ANTICIPATING THE REGIONAL IMPACTS OF CONNECTED AND AUTOMATED VEHICLE TRAVEL IN AUSTIN, TEXAS

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ABSTRACT

Automated vehicles are undergoing development at an incredible speed and have potential to revolutionize the existing transportation system. The paper investigates the impacts of connected automated vehicles (CAVs) and shared automated vehicles (SAVs) using a conventional travel demand model for the Austin, Texas region. A series of eight test scenarios on the year 2020 setting suggests that the introduction of CAVs and SAVs will add 20 percent or more demand for new vehicle-miles traveled (VMT) to the 6-county region's roadway network. Relatively low values of travel time for passengers of automated vehicles and relatively competitive pricing assumptions of SAV use result in greater demand for longer distance travel and less transit system use. Empty-vehicle travel for self-parking and SAVs will add even further to the network's VMT, presumably increasing roadway congestion further, unless rides can be shared, traffic flows can be smoothed, and inter-vehicle headways tightened. The scenario simulations are sensitive to parking cost and vehicle operating cost assumptions. Policy makers, transportation planners, systems operators and designers may do well to simulate additional scenarios.

Key Words: travel demand modeling, connected and autonomous vehicles, shared autonomous vehicles, travel behavior

INTRODUCTION

Advanced transportation technologies, including connected vehicles (CVs), automated vehicles (AVs), and connected autonomous vehicles (CAVs), are undergoing development at an incredible speed. CAVs, which incorporate the advantages of CVs and AVs, have the potential to revolutionize the existing transportation system. One of the most significant benefits CAVs offer is a more pleasant travel experience for drivers, effectively reducing their value of travel time

(VOTT). VOTT is defined as an individual's willingness to pay to avoid another hour of travel. If an individual is able to both reduce stress and increase productivity while traveling, by becoming a passenger, rather than being forced to maintain focus on driving, his/her VOTT falls. This makes CAVs relatively attractive for current drivers, if not for current passengers. Moreover, many believe CAVs will eventually increase lane and roadway capacity by reacting faster to changes in preceding vehicles' speeds and positions (via dedicated short-ranage communications (DSRC), cameras, light-detecting and radio-detecting and ranging devices). Technical competence and rising confidence in CAV response times can lead to shorter following distances and headways between vehicles. Parking costs for CAVs may also fall, since AVs may be able to drop off their passengers and seek lower-cost parking elsewhere, or otherwise serve someone else's trip-making needs (as in the case of shared autonomous vehicles [SAVs] or a privately-owned CAV that is sent to another household member, for his/her trip).

SAVs are self-driving taxis, and so carry no driver costs. They can be "shared" as a rental fleet, and are likely to be quite cost competitive (as shown in Fagnant and Kockelman [2015], Chen et al. [2016], and Chen and Kockelman [2016]). Like taxis and buses, SAVs are a form of public transportation, and may be operated by public transit operators, such as a regional transit authority (e.g., CapMetro in Austin, TX), or private entities, like Lyft and Uber. Although SAV use may be more costly than buses, they can provide on-demand, door-to-door, and lower-occupant services. SAV users will benefit from more flexible schedules and pickup/dropoff locations, shorter waiting times, privacy, and possibly greater comfort.

This paper uses regional travel demand models to evaluate the system benefit brought by CAVs and SAVs. Travel demand models currently in use by most MPOs, DOTs, and their consultants are not set up to investigate the potential traffic impacts of CAVs and SAVs, though such vehicles are expected to be quite common over the next 20 to 30 years (Gulipalli and Kockelman 2015). Long-range city, regional, state, and national transportation planning activities should work to reflect the tremendous technological changes expected in the transportation sector, via self-driving vehicles (shared and private, passenger and freight, short-distance and long-distance). To this end, this study investigated how to best modify an existing, trip-based travel demand model in use in Texas, for the Austin region, to illustrate how MPOs and DOTs can start to account for CAVs' travel demand and traffic impacts. Such behavioral changes also affect emissions and air quality, crash counts, noise levels, goods delivery and product prices. Given the uncertainty surrounding CAVs' effects on behavior and travel costs, multiple model scenarios were developed to illuminate a range of possible transportation system futures for the Austin region. These scenarios vary the VOTTs, parking costs, headways, and other important travel choice factors. While these are initial rough estimates, they are still useful for transportation and urban system planners and decision-makers, when charting a course for future investments and policies. The methods applied should also prove useful to travel demand modelers and planners.

