees a modest increase of 11% from the base, totaling 22,050,669, while congested VMT drops by 18%. Capacity 2, representing approximately 75% of the Medium-High scenario capacity, also exhibits a rise in total VMT by 12%, and a decrease in congested VMT by 31%. The relationship between changes in capacity and congested VMT appears closer to linear compared to total VMT, reflecting a more predictable response in congestion levels relative to total vehicle miles, yet the overall trend suggests that capacity changes affect both VMT and congestion in significant yet non-linear ways during peak periods.

Table D-19 Peak Period VMT and Congested VMT by Scenario

Base		Medium-High				Capacity 1				Capacity 2			
VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
19,951,727	3,023,255	22,575,659	13%	1,526,009	-50%	22,050,669	11%	2,467,823	-18%	22,348,460	12%	2,072,786	-31%

Table D-20 illustrates variations in Daily VMT and Congested VMT across different facility types under three scenarios compared to a base scenario. The data shows that mobility-oriented facilities like freeways experience notable increases in daily VMT in the MH scenario, with a 16% rise, while congested VMT significantly decreases by 70%. This suggests that increased capacity in mobility-oriented facilities effectively mitigates congestion.

In contrast, the Capacity 1 and Capacity 2 scenarios, which represent reductions to 50% and 75% of MH scenario capacity, respectively, reveal less linear impacts on VMT and congested VMT. For example, Capacity 1 leads to an 11% increase in freeway VMT but a 34% reduction in congested VMT, demonstrating that decreased capacity does not straightforwardly lead to increased congestion in these facilities.

Interestingly, accessibility-oriented facilities such as local roads and collectors show different trends. Under the Capacity 2 scenario, congested VMT in collector roads increases by 6%, indicating that reduced capacity tends to exacerbate congestion more in accessibility-oriented facilities. This increase is likely due to not changing their capacity and also the traffic spillover and rerouting from the constrained mobility-oriented roads to accessibility-oriented roads, highlighting the overflow effects in areas serving more localized traffic functions. Such patterns underscore the complex interaction between different types of road networks and how capacity changes influence traffic flow and congestion distribution under varying capacity scenarios.

Table D-20 Daily VMT and Congested VMT by Facility Type and Scenario

Facility Type	Base		Medium-High				Capacity 1				Capacity 2			
	VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
Freeway	36,868,915	6,256,314	42,825,329	16%	1,888,472	-70%	41,091,792	11%	4,155,428	-34%	42,049,737	14%	3,019,814	-52%
ML Highway	3,194,051	371,833	3,618,003	13%	96,116	-74%	3,510,302	10%	232,079	-38%	3,569,463	12%	178,193	-52%
TL Highway	601,669	18,035	614,287	2%	0	100%	617,955	3%	0	-100%	615,546	2%	0	-100%
Major Arterial	14,372,606	525,916	16,202,527	13%	299,152	-43%	15,953,154	11%	476,693	-9%	16,125,139	12%	365,696	-30%
Arterial	22,643,077	515,891	24,417,203	8%	269,205	-48%	24,518,974	8%	421,163	-18%	24,489,432	8%	342,249	-34%
Superstreet	999,943	84,795	1,231,226	23%	58,379	-31%	1,152,549	15%	75,316	-11%	1,194,712	19%	61,020	-28%
Major Collector	2,284,146	77,622	2,245,386	-2%	57,763	-26%	2,320,810	2%	73,666	-5%	2,278,889	0%	61,289	-21%
Collector	5,522,634	104,958	5,467,283	-1%	110,914	6%	5,642,999	2%	117,196	12%	5,547,750	0%	111,768	6%
Local	2,020,949	16,559	2,000,862	-1%	16,819	2%	2,072,635	3%	17,183	4%	2,032,084	1%	17,266	4%

Table D-21 provides a comparative analysis of daily delays across various facility types under three scenarios against a base scenario. The data shows that in mobility-oriented facilities such as freeways and multi-lane highways, the effect of capacity changes on daily delay appears almost linear. For instance, in the MH scenario, freeways see a significant reduction in delay of 60.45% from the base, and lower reductions are noted in the Capacity 1 and Capacity 2 scenarios by 33.90% and 47.79%, respectively. This trend indicates that increases in capacity effectively decrease delays in these high-volume roads. Conversely, in accessibility-oriented facilities like local roads and collectors, delays tend to increase when capacity is not adjusted, exacerbated by the traffic spillover from the more congested mobility-oriented roads. For example, in the MH scenario, local roads see a slight decrease in delay by 0.46% from the base. On the other hand, under Capacity 1 and Capacity 2, the delays continue to rise by 6.62% and 2.74%, respectively. These increases underscore the overflow effects where localized traffic functions are stressed due to rerouted flows from main arterials and highways under constrained conditions.

Table D-21 Daily Delay (min) by Facility Type and Scenario

Facility Type	Base	Medium-High		Capacity 1		Capacity 2	
	Delay	Delay	% Diff	Delay	% Diff	Delay	% Diff
Freeway	110,423	43,676	-60.45%	72,990	-33.90%	57,651	-47.79%
ML Highway	10,921	4,626	-57.64%	7,270	-33.43%	5,883	-46.13%
TL Highway	1,088	352	-67.65%	625	-42.60%	472	-56.62%
Major Arterial	44,480	25,678	-42.27%	37,508	-15.68%	31,141	-29.99%
Arterial	46,324	28,382	-38.73%	40,332	-12.93%	33,867	-26.89%
Superstreet	3,669	2,960	-19.32%	3,728	1.60%	3,336	-9.08%
Major Collector	7,070	6,170	-12.73%	7,009	-0.86%	6,531	-7.62%
Collector	18,594	18,151	-2.38%	19,633	5.59%	18,807	1.15%
Local	7,690	7,655	-0.46%	8,199	6.62%	7,901	2.74%

Table D-22 offers a sensitivity analysis for the I-40 Project during PM peak hour, comparing traffic metrics across various capacity scenarios to a base scenario. The base scenario shows a capacity of 12,329 vehicles per hour, resulting in a daily delay of 1,815 minutes. With the introduction of CAVs in the Build MH CAV scenario, capacity increases to 18,124, reducing the daily delay dramatically to 389 minutes. However, when capacity is slightly reduced in subsequent scenarios—15,289 in Capacity Level 1 and 16,645 in Capacity Level 2—delays increase to 923 and 609 minutes, respectively.

Table D-22 I-40 MH Build Project Sensitivity Analysis for Capacity – PM Peak Hour (Project 1)

	Base (Build No CAV)	Build MH CAV	Build MH CAV – Capacity Level 1	Build MH CAV – Capacity Level 2
Capacity (hourly)	12,329	18,124	15,289	16,645
Demand (peak hour)	8,473	9,519	9,217	9,382
D/C	0.69	0.53	0.60	0.56
Daily Delay (min)	1,815	389	923	609

Appendix E – Tier 2 Model Design Changes

Systems Level Performance Measures

Average Trip Length by Trip Purpose

Table E-1 summarizes the average trip length for home-based trips by trip purpose for the scenario with no CAVs (base), scenario with medium-high CAV adoption, and scenario with high CAV adoption. All scenarios reflect a 2050 forecast year. The analysis shows a large increase in trip length for work and recreational trip purposes, where the congested travel time coefficients are modified in the destination choice model. Although the coefficients of K12, K12 drop off on work tour, and medical trips are not adjusted, there is still slight increase in trip length for these purposes as a result of less congestion experienced with the prevalence of CAVs.

Table E-1 Average Trip Length in Miles by Home-based Trip Purpose and Scenario

Trip Purpose	Base	Medium-High		High	
	Avg. Trip Length (mi)	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff
K12 trips	6.04	6.26	4%	6.32	5%
Long duration discretionary trips	8.96	11.49	28%	12.80	43%
Short duration discretionary trips	4.92	6.34	29%	6.98	42%
Medical trips	10.11	10.81	7%	11.09	10%
Shop, dine, other trips	6.58	8.45	28%	9.40	43%
Work tour – drop off kids K12	6.12	6.41	5%	6.51	6%
Work tour - interim stop	8.39	10.99	31%	11.72	40%
Work tour	13.29	14.68	10%	15.18	14%

Vehicle Miles Traveled

Table E-2 summarizes the daily VMT and congested VMT by facility type and scenario. **Table E-3** summarizes the PM peak period VMT and congested VMT for the region and each scenario. As with the Tier 1 results, total VMT increases for all facility types, while congested VMT decreases for all but the lower-level facilities. The capacity values for these facilities were not adjusted as no supporting evidence for doing so was found in the literature.