The following section discusses existing literature on the travel demand effects of AVs, CVs, CAVs, and SAVs, and several proposed frameworks to anticipate their transportation system impacts. Subsequent sections include key modeling assumptions (e.g., preference for using CAVs and SAVs due to the reduction of travel time disutility) and methods (e.g., modification of the existing models to consider the impacts of CAVs and SAVs) used here. This memorandum then presents around 30 model scenarios to forecast the traffic impacts of CAVs and SAVs on

Austin's year 2020 networks, under different assumption scenarios. The memo concludes with recommendations and suggestions for modeling extensions.

LITERATURE REVIEW

With the advent of CAVs, researchers and planners are investigating their potential travel-demand and traffic impacts, using existing travel demand modeling methods, including trip-based models and activity-based models. Spieser et al. (2014) specified a new transportation system for Singapore by replacing all modes of personal transportation with a fleet of SAVs. Their results suggest that the new system can meet personal travel needs while reducing the number of passenger vehicles currently in operation by about 67 percent. Researchers at the International Transport Forum (ITF 2015) examined the potential traffic impacts of widespread use of an SAV fleet in Lisbon, Portugal, a mid-sized European city. They explored the implementation of what they call "TaxiBot" (an AV shared by multiple passengers simultaneously, or a mini-bus SAV with ride-sharing) and AutoVot (an SAV that can pick up and drop off individual travel parties or passengers sequentially). Their findings suggest that such services can meet travelers' needs while reducing private vehicle ownership by 80 percent, although VMT also rose. The reduced parking needs as a result of this SAV fleet implementation would free up significant public and private space.

Childress et al. (2015) examined CAVs' potential outcomes by using the Seattle region's (PSRC MPO's) activity-based model. CAVs were assumed to follow more tightly, thus increasing roadway capacity, but also cost more, and so increase operating costs. They reduced VOTT and parking costs for those choosing the CAV mode. Their scenario results indicated that improvements in roadway capacity and travel utilities will result in noticeable increases in VMT and VHT, although higher ownership and operating costs for CAVs and SAVs, respectively, somewhat counteract such trends.

Kim et al. (2015) analyzed the availability of AVs across the Atlanta, Georgia region, using the MPO's (ARC's) existing activity-based model. They assumed increases in roadway capacity, lower VOTT, lower parking costs, and 100-percent market penetration of the new technology (so no conventional vehicles in the mix). Their findings suggested that Atlanta travelers will make longer trips, on average, relative to the status quo or business as usual scenario (without CAV technology), due to a reduction in VOTT, resulting in increases in both VMT and VHT. However, their models predicted that annual delay per person would fall, due to higher speed travel across the network. Fagnant et al. (2015) anticipated the traffic impacts of SAVs for Austin's 12 mi x 24 mi core using the real network, and microsimulations of travelers and vehicles; but used fixed travel times (as used in all other micro-simulations for SAV fleets). Their results suggested that one SAV can replace about 8 conventional vehicles with low wait times, on average, and while meeting current passenger-travel demands across that 288 sq mi region. Chen et al. (2016) and Chen and Kockelman (2016) micro-simulated a much larger (100 mi x 100 mi) region, with a gridded network (and fixed travel times). In some model applications, they allowed for non-SAV mode choices and used the Austin region's trip tables; they estimated strong mode splits for the SAV choice and vehicle replacement rates of about 7 to 1, even though there were many long-distance trips to serve in their simulations. Their battery-only electric vehicle simulations of these settings suggest lower replacement rates, due to long charge times and longer travel to reach a network of charging stations (vs. gasoline vehicle refueling times and gas-station locations)