Table E-2 Daily VMT and Congested VMT by Facility Type and Scenario

Facility Type	Base		Medium-High				High			
	VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
Freeway	36,868,915	6,256,314	45,314,230	23%	3,403,121	-46%	50,419,827	37%	2,314,891	-63%
ML Highway	3,194,051	371,833	3,870,402	21%	114,679	-69%	4,336,212	36%	0	-100%
TL Highway	601,669	18,035	629,169	5%	0	-100%	666,118	11%	0	-100%
Major Arterial	14,372,606	525,916	17,084,034	19%	389,633	-26%	18,982,199	32%	322,294	-39%
Arterial	22,643,077	515,891	25,405,121	12%	313,466	-39%	27,663,082	22%	272,670	-47%
Superstreet	999,943	84,795	1,278,221	28%	65,883	-22%	1,475,020	48%	62,120	-27%
Major Collector	2,284,146	77,622	2,278,686	0%	74,850	-4%	2,338,540	2%	81,905	6%
Collector	5,522,634	104,958	5,587,346	1%	119,483	14%	5,778,148	5%	137,346	31%
Local	2,020,949	16,559	2,058,798	2%	18,715	13%	2,137,703	6%	33,664	103%
Total	88,507,990	7,971,923	103,506,007	17%	4,499,830	-44%	113,796,849	29%	3,224,890	-60%

Regionally, total VMT increases for both scenarios, but congested VMT goes down by a significant amount indicating a strong benefit for CAVs in the travel stream.

Table E-3 Peak Period VMT and Congested VMT by Scenario

Base		**Medium-High**				**High**			
VMT	**Cong. VMT**	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
19,951,727	3,023,255	23,138,507	16%	1,988,373	-34%	25,752,927	29%	1,585,389	-48%

Delay

The capacity improvements resulting from CAV adoption led to reductions in delay, with the bigger benefits realized on the higher level facilities as shown in **Table E-4**. This is expected given higher level facilities receive larger capacity benefits from the presence of CAVs.

Table E-4 Daily Delay by Facility Type and Scenario

Facility Type	**Base**	**Medium-High**		**High**	
	Delay (min)	**Delay (min)**	**% Diff**	**Delay (min)**	**% Diff**
Freeway	110,423	61,731	-44%	51,369	-53%
ML Highway	10,921	5,556	-49%	4,616	-58%
TL Highway	1,088	381	-65%	288	-73%
Major Arterial	44,480	31,765	-29%	28,085	-37%
Arterial	46,324	32,803	-29%	28,812	-38%
Superstreet	3,669	3,513	-4%	3,370	-8%
Major Collector	7,070	6,559	-7%	7,187	2%
Collector	18,594	19,234	3%	21,529	16%
Local	7,690	9,160	19%	11,008	43%
Total	250,259	170,702	-32%	156,264	-38%

Figures E-1 to E-4 provide a geographic representation of the differences in the systems level performance measures for VMT and Delay for the MH and H scenarios as compared to the Base scenario.

Looking at the change in total VMT spatially between the MH and Base scenario as shown in **Figure E-1**, capacity oriented facilities experience higher increase in VMT compared to accessibility oriented roadways as they receive more capacity benefits. Following the same pattern, with more capacity added, even more VMT is generated in the H scenario as illustrated in **Figure E-2**.

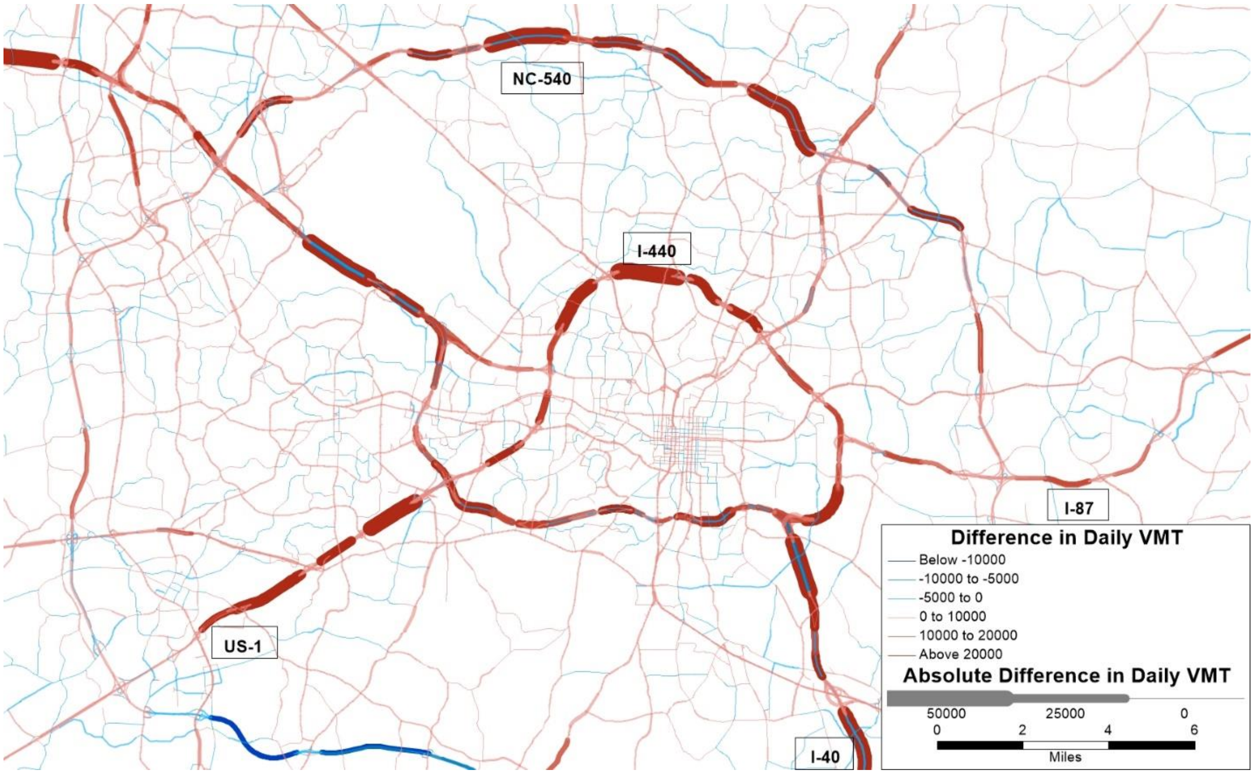


Figure E-1 Difference in Daily VMT between MH and Base Scenario

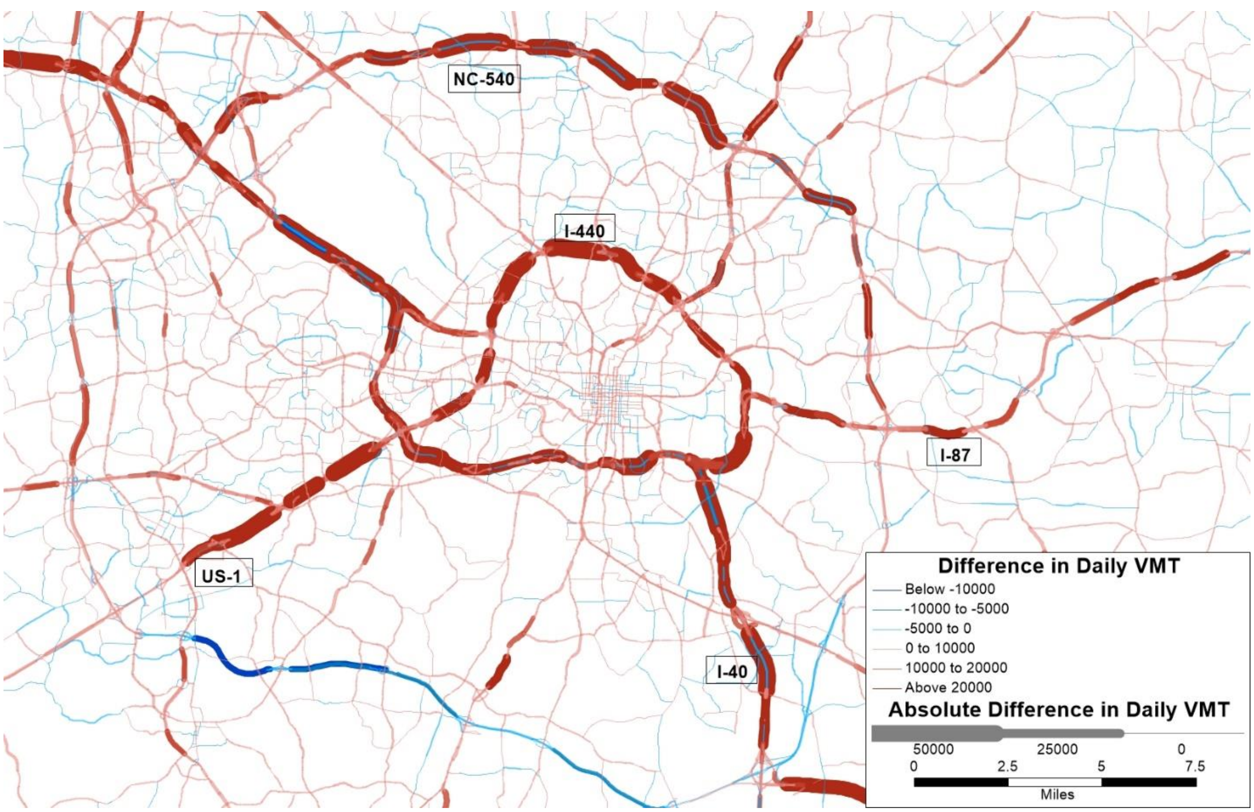


Figure E-2 Difference in Daily VMT between H and Base Scenario

Regarding the spatial difference in daily delay, for both MH and H scenario, generally higher-level facilities experience much less congestion compared to the base as shown in **Figure E-3 and E-4**. However, there are three hot spots that emerged that do not fit in the overall pattern. The first one is a congestion bottleneck that appeared near the RDU airport which is counterintuitive. Upon further investigation, this is the result of additional airport ZOV trips added to reflect the behavior that CAV travelers will send their vehicles back home to avoid paying airport parking fee. The other two congestion spots are located on Capital Boulevard coming off Buffaloe Rd and I-40 heading onto I-440. Congestion happens on ramp-like facilities without capacity enhancement but coming off roadways with capacity benefits.

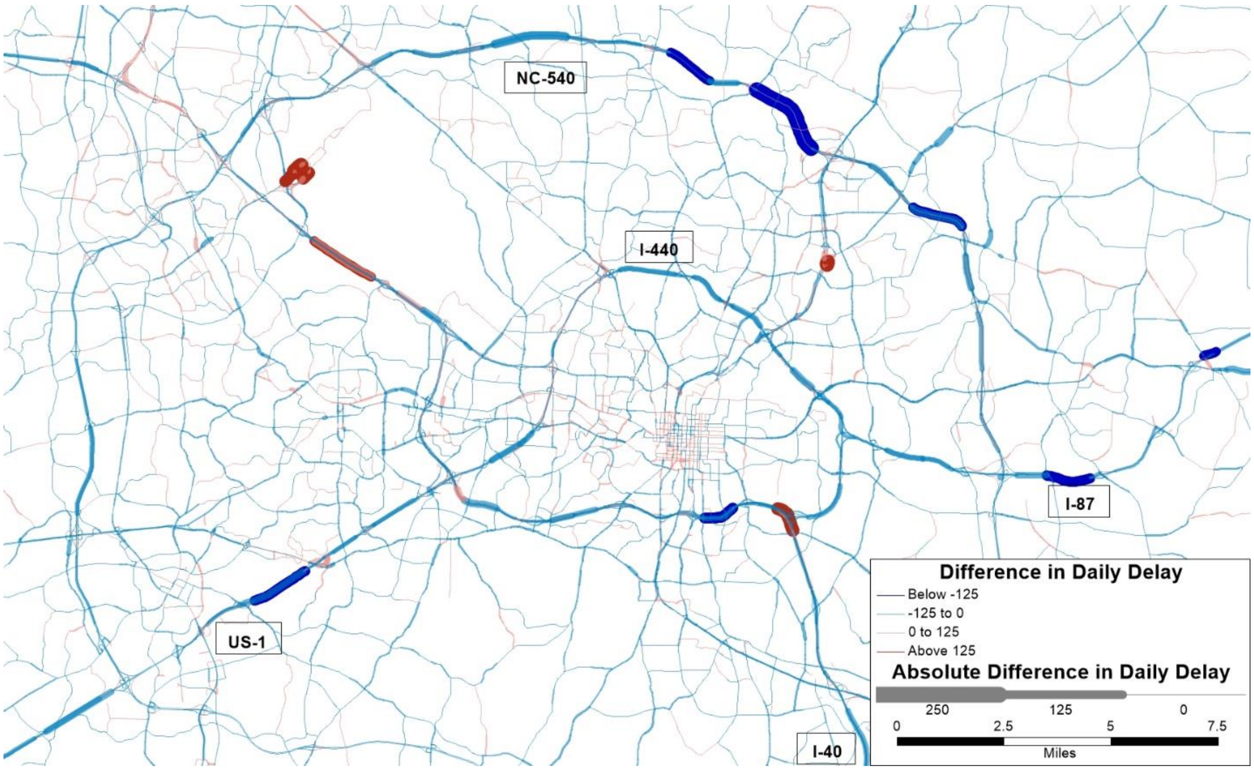


Figure E-3 Difference in Daily Delay between MH and Base Scenario

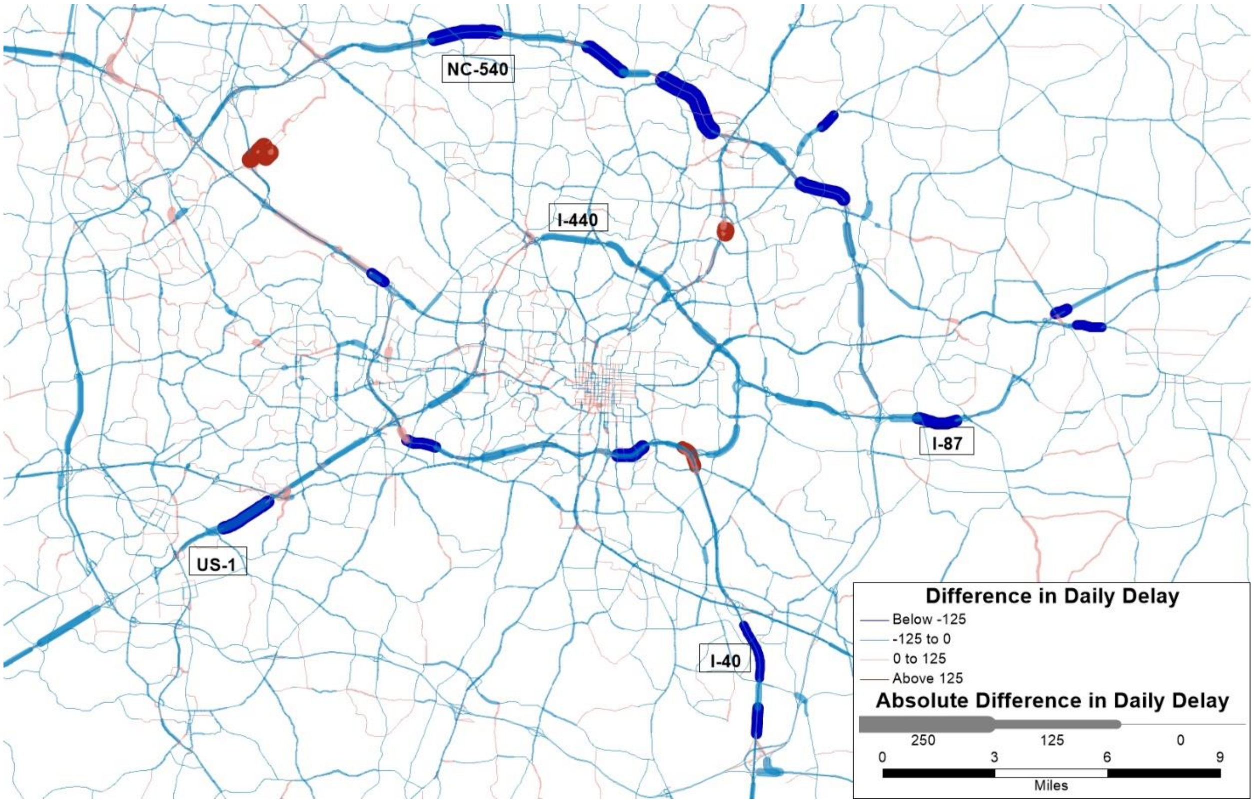


Figure E-4 Difference in Daily Delay between H and Base Scenario

Project Level Performance Measures

To evaluate changes at a project level, performance measures were summarized for the individual projects described previously, see **Table E-5**. The demand increases for all projects in both the medium-high and high CAV scenarios as compared to the base. Project level demand increases, but the D/C ratio decreases reflecting the capacity benefits of the CAV scenarios.

Table E-5 Project Level PM Peak Hour Demand and Demand/Capacity (D/C) by Scenario

Project	Base		Medium-High			High		
	Demand	D/C	Demand	% Diff	D/C	Demand	% Diff	D/C
P1	8,473	0.69	10,165	20%	0.56	11,352	34%	0.52
P2	2,529	0.20	2,844	12%	0.15	3,110	23%	0.14
P3	12,555	1.02	15,333	22%	0.85	17,237	37%	0.79
P4	11,123	0.83	13,786	24%	0.71	15,742	42%	0.67
P5	3,420	0.63	4,199	23%	0.55	4,791	40%	0.52
P6	2,370	0.45	2,675	13%	0.37	2,899	22%	0.33
P7	1,018	0.38	1,078	6%	0.29	1,153	13%	0.25
	398	0.08	460	16%	0.06	498	25%	0.06
	1,087	0.41	1,225	13%	0.33	1,324	22%	0.30

Build vs. No-build Project Evaluation

A subset of the case study projects was further evaluated under a build condition with and without CAVs, and a no-build condition with CAVs. The focus of this analysis was on trying to determine whether or not the presence of CAVs changes both the supply and demand side of transportation enough to reconsider whether the project should be build, built differently, or delayed. This analysis considers capacity, demand, D/C, and delay for the medium-high (MH) scenario only. Delay is further evaluated using an average wage rate for the county where the project mostly resides.

I-40 (Project 1)

The capacity benefits derived from the presence of CAVs far exceed any increases in travel demand resulting from changes in travel behavior as shown in **Table E-6**. Without the project, but with the presence of CAVs, the D/C ratio does increase, as does daily delay. This results in a small loss of benefit without the project as shown in **Table E-7**, but these results would suggest that the loss is so small that this project is likely not needed by the horizon year and could possibly be delayed.