Many aspects of the travel choice and traffic impacts remain to be examined. Most travel models track trip-makers, not vehicles. They are aggregate in space (with traffic analysis zones) and in time (with multi-hour times of day) and do not allow empty-vehicle driving, shared vehicles, or dynamic (real-time) ride-sharing. They are not designed to anticipate CAVs' impacts. Additionally, many modelers are already assuming that capacities rise notably, but such changes can only be obtained after manufacturers feel confident using their vehicles with tight headways, and passengers and traffic managers are comfortable with such operations. This work takes a traditional trip-based "four-step" model for the Austin region, and changes many key parameters and sub-model specifications to introduce new modes (private CAVs and shared AVs), with and without capacity changes, to get an initial sense of how travelers and network conditions may respond. Road pricing is also tested, to get a sense of how flexible the behavioral models are in response to such travel demand management techniques.

CASE STUDY

A case study of Austin, TX is presented here, with the travel demand model data from the Capital Area Metropolitan Planning Organization (CAMPO). The original CAMPO model is not designed to study the CAVs so the modeling process has been modified. Specifically the trip distribution step's gravity model has been replaced with a destination choice model to accommodate the redistribution of the trips after introducing the CAVs and SAVs. The model was implemented in TransCAD and its details are described as follows.

TAZs and Network

The CAMPO travel demand model covers the greater Austin area's 6 counties, with 2,258 traffic analysis zones (TAZs). Figure 1 illustrates this zoning structure. The highway network contains 21,738 links and 14,634 nodes.