Table E-6 I-40 MH Build and No-Build Project Level Performance Measures – PM Peak Hour

	Build No CAV	Build MH CAV	No Build MH CAV
Length (mi)	23.17		
Capacity	12,329	18,124	12,083
Demand (peak hour)	8,473	10,165	9,891
D/C	0.69	0.56	0.82
Daily Delay (min)	1,815	500	2,223

Table E-7 I-40 MH Build and No-Build Annual Cost of Delay – PM Peak Hour

Cost of delay **per minute** per mile with project but no CAVs	$114
Cost of delay **per minute** per mile with project and CAVs	$31
Savings	$82
Cost of delay **per minute** per mile with CAVs but no project	$139
Loss	($26)

US 1 South (Project 3)

As with the I-40 project, the capacity benefits derived from the presence of CAVs exceed increases in travel demand resulting from changes in travel behavior. As summarized in **Table E-8**, without the project, but with the presence of CAVs, the D/C ratio increases above one, resulting in a near doubling of delay. The cost of delay per mile with CAVs, but no project results in an overall loss of benefit as discussed in **Table E-9**. These results suggest that even with the benefits of CAVs, this project may still be needed.

Table E-8 US 1 South MH Build and No-Build Project Level Performance Measures – PM Peak Hour

	Build No CAV	Build CAV	No Build CAV
Length (mi)	6.78		
Capacity	12,277	18,048	12,032
Demand (peak hour)	12,555	15,333	14,458
D/C	1.02	0.85	1.20
Delay (min)	833	497	1,823

Table E-9 US 1 South MH Build and No-Build Annual Cost of Delay – PM Peak Hour

Cost of delay **per minute** per mile with project but no CAVs	$147
Cost of delay **per minute** per mile with project and CAVs	$88
Savings	$59
Cost of delay **per minute** per mile with CAVs but no project	$322
Loss	($175)

US 1 North (Project 4)

As with earlier projects, the capacity benefits derived from the presence of CAVs exceed increases in travel demand. This leads to a reduction in delay and the D/C ratio. Without the project, but with the presence of CAVs, the D/C ratio increases above one, more than tripling the peak hour delay as seen in **Table E-10**. The cost of delay per mile with CAVs but no project also results in a huge loss, see **Table E-11** suggesting that even with the benefits of CAVs, this project would still be needed.

Table E-10 US 1 North MH Build and No-Build Project Level Performance Measures – PM Peak Hour

	Build No CAV	Build CAV	No Build CAV
Length (mi)	4.18		
Capacity	13,440	19,393	9,297
Demand (peak hour)	11,123	13,786	12,635
D/C	0.83	0.71	1.36
Delay (min)	506	404	3077

Table E-11 US 1 North MH Build and No-Build Annual Cost of Delay – PM Peak Hour

Cost of delay **per minute** per mile with project but no CAVs	$145
Cost of delay **per minute** per mile with project and CAVs	$115
Savings	$29
Cost of delay **per minute** per mile with CAVs but no project	$443
Loss	($298)

Sensitivity Analysis

A sensitivity analysis was conducted to better capture the contribution of the original asserted values for key variables in the model, including capacity, trip rates, and land use. The MH scenario was selected for the sensitivity analysis to reflect a more conservative approach for CAV adoption. This analysis focused on both system and project level outputs.

Capacity

Feedback from experts in the field suggests that the anticipated capacity benefits from CAVs may be overly optimistic in this study. To address these concerns, we conducted two levels of sensitivity tests to identify a potential breakpoint where capacity ceases to be the primary influencing factor. **Table E-12** summarizes the capacity adjustment factors for each scenario tested. In the first scenario, labeled as Capacity 1, the capacity benefits are reduced by 50% from the Medium-High scenario. The second scenario serves as an intermediate point between the Medium-High scenario and Capacity 1. This scenario is labeled as Capacity 2.

Table E-12 Capacity Adjustment Factors by Facility Type and Scenario

Facility Type	Base	Medium-High	Capacity 1	Capacity 2
Control Access	0	47%	24%	35%
Signalized	0	40%	20%	30%

Table E-13 to E-19 summarizes the results from this comparison analysis. In all scenarios, the average trip lengths increase compared to the base scenario by a similar amount. Trip lengths tend to get longer as more capacity is added and less congestion occurs on the road. **Table E-15 to E-16** shift the focus to peak period and daily VMT and congested VMT. Both peak period and daily VMT become higher as travelers making longer trips. However, in the Capacity 1 scenario, peak period congested VMT slightly increases compared to the base, where the capacity benefits are halved. This indicates that at this point, the induced demand coming from CAVs outweighs the additional capacity provided by CAVs. Similarly, the system experienced more delay as less capacity is added to each facility type, as illustrated in **Table E-16**. In all scenarios, local and collector roads show higher delay because they don't receive any capacity adjustments. The capacity impacts on project level are shown in **Tables E-17 to E-19**. Like VMT, congested VMT, and delay discussed earlier, as capacity increases, the Demand/Capacity (D/C) ratio and delay decrease.

Table E-13 Average Trip Length in Miles by Home-based Trip Purpose and Scenario

Trip Purpose	Base	Medium-High		Capacity 1		Capacity 2	
	Avg. Trip Length (mi)	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff
K12 trips	6.04	6.26	4%	6.11	1%	6.19	3%
Long duration discretionary trips	8.96	11.49	28%	11.32	26%	11.42	27%
Short duration discretionary trips	4.92	6.34	29%	6.17	25%	6.27	27%
Medical trips	10.11	10.81	7%	10.64	5%	10.74	6%
Shop, dine, other trips	8.39	8.45	31%	10.78	29%	10.90	30%
Work tour – drop off kids K12	6.12	6.41	5%	6.21	2%	6.32	3%
Work tour - interim stop	8.39	10.99	31%	10.78	29%	10.90	30%
Work tour	13.29	14.68	10%	14.48	9%	14.60	10%

Table E-14 Peak Period VMT and Congested VMT by Scenario

Base		Medium-High				Capacity 1				Capacity 2			
VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
19,951,727	3,023,255	23,597,928	18%	1,988,373	-34%	23,011,020	15%	3,094,424	2%	23,325,255	17%	2,693,845	-11%

Table E-15 Daily VMT and Congested VMT by Facility Type and Scenario

Facility Type	Base		Medium-High				Capacity 1				Capacity 2			
	VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
Freeway	36,868,915	6,256,314	45,314,230	23%	3,403,121	-46%	43,174,244	17%	5,895,512	-6%	44,319,252	20%	4,747,785	-24%
ML Highway	3,194,051	371,833	3,870,402	21%	114,679	-69%	3,744,371	17%	246,313	-34%	3,811,058	19%	195,519	-47%
TL Highway	601,669	18,035	629,169	5%	0	-100%	636,919	6%	0	-100%	631,971	5%	0	-100%
Major Arterial	14,372,606	525,916	17,084,034	19%	389,633	-26%	16,821,822	17%	591,981	13%	16,976,215	18%	475,629	-10%
Arterial	22,643,077	515,891	25,405,121	12%	313,466	-39%	25,568,962	13%	481,902	-7%	25,489,281	13%	402,585	-22%
Superstreet	999,943	84,795	1,278,221	28%	65,883	-22%	1,192,969	19%	89,509	6%	1,238,722	24%	81,818	-4%
Major Collector	2,284,146	77,622	2,278,686	0%	74,850	-4%	2,397,159	5%	85,275	10%	2,320,332	2%	76,351	-2%
Collector	5,522,634	104,958	5,587,346	1%	119,483	14%	5,794,552	5%	127,083	21%	5,683,532	3%	123,071	17%
Local	2,020,949	16,559	2,058,798	2%	18,715	13%	2,162,469	7%	19,851	20%	2,097,553	4%	19,509	18%

Table E-16 Daily Delay by Facility Type and Scenario

Facility Type	Base	Medium-High		Capacity 1		Capacity 2	
	Delay (min)	Delay (min)	% Diff	Delay (min)	% Diff	Delay (min)	% Diff
Freeway	110,423	61,731	-44%	93,472	-15%	77,532	-30%
ML Highway	10,921	5,556	-49%	8,496	-22%	6,941	-36%
TL Highway	1,088	381	-65%	710	-35%	520	-52%
Major Arterial	44,480	31,765	-29%	46,507	5%	38,025	-15%
Arterial	46,324	32,803	-29%	45,940	-1%	38,956	-16%
Superstreet	3,669	3,513	-4%	4,350	19%	3,929	7%
Major Collector	7,070	6,559	-7%	7,802	10%	6,986	-1%
Collector	18,594	19,234	3%	21,006	13%	19,991	8%
Local	7,690	9,160	19%	9,792	27%	9,427	23%

Table E-17 I-40 MH Build Project Sensitivity Analysis for Capacity – PM Peak Hour (Project 1)

	Base (Build No CAV)	Build MH CAV	Build MH CAV – Capacity Level 1	Build MH CAV – Capacity Level 2
Capacity (hourly)	12,329	18,124	15,297	16,645
Demand (peak hour)	8,473	10,165	9,813	10,004
D/C	0.69	0.56	0.64	0.60
Daily Delay (min)	1,815	500	1,159	779