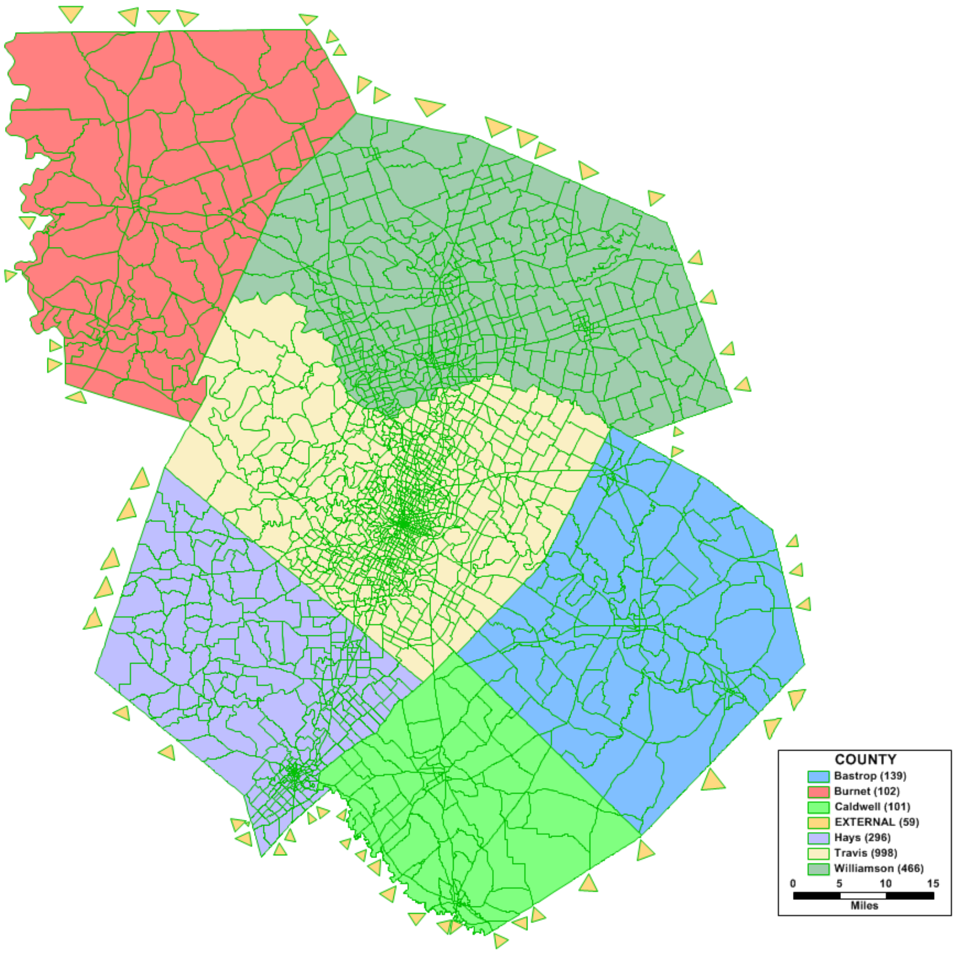

FIGURE 1 TAZ system for CAMPO region.
(Source: CAMPO 2015)