Table E-18 US 1 South Build Project Sensitivity Analysis for Capacity – PM Peak Hour (Project 3)

	Base (Build No CAV)	Build MH CAV	Build MH CAV – Capacity Level 1	Build MH CAV – Capacity Level 2
Capacity (hourly)	12,227	18,048	15,225	16,574
Demand (peak hour)	12,555	15,333	14,590	15,037
D/C	1.02	0.85	0.96	0.91
Daily Delay (min)	833	497	772	637

Table E-19 US 1 North Build Project Sensitivity Analysis for Capacity – PM Peak Hour (Project 4)

	Base (Build No CAV)	Build MH CAV	Build MH CAV – Capacity Level 1	Build MH CAV – Capacity Level 2
Capacity (hourly)	13,440	19,393	16,460	17,887
Demand (peak hour)	11,123	13,786	13,222	13,544
D/C	0.83	0.71	0.80	0.76
Daily Delay (min)	506	404	506	447

Trip Rates

Another feedback from the field of experts is that CAVs may have a varying impact on trip generation depending on the trip purpose. Essential travel, such as school and medical trips, is less likely to change simply because travelers own CAVs. Conversely, households with CAVs might make more recreational trips, like shopping and dining, due to the convenience provided by CAVs. Therefore, two levels of sensitivity analysis are conducted to assess whether this variation impacts system and project-level performance.

Table E-20 shows the trip generation adjustment factors for each scenario. The medium-high scenario serves as a reference, with all trip purposes increased by 9% compared to the base scenario. The first scenario, labeled Trip Rate 1, allocates a higher increase (12%) to discretionary and shopping and dining trips, with a smaller increase for the remaining purposes. The second scenario, labeled Trip Rate 2, maintains the same level of essential travel by providing only a 1% adjustment while increasing discretionary and shopping and dining trips by 14%. All three scenarios increase overall trip generation by 9%.

Table E-20 Trip Generation Adjustment Factors by Home-based Trip Purpose and Scenario

Trip Purpose	Medium-High	Trip Rate 1	Trip Rate 2
K12 trips	9%	4%	1%
Long duration discretionary trips	9%	12%	14%
Short duration discretionary trips	9%	12%	14%
Medical trips	9%	4%	1%
Shop, dine, other trips	9%	12%	14%
Work tour – drop off kids K12	9%	4%	1%
Work tour - interim stop	9%	4%	1%
Work tour	9%	4%	1%
Overall	9%	9%	9%

Tables E-21 to E-27 summarize the comparison results. Both trip rate scenarios resulted in similar increases in average trip length, peak hour VMT, and daily VMT compared to the medium-high scenario. As fewer trip generation allocates to essential purposes, scenarios show more reduction in congestion and delay. It indicates that essential travel, especially work-related trips, contributes more to the congestion as they tend to occur within the same period, while recreational trips can spread out through the day and utilize roadway capacity better. The impact of different trip generation allocation on project 1,3, and 4 is minimal. These results suggest that different allocation of trip growth resulting from CAV adoption will not have significant systems level or project level impacts beyond the changes brought on by the presence of CAVs.

Table E-21 Average Trip Length in Miles by Home-based Trip Purpose and Scenario

	Base	Medium-High		Trip Rates 1		Trip Rates 2	
Trip Purpose	**Avg. Trip Length (mi)**	**Avg. Trip Length (mi)**	**% Diff**	**Avg. Trip Length (mi)**	**% Diff**	**Avg. Trip Length (mi)**	**% Diff**
K12 trips	6.04	6.26	4%	6.27	4%	6.28	4%
Long duration discretionary trips	8.96	11.49	28%	11.52	29%	11.52	29%
Short duration discretionary trips	4.92	6.34	29%	6.37	29%	6.38	30%
Medical trips	10.11	10.81	7%	10.82	7%	10.81	7%
Shop, dine, other trips	8.39	8.45	31%	11.00	31%	10.98	31%
Work tour – drop off kids K12	6.12	6.41	5%	6.44	5%	6.45	5%
Work tour - interim stop	8.39	10.99	31%	11.00	31%	10.98	31%
Work tour	13.29	14.68	10%	14.70	11%	14.69	11%

Table E-22 Daily VMT and Congested VMT by Facility Type and Scenario

Facility Type	Base		Medium-High				Trip Rates 1				Trip Rates 2			
	VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
Freeway	36,868,915	6,256,314	45,314,230	23%	3,403,121	-46%	45,219,843	23%	3,370,144	-46%	45,121,986	22%	3,199,238	-49%
ML Highway	3,194,051	371,833	3,870,402	21%	114,679	-69%	3,864,034	21%	114,771	-69%	3,857,758	21%	114,516	-69%
TL Highway	601,669	18,035	629,169	5%	0	-100%	628,535	4%	0	-100%	627,885	4%	0	-100%
Major Arterial	14,372,606	525,916	17,084,034	19%	389,633	-26%	17,041,962	19%	381,231	-28%	16,998,953	18%	370,574	-30%
Arterial	22,643,077	515,891	25,405,121	12%	313,466	-39%	25,318,377	12%	310,049	-40%	25,253,273	12%	298,421	-42%
Superstreet	999,943	84,795	1,278,221	28%	65,883	-22%	1,277,134	28%	65,911	-22%	1,275,548	28%	65,833	-22%
Major Collector	2,284,146	77,622	2,278,686	0%	74,850	-4%	2,274,237	0%	73,182	-6%	2,271,194	-1%	73,133	-6%
Collector	5,522,634	104,958	5,587,346	1%	119,483	14%	5,573,135	1%	117,685	12%	5,563,222	1%	115,954	10%
Local	2,020,949	16,559	2,058,798	2%	18,715	13%	2,052,623	2%	19,155	16%	2,048,335	1%	19,140	16%

Table E-23 Peak Hour VMT and Congested VMT by Scenario

Base		Medium-High				Trip Rates 1				Trip Rates 2			
VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
19,951,727	3,023,255	23,597,928	18%	1,988,373	-34%	23,519,346	18%	1,982,382	-34%	23,428,329	17%	1,926,157	-36%

Table E-24 Daily Delay by Facility Type and Scenario

Facility Type	Base	Medium-High		Trip Rates 1		Trip Rates 2	
	Delay (min)	Delay (min)	% Diff	Delay (min)	% Diff	Delay (min)	% Diff
Freeway	110,423	61,731	-44%	61,025	-45%	60,119	-46%
ML Highway	10,921	5,556	-49%	5,529	-49%	5,475	-50%
TL Highway	1,088	381	-65%	378	-65%	373	-66%
Major Arterial	44,480	31,765	-29%	31,365	-29%	30,896	-31%
Arterial	46,324	32,803	-29%	32,385	-30%	31,953	-31%
Superstreet	3,669	3,513	-4%	3,505	-4%	3,479	-5%
Major Collector	7,070	6,559	-7%	6,494	-8%	6,440	-9%
Collector	18,594	19,234	3%	19,031	2%	18,871	1%
Local	7,690	9,160	19%	9,080	18%	9,023	17%

Table E-25 I-40 MH Build Project Sensitivity Analysis for Trip Rates – PM Peak Hour (Project 1)

	Base (Build No CAV)	Build MH CAV	Build MH CAV – Trip Rates 1	Build MH CAV – Trip Rates 2
Capacity (hourly)	12,329	18,124	18,124	18,124
Demand (peak hour)	8,473	10,165	10,192	10,175
D/C	0.69	0.56	0.56	0.56
Daily Delay (min)	1,815	500	499	494

Table E-26 US 1 South MH Build Project Sensitivity Analysis for Trip Rates – PM Peak Hour (Project 3)

	Base (Build No CAV)	Build MH CAV	Build MH CAV – Trip Rates 1	Build MH CAV – Trip Rates 2
Capacity (hourly)	12,227	18,048	18,048	18,048
Demand (peak hour)	12,555	15,333	15,318	15,256
D/C	1.02	0.85	0.85	0.85
Daily Delay (min)	833	497	491	483

Table E-27 US 1 North MH Build Project Sensitivity Analysis for Trip Rates – PM Peak Hour (Project 4)

	Base (Build No CAV)	Build MH CAV	Build MH CAV – Trip Rates 1	Build MH CAV – Trip Rates 2
Capacity (hourly)	13,440	19,393	19,393	19,393
Demand (peak hour)	11,123	13,786	13,747	13,687
D/C	0.83	0.71	0.71	0.71
Daily Delay (min)	506	404	401	397

Land Use

Based on findings in the literature, the sensitivity test for land use included two separate land use scenarios. The first scenario evaluated the impacts of increased downtown density (Llocra, et al, 2022; Stein, G.M., 2021; Bardaka, et al. 2021; Hummer, J., 2020). This scenario is labeled as Land Use 1. A second scenario focused on an increase in suburban and rural development (Llocra, et al, 2022; Bardaka, et al. 2021). This scenario is labeled as Land Use 2. For both scenarios the regional control totals for households and population remained constant. For Land Use 1, the rural households and population were reduced to account for increases in downtown density. For Land Use 2, the downtown and urban households and population decreased to account for increases in suburban and rural households and population.

Tables E-28 to E-31 summarize the results of this analysis in comparison to the base alternative. Both land use scenarios resulted in increased trip lengths as compared to the base scenario, the increase was like that seen for the medium-high scenario. As with the medium-high scenario, there was a reduction in congested VMT as compared to the base, but slightly less for the land use scenarios. The changes in VMT between the three scenarios was very similar with increases in regional VMT for all. This trend follows for the VMT and congested VMT by facility type, though increases in downtown density resulted in a small decrease in congested VMT for major collectors as compared to the medium-high scenario. The land use pattern that increased suburban and rural household resulted in small decrease in congested VMT for local roads as compared to the medium-high scenario. The impacts to delay were also mostly neutral with no big changes in measured delay by facility type.

The land use impacts to Projects 1, 3 and 4 shown in **Tables E-32 to E-34**, are without consequence in comparison to the medium-high scenario. These results suggest that conservative shifts in land development patterns resulting from CAV adoption will not have the systems level or project level impacts over and above the changes brought on by the presence of CAVs.

Table E-28 Average Trip Length in Miles by Home-based Trip Purpose and Scenario

	Base	Medium-High		Land Use 1		Land Use 2	
Trip Purpose	Avg. Trip Length (mi)	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff	Avg. Trip Length (mi)	% Diff
K12 trips	6.04	6.26	4%	6.26	4%	6.28	4%
Long duration discretionary trips	8.96	11.49	28%	11.49	28%	11.59	29%
Short duration discretionary trips	4.92	6.34	29%	6.35	29%	6.40	30%
Medical trips	10.11	10.81	7%	10.82	7%	10.91	8%
Shop, dine, other trips	8.39	8.45	31%	10.99	31%	11.10	32%
Work tour – drop off kids K12	6.12	6.41	5%	6.42	5%	6.45	5%
Work tour - interim stop	8.39	10.99	31%	10.99	31%	11.10	32%
Work tour	13.29	14.68	10%	14.69	11%	14.80	11%

Table E-29 Daily VMT and Congested VMT by Facility Type and Scenario

Facility Type	Base		Medium-High				Land Use 1				Land Use 2			
	VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
Freeway	36,868,915	6,256,314	45,314,230	23%	3,403,121	-46%	45,363,355	23%	3,465,129	-45%	45,504,530	23%	3,478,506	-44%
ML Highway	3,194,051	371,833	3,870,402	21%	114,679	-69%	3,864,572	21%	115,393	-69%	3,907,996	22%	115,937	-69%
TL Highway	601,669	18,035	629,169	5%	0	-100%	628,963	5%	0	0%	632,886	5%	0	0%
Major Arterial	14,372,606	525,916	17,084,034	19%	389,633	-26%	17,118,305	19%	401,343	-24%	17,128,006	19%	398,604	-24%
Arterial	22,643,077	515,891	25,405,121	12%	313,466	-39%	25,394,685	12%	316,177	-39%	25,728,501	14%	325,480	-37%
Superstreet	999,943	84,795	1,278,221	28%	65,883	-22%	1,280,138	28%	66,033	-22%	1,284,636	28%	65,988	-22%
Major Collector	2,284,146	77,622	2,278,686	0%	74,850	-4%	2,274,807	0%	72,068	-7%	2,306,135	1%	76,169	-2%
Collector	5,522,634	104,958	5,587,346	1%	119,483	14%	5,582,226	1%	119,812	14%	5,651,537	2%	119,636	14%
Local	2,020,949	16,559	2,058,798	2%	18,715	13%	2,057,640	2%	19,415	17%	2,078,421	3%	18,279	10%

Table E-30 Peak Period VMT and Congested VMT by Scenario

Base		Medium-High				Land Use 2				Land Use 2			
VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
19,951,727	3,023,255	23,597,928	18%	1,988,373	-34%	23,627,394	18%	2,044,961	-32%	23,785,306	19%	2,026,823	-33%

Table E-31 Daily Delay by Facility Type and Scenario

Facility Type	Base	Medium-High		Land Use 1		Land Use 2	
	Delay	Delay	% Diff	Delay	% Diff	Delay	% Diff
Freeway	110,423	61,731	-44%	62,513	-43%	62,495	-43%
ML Highway	10,921	5,556	-49%	5,560	-49%	5,721	-48%
TL Highway	1,088	381	-65%	385	-65%	388	-64%
Major Arterial	44,480	31,765	-29%	32,188	-28%	32,081	-28%
Arterial	46,324	32,803	-29%	33,064	-29%	33,595	-27%
Superstreet	3,669	3,513	-4%	3,550	-3%	3,552	-3%
Major Collector	7,070	6,559	-7%	6,522	-8%	6,911	-2%
Collector	18,594	19,234	3%	19,219	3%	19,479	5%
Local	7,690	9,160	19%	9,183	19%	9,203	20%

Table E-32 I-40 MH Build Project Sensitivity Analysis for Land Use – PM Peak Hour (Project 1)

	Base (Build No CAV)	Build MH CAV	Build MH CAV – Land Use 1	Build MH CAV – Land Use 2
Capacity (hourly)	12,329	18,124	18,124	18,124
Demand (peak hour)	8,473	10,165	10,223	10,204
D/C	0.69	0.56	0.56	0.56
Daily Delay (min)	1,815	500	513	508

Table E-33 US 1 South MH Build Project Sensitivity Analysis for Land Use – PM Peak Hour

	Base (Build No CAV)	Build MH CAV	Build MH CAV – Land Use 1	Build MH CAV – Land Use 2
Capacity (hourly)	12,227	18,048	18,048	18,048
Demand (peak hour)	12,555	15,333	15,385	15,322
D/C	1.02	0.85	0.85	0.85
Daily Delay (min)	833	497	506	496

Table E-34 US 1 North MH Build Project Sensitivity Analysis for Land Use – PM Peak Hour

	Base (Build No CAV)	Build MH CAV	Build MH CAV – Land Use 1	Build MH CAV – Land Use 2
Capacity (hourly)	13,440	19,393	19,393	19,393
Demand (peak hour)	11,123	13,786	13,826	13,903
D/C	0.83	0.71	0.71	0.72
Daily Delay (min)	506	404	409	419

Appendix F – Tier 3 NCDOT RTDM

Systems Level Performance Measures

Average Trip Length by Trip Purpose

Table F-1 summarizes the average trip length for home to work, home to other and home to school trips for both HVs and CAVs. All scenarios reflect a 2050 forecast year. The trip lengths were adjusted as documented in the earlier Table 3, but the analysis shows a trip length decrease for all HV trips in both the MH and H scenarios. This is somewhat counterintuitive, and not clear why HV trip lengths would decrease with the increasing presence of CAVs in the traffic stream. The only increase in trip lengths for CAVs is for the work trip purpose. Trip length for other trip purposes made by CAVs decrease for both the MH and H scenarios. Unlike the Triangle region, this region does not experience a great deal of system-wide congestion in 2050, as will be shown in later data summaries. The lower congestion dampens the benefits of the CAV capacity improvements but does not fully explain the decrease in trip lengths. A cursory model design review did not reveal any obvious reason. To fully understand this behavior deep modeling forensics of this model would be required. Such analysis is beyond the scope of this research project.

Table F-1 Average Trip Length in Miles by Home-based Trip Purpose and Scenario (PM Peak Period)

	Base	Medium-High		High	
Trip Purpose	**Avg. Trip Length (mi)**	**Avg. Trip Length (mi)**	**% Diff from Base**	**Avg. Trip Length (mi)**	**% Diff from Base**
Home to work – HV	10.93	8.81	-19.4%	8.58	-21.5%
Home to work – CAV		12.54	14.7%	12.44	13.8%
Home to other – HV	9.17	7.44	-18.9%	7.23	-21.2%
Home to other – CAV		8.90	-2.9%	8.67	-5.5%
Home to school – HV	7.98	7.05	-11.7%	7.13	-10.7%
Home to school – CAV		4.33	-45.7%	4.13	-48.2%

Vehicle Miles Traveled

Table F-2 summarizes the PM peak period VMT and the peak period congested VMT for each scenario. The PM peak period is 3 hours long and covers the period between 3 p.m. and 6 p.m. **Table F-3** reports this same information by facility type. Unexpectedly, but trending with the reduced trip lengths, total VMT decreases slightly for both scenarios. Congested VMT increases slightly, which is an unexpected result, but it’s also important to note that there is very little congested VMT in this region. In this analysis CAVs in the travel stream appear to offer little benefit.

Table F-2 PM Peak Period VMT and Congested VMT by Scenario

Base		**Medium-High**				**High**			
VMT	**Cong. VMT**	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
1,524,190	6,837	1,519,491	-0.3%	6,866	0.4%	1,523,219	-0.1%	6,864	0.4%

There are no VMT nor congested VMT trends by facility type in this region. For most facilities, there is no congested VMT under any scenario. Two lane highways and major collectors see the biggest decline in VMT, but neither facility has any congested VMT. Minor arterials and local streets have a high percentage increase in congested VMT, but the absolute difference is very small. These results may suggest that the benefits of CAVs are not fully realized in regions operating under mostly uncongested conditions.