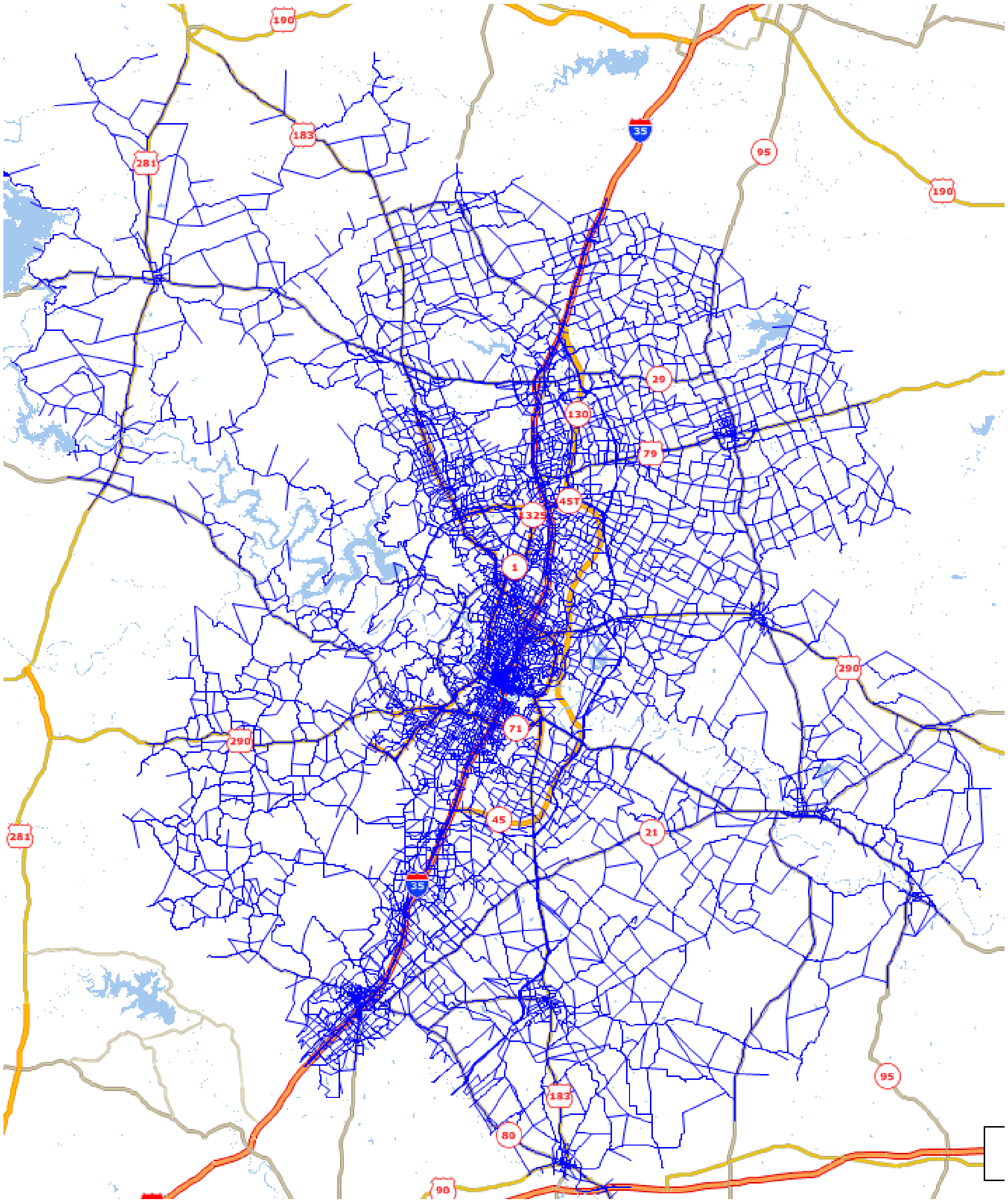

FIGURE 2 CAMPO model network.

Trip Generation

The CAMPO model uses a cross-classification model for generation of 13 trip types/purposes, using household size and income as the classification variables. Trip attractions are based on a cross-classification of demographic and employment data by area type. All trips are balanced to production except the higher education trips (mainly University of Texas trips) are balanced to attractions. Since this step is not sensitive to travel times and costs, total trip productions and attractions, by TAZ, were assumed fixed in this study.

Trip Distribution

The CAMPO model uses a gravity model for trip distribution. The impedance variable in this model is based on the highway's congested travel time, which does not reflect other modes' travel characteristics. Therefore, this study replaced the gravity model with a multinomial logit (MNL) model for destination choice, using Table 1's parameter values and where the logsum is a measure of overall access across available modes, from any specific origin to any specific destination TAZ. The parameters of this logsum come from Table 2's mode choice parameters, interacted with travel time and travel costs for each mode, between each OD pair. Please note that using the destination choice model only constrains on the production side.

Table 1 Destination Choice Model Parameters

Variable	Parameter
Zonal Average Parking Cost	-0.0166
Logsum	0.855

Mode Choice Model

Instead of using CAMPO's rather complex and nested MNL model for 20+ mode combinations (e.g., kiss-and-ride or walk or bike to a transit stop), a simplified model of mode choice is used here. Figure 3's MNL model of four competing alternatives (Auto, CAV, SAV and BUS) provides greater transparency in the model application process. Parameter assumptions come from a combination of the CAMPO model (CAMPO 2015) and NCHRP Report 716 (Cambridge Systematics et al. 2012).

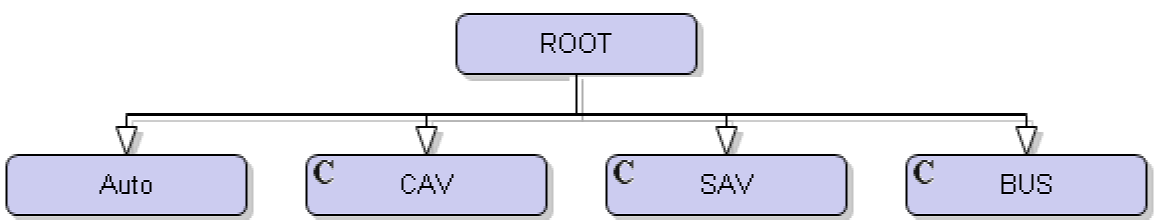

FIGURE 3 Mode choice model structure

The model specification is shown in Table 2. Note that the time and cost coefficients of each mode also suggested a value of time.

Table 2 Multinomial Logit Model Parameters in the Scenarios

Variables	Auto	CAV	SAV	Bus
Constant		-0.05	-0.2	-2.8
In-vehicle Time	-0.019	-0.095	-0.095	-0.019
Operating costs	-0.072	-0.072	-0.072	-0.14

Implied VOTT ($/hr)	$15.83	$7.92	$7.92	$8.14

Time-of-Day Model

The daily trip tables from previous steps were disaggregated into four time periods, as defined in Table 3. To create the time period trip table, the daily trip table was first disaggregated in to hourly table based on hourly traffic data. Then the hourly trip tables were summarized into the four time periods. The final assignments use only the AM peak trip tables.