Table F-3 PM Peak Period VMT and Congested VMT by Facility Type and Scenario

Facility Type	Base		Medium-High				High			
	VMT	Cong. VMT	VMT	% Diff	Cong. VMT	% Diff	VMT	% Diff	Cong. VMT	% Diff
Freeway	78,074	-	77,428	-0.8%	-		77,532	-0.7%	-	
ML Highway	315,895	-	314,159	-0.5%	-		314,378	-0.5%	-	
TL Highway	78,415	-	76,634	-2.3%	-		76,528	-2.4%	-	
Principal Arterial	272,180	244	274,402	0.8%	-		275,742	1.3%	-	
Minor Arterial	192,302	309	194,317	1.0%	549	77.9%	195,262	1.5%	553	79.2%
Major Collector	299,974	-	288,642	-3.8%	-		288,936	-3.7%	-	
Minor Collector	143,309	6,129	146,016	1.9%	6,150	0.3%	146,289	2.1%	6,143	0.2%
Local	144,041	156	147,893	2.7%	167	7.4%	148,552	3.1%	168	7.7%
Total	1,524,190	6,838	1,519,491	-0.3%	6,866	0.4%	1,523,219	-0.1%	6,864	0.4%

Delay

As with congested VMT, most facilities in the Albemarle RPO experience little to no delay in the PM peak period. The slight increase in delay for multilane and two-lane highways seem to suggest that the CAV associated capacity improvements are not sufficient to offset the increased travel resulting from CAVs at both the MH and H scenarios. **Table F-4** summarizes daily delay by facility type and scenario.

Table F-4 Daily Delay by Facility Type and Scenario

Facility Type	Base	Medium-High		High	
	Delay (min)	Delay (min)	% Diff	Delay (min)	% Diff
Freeway	-	-	-	-	-
ML Highway	1,264	1,289	1.9%	1,300	2.8%
TL Highway	4,638	4,841	4.4%	4,963	7.0%
Principal Arterial	602	600	-0.3%	602	-0.1%
Minor Arterial	-	-	-	-	-
Major Collector	-	-	-	-	-
Minor Collector	-	-	-	-	-
Local	-	-	-	-	-
Total	6,504	6,730	3.5%	6,865	5.6%

Project Level Performance Measures

To evaluate changes at a project level, performance measures were summarized for the individual projects described previously.

Project 1 is a widening project for US 158 between NC 34 and NC 168 in Pasquotank County. The facility type is arterial, and the project is approximately 10 miles long.

Project 2 is a widening project for US 17 between US 158 in Pasquotank County and the Virginia State Line in Camden County. The facility type is arterial, and the project is approximately 38 miles long. This project has been segmented into four separate segments to better capture changes in the cross-section along this stretch of highway.

Table F-5 summarizes the project demand and demand to capacity ratio (D/C) for the base 2050 scenario with no CAVs, 2050 with MH CAV adoption, and 2050 H CAV adoption. For Project 1, the presence of CAVs in the MH scenario shows a slight decrease in demand for Project 1, while the H scenario shows an increase in demand. Project 2 shows an increase in demand for both the MH and H scenario. The capacity is more than sufficient for both projects under all scenarios.

Table F-5 Project Level Peak Hour Demand and Demand/Capacity (D/C) by Scenario

Project	Base		Medium-High			High		
	Demand	D/C	Demand	% Diff	D/C	Demand	% Diff	D/C
P1	2,354	0.1	2,308	-2.0%	0.1	2,844	20.8%	0.1
P2								
Segment1	3,130	0.1	3,435	9.7%	0.1	3,363	7.5%	0.1
Segment2	2,355	0.1	2,554	8.4%	0.1	2,501	6.2%	0.1
Segment3	3,199	0.1	3,393	6.1%	0.1	3,343	4.5%	0.1
Segment4	2,079	0.1	2,096	0.8%	0.1	2,080	0.1%	0.1

Project Evaluation

The case study projects were further evaluated under a build condition with and without CAVs, and a no-build condition with CAVs. The focus of this analysis was on trying to determine whether or not the presence of CAVs changes both the supply and demand side of transportation enough to reconsider whether the project should be build, built differently, or delayed. This analysis considers capacity, demand, D/C, and delay for the medium-high (MH) scenario only. Delay is further evaluated using an average wage rate for the county where the project mostly resides. For both Project 1 and Project 2, this is Pasquotank County with an average wage rate of $20.83 (https://www.commerce.nc.gov/north-carolina-county-average-wages).

US 158 (Project 1)

Capacity benefits are realized through the implementation of the US 158 project, and even more capacity benefits are derived from the presence of CAVs, see **Table F-6**. The peak hour demand on the facility is much less than the peak hour capacity, and as such, the D/C and delay are not a concern under any condition. Under higher demand conditions, the increased capacity from the CAVs will provide benefits. An unexpected result is the increase in demand for the no-build CAV scenario. A high-level investigation was conducted to confirm that no errors were made in the model coding and/or execution. A review of the model development documentation indicates that zonal characteristics, including accessibility, are modified prior to execution of the main model components. These characteristics are "utilized for CAV trip estimation and selected trip purposes for the visitor model" (Stantec, 2003). Without in-depth modeling forensics that are beyond the scope of this research project, it is impossible to fully explain the increased demand for the US 158 facility, and in fact most facilities and zonal centroid connectors in the general vicinity of this project. The increased demand for the no-build facility paired with the lower capacity results in increased delay and increased cost of delay as shown in **Table F-7**.

Table F-6 US 158 MH Build and No-Build Project Level Performance Measures – PM Peak Hour

	Build No CAV	Build CAV	No Build CAV
Length (mi)	10.3		
Capacity	16,790	22,740	11,340
Demand (peak hour)	2,354	2,308	2,767
D/C	0.14	0.10	0.24
Delay (min)	0.70	0.67	2.8

Table F-7 US 158 MH Build and No-Build Annual Cost of Delay – PM Peak Hour

Cost of delay per mile with project but no CAVs	$6.10
Cost of delay per mile with project and CAVs	$5.86
Savings	$0.24
Cost of delay per mile with CAVs but no project	$24.51
Loss	($18.41)

US 17 (Project 2)

As with the US 158 project, capacity benefits are realized through the implementation of the US 158 project, and even more capacity benefits are derived from the presence of CAVs, see **Table F-8**. The peak hour demand for all segments of the facility is much less than the peak hour capacity, and as such, the D/C and delay are not a concern under any condition. Under higher demand conditions, the increased capacity from the CAVs will provide more benefits than the project alone.

Regarding delay and the cost of delay, **Table F-9**, the capacity benefits of CAVs alone does not overcome the increase in demand, and while the D/C is still well below congested conditions, some additional delay is still experienced. This leads to a very low increase in the cost of delay with the addition of CAVs in the travel stream.

Table F-8 US 17 MH Build and No-Build Project Level Performance Measures – PM Peak Hour

	Build No CAV	Build CAV	No Build CAV
Segment 1			
Length (mi)	1.01		
Capacity	26,731	34,618	23,064
Demand (peak hour)	3,146	3,435	3,380
D/C	0.1	0.1	0.1
Delay (min)	0.06	0.08	0.12
Segment 2			
Length (mi)	0.46		
Capacity	15,782	20,577	13,711
Demand (peak hour)	2,355	2,554	2,527
D/C	0.1	0.1	0.2
Delay (min)	0.07	0.08	0.14
Segment 3			
Length (mi)	2.8		
Capacity	29,188	38,932	25,904
Demand (peak hour)	3,199	3,393	3,347
D/C	0.1	0.1	0.1
Delay (min)	0.07	0.09	0.14
Segment 4			
Length (mi)	34.0		
Capacity	16,718	22,713	15,141
Demand (peak hour)	2,079	2,096	2,092
D/C	0.1	0.1	0.1
Delay (min)	0.57	0.58	0.99

Table F-9 US 17 MH Build and No-Build Annual Cost of Delay – PM Peak

Cost of delay per mile with project but no CAVs	$22.62
Cost of delay per mile with project and CAVs	$26.17
Loss	($3.55)
Cost of delay per mile with CAVs but no project	$45.65
Loss	($23.03)

Appendix G – Comparison of Tier 1 and Tier 2

In this appendix, we focus solely on comparing the results of the Model Design Changes (Tier 2) to the Existing Model Design (Tier 1). All percentage comparisons are expressed as the relative difference between Tier 2 and Tier 1, calculated as (Tier 2 – Tier 1) / Tier 1 when assessing the effects of CAVs on travel demand models, specifically under various MH scenario types. A detailed summary of these comparisons, including insights into the key differences between these methods, is provided in the main section of the report.

Systems Level Performance Measures

Average Trip Length by Trip Purpose

In the Tier 2 analysis, adjustments were made to the travel time coefficients within the destination choice model for work tours, long duration discretionary trips, and shop, dine, other trips. These modifications led to longer average trip lengths compared to Tier 1, see **Table G-1**. For example, shop, dine, other trips exhibited an 18.58% increase in trip length, long duration discretionary trips increased by 18.28%, and work tours experienced a 7.29% increase. These changes reflect a more refined recalibration of the model in Tier 2, aiming to better capture the effects of CAVs on travel behavior. In contrast, coefficients for K12 trips, medical trips, and short duration discretionary trips remained unchanged between the two tiers. As a result, the differences in average trip lengths for these purposes were minimal, with K12 trips showing a slight decrease of -0.64%, medical trips with a -0.09% change, and short duration discretionary trips seeing a modest increase of 1.26%. These minimal differences suggest that these trip purposes were less affected by the model adjustments between Tier 1 and Tier 2.

Table G-1 Average Trip Length in Miles by Home-based Trip Purpose

Trip Purpose	Avg. Trip Length (mi)		
	Tier 1	Tier 2	% Diff
K12 trips	6.30	6.26	-0.64%
Long duration discretionary trips	9.39	11.49	18.28%
Short duration discretionary trips	6.26	6.34	1.26%
Medical trips	10.82	10.81	-0.09%
Shop, dine, other trips	6.88	8.45	18.58%
Work tour – drop off kids K12	6.46	6.41	-0.78%
Work tour - interim stop	8.82	10.99	19.75%
Work tour	13.61	14.68	7.29%

Vehicle Miles Traveled

A comparison of VMT is provided in **Table G-2** and **Table G-3**. In the Tier 2 analysis, additional travel demand factors, including CAV empty parking trips, airport parking trips, and empty sCAV trips, were incorporated. These factors led to higher VMT and greater delays across the network. As a result, VMT increased significantly across various facility types. For example, ML Highway saw a 6.52% rise in VMT, Freeway experienced a 5.49% increase, and Major Arterial showed a 5.16% rise compared to Tier 1.

Similarly, Congested VMT also surged, with Freeway experiencing a substantial 44.51% increase and Major Arterials a 23.22% rise. During the peak period, these trends continued, with overall VMT increasing by 2.43% and Congested VMT rising sharply by 23.25%. These results underscore the impact of the additional demand in Tier 2, particularly due to CAV and sCAV dynamics, which led to higher traffic volumes and congestion levels, especially on heavily utilized facilities such as Freeway and Major Arterial.

Table G-2 Daily VMT and Congested VMT by Facility Type

Facility Type	VMT			Cong. VMT		
	Tier 1	Tier 2	% Diff	Tier 1	Tier 2	% Diff
Freeway	42,825,329	45,314,230	5.81%	1,888,472	3,403,121	80.21%
ML Highway	3,618,003	3,870,402	6.98%	96,116	114,679	19.31%
TL Highway	614,287	629,169	2.42%	0	0	-
Major Arterial	16,202,527	17,084,034	5.44%	299,152	389,633	30.25%
Arterial	24,417,203	25,405,121	4.05%	269,205	313,466	16.44%
Superstreet	1,231,226	1,278,221	3.82%	58,379	65,883	12.85%
Major Collector	2,245,386	2,278,686	1.48%	57,763	74,850	29.58%
Collector	5,467,283	5,587,346	2.20%	110,914	119,483	7.73%
Local	2,000,862	2,058,798	2.90%	16,819	18,715	11.27%
Total	98,622,106	103,506,007	4.95%	2,796,820	4,499,830	60.89%

Table G-3 Peak Period VMT and Congested VMT

VMT			Cong. VMT		
Tier 1	Tier 2	% Diff	Tier 1	Tier 2	% Diff
22,575,659	23,138,507	2.43%	1,526,009	1,988,373	23.25%

Delay

Again, additional demand in the Tier 2 analysis, including CAV empty parking trips, airport parking trips, and empty sCAV trips, resulted in higher VMT and greater delay, with delay following a similar trend to Congested VMT, as both experienced substantial increases across various facility types. Results are summarized in **Table G-4**.

Table G-4 Daily Delay by Facility Type

Facility Type	Daily Delay (min)		
	Tier 1	Tier 2	% Diff
Freeway	43,676	61,731	41.34%
ML Highway	4,626	5,556	20.10%
TL Highway	352	381	8.24%
Major Arterial	25,678	31,765	23.71%
Arterial	28,382	32,803	15.58%
Superstreet	2,960	3,513	18.68%
Major Collector	6,170	6,559	6.30%
Collector	18,151	19,234	5.97%
Local	7,655	9,160	19.66%
Total	137,650	170,702	24.01%

Project Level Performance Measures

Different demand rates impact project-level results like system-level results, with both experiencing comparable shifts in metrics such as demand, D/C, and delay because of varying demand, see **Table G-5**.

Table G-5 Project Level Peak Hour Demand and Demand/Capacity (D/C)

Project	Demand			D/C		
	Tier 1	Tier 2	% Diff	Tier 1	Tier 2	% Diff
P1	9,519	10,165	6.36%	0.53	0.56	5.36%
P2	2,636	2,844	7.31%	0.14	0.15	6.67%
P3	14,845	15,333	3.18%	0.82	0.85	3.53%
P4	13,105	13,786	4.94%	0.68	0.71	4.23%
P5	3,710	4,199	11.65%	0.48	0.55	12.73%
P6	2,683	2,675	-0.30%	0.37	0.37	0.00%
P7	1,085	1,078	-0.65%	0.29	0.29	0.00%
	449	460	2.39%	0.06	0.06	0.00%
	1,227	1,225	-0.16%	0.33	0.33	0.00%

Project Evaluation

The project level evaluation results are summarized in **Tables G-6 to G-11**. Under the build and no-build scenarios the question is whether the two different approaches yield different results with respect to decision making about whether to build or delay a specific project. For Projects 1 and 3 the D/C results between the two tiers is very similar. The no-build Tier 2 D/C for Project 4 is much higher (1.36) than that for Tier 1 (1.04). Both suggest the need for the project, even with a MH CAV adoption, but the higher demand generated with the more behaviorally realistic model design changes show an even greater need for the project. These results indicate the benefit of either approach for evaluating the impacts of CAVs on project level traffic forecasts, with perhaps a greater need for conducting sensitivity, e.g. risk and uncertainly analysis for the Tier 1 applications.

I-40 (Project 1)

Table G-6 I-40 MH Build and No-Build Project Level Performance Measures – PM Peak Hour

Performance Measure	Build MH CAV			No Build MH CAV		
	Tier 1	Tier 2	% Diff	Tier 1	Tier 2	% Diff
Capacity	18,124	18,124	0.00%	12,083	12,083	0.00%
Demand (peak hour)	9,519	10,165	6.36%	9,270	9,891	6.28%
D/C	0.53	0.56	5.36%	0.77	0.82	6.10%
Daily Delay (min)	389	500	22.20%	1,749	2,223	21.32%

Table G-7 I-40 MH Build and No-Build Annual Cost of Delay

	Tier 1	Tier 2	% Diff
Cost of delay per mile with project but no CAVs	$56.94	$114	50.05%
Cost of delay per mile with project and CAVs	$12.20	$31	60.65%
Savings	$44.74	$82	45.44%
Cost of delay per mile with CAVs but no project	$54.87	$139	60.53%
Loss	$(2.07)	($26)	92.04%

US 1 South of Cary (Project 3)

Table G-8 US 1 South MH Build and No-Build Project Level Performance Measures – PM Peak Hour

Performance Measure	Build MH CAV			No Build MH CAV		
	Tier 1	Tier 2	% Diff	Tier 1	Tier 2	% Diff
Capacity	18,048	18,048	0.00%	12,032	12,032	0.00%
Demand (peak hour)	14,845	15,333	3.18%	13,963	14,458	3.42%
D/C	0.82	0.85	3.53%	1.16	1.20	3.33%
Daily Delay (min)	449	497	9.66%	1,712	1,823	6.09%

Table G-9 US 1 South MH Build and No-Build Annual Cost of Delay

	Tier 1	Tier 2	% Diff
Cost of delay per mile with project but no CAVs	$73.72	$147	49.85%
Cost of delay per mile with project and CAVs	$39.73	$88	54.85%
Savings	$34.00	$59	42.37%
Cost of delay per mile with CAVs but no project	$151.47	$322	52.96%
Loss	$(77.75)	($175)	55.57%

US 1 North (Project 4)

Table G-10 US 1 North MH Build and No-Build Project Level Performance Measures – PM Peak Hour

Performance Measure	Build MH CAV			No Build MH CAV		
	Tier 1	Tier 2	% Diff	Tier 1	Tier 2	% Diff
Capacity	19,393	19,393	0.00%	9,297	9,297	0.00%
Demand (peak hour)	13,105	13,786	4.94%	9,692	12,635	23.29%
D/C	0.68	0.71	4.23%	1.04	1.36	23.53%
Daily Delay (min)	367	404	9.16%	1,492	3077	51.51%

Table G-11 US 1 North MH Build and No-Build Annual Cost of Delay

	Tier 1	Tier 2	% Diff
Cost of delay per mile with project but no CAVs	$72.63	$145	49.91%
Cost of delay per mile with project and CAVs	$52.64	$115	54.23%
Savings	$19.98	$29	31.10%
Cost of delay per mile with CAVs but no project	$214.02	$443	51.69%
Loss	$(141.39)	($298)	52.55%