Table 2 CAMPO Model Time of Day Periods Definition

Period	Hours
AM Peak (AM)	6:00 am to 9:00 am (3 Hours)
Mid-Day (MD)	9:00 am to 3:30 pm (6.5 hours)
PM Peak (PM)	3:30 pm to 6:30 pm (3 hours)
Night (NT)	6:30 pm to 6:00 am (11.5 hours)

Traffic Assignment

Finally, a multi-modal multi-class traffic assignment was carried out for the region's four modes: traditional automobile, CAV, SAV, and commercial trucks. The transit buses were preloaded onto the network since they are rather fixed based on routes and schedule.

Travel Cost Feedback

Feedback of congested travel time information was used here, in the trip distribution step, over 10 iterations per scenario. This is consistent with the current CAMPO feedback settings, and typically reaches reasonable relative gaps.

Sensitivity Test Results

Economists and others are likely to argue that the most significant advantage of electing to ride in CAVs and SAVs is the reduction in the perceived travel-time burden (at least for former drivers). While en route, those who previously drove can instead perform other activities (like working, resting, making phone calls, and interacting very directly with other vehicle occupants), thus decreasing the perceived disutility of their travel time. This situation provides reduction in the effective VOTT, which is the willingness to pay to save on one's travel time (Litman, 2014).

Here, a pre-technology base-case scenario offers trip-makers only two modes: automobile and bus. The other 7 scenarios offer CAVs as privately owned vehicle options (at relatively high monetary cost, but lowered perceived travel time burden) and SAVs as shared AV options (at relatively competitive monetary cost and lowered travel time burden). CAVs' and SAVs' VOTT parameters were set to be 25%, 50%, and 75% of those for conventional vehicles, as shown in Table 2. In reality, many conventional vehicle users are occupants, rather than drivers, so they probably will not experience any benefits of reduced travel burden, from being in an AV. However, they may ultimately perceive that AVs offer a safer ride, and/or a more enjoyable ride, where they can interact more naturally with whoever was previously driving; those kinds of perceived benefits can also bring down the VOTT.

Parking costs can also be lowered by the arrival of CAVs and SAVs. Users can send their CAVs to lower-cost parking lots, although this practice will generate extra VMT. SAVs generally will not be required to park in space-constrained locations (but can use local on-street and off-street parking areas, for temporary storage, as needed). SAVs can relocate to serve other customers, or find low-cost storage locations when demand is low. Therefore, the parking costs of SAVs are set here to zero, for their users (though fleet operators may have storage costs, and this can be wrapped into the per-mile or per-trip prices incurred by users), and CAV parking costs are assumed to be 100%, 50%, and 0% of conventional vehicles' parking costs, since it is not known whether privately-held CAVs will be allowed to travel empty to find low-cost parking.

In terms of operating costs, the American Automobile Association (AAA 2015) estimates the full cost of conventional vehicle ownership and operation to be about \$0.60/mile, recognizing depreciation, insurance, maintenance, and operations and assuming 15,000 vehicle-miles per year in travel. Since CAVs will cost more, their full ownership and operating costs are generally assumed to be \$1.00/mile here. Similarly, SAVs' operation costs are assumed to be \$1.50/mile under most scenarios. The results of different combinations of CAV and SAV operation costs were simulated here, as listed in Table 4.

Table 4 Scenario assumptions on key parameters (relative to base-case/no-AV scenario)

Scenario	VOTTs of those in CAVs & SAVs, as a % of current VOTT	Parking costs of CAVs, as % of conventional parking costs	CAV operating costs (\$/mile)	SAV operating costs (\$/mile)
1	50%	100%	1	1.5
2	25%	100%	1	1.5
3	75%	100%	1	1.5
4	50%	50%	1	1.5
5	50%	0%	1	1.5
6	50%	100%	1	1
7	50%	100%	1.5	1.5

Model Results

Table 5 presents regional VMT forecasts across different vehicle types, including automobiles (i.e., conventional vehicles), CAVs and SAVs. Truck and bus traffic remain separate from the above modes and so are excluded from the table.

In comparing this base case scenario's results, where only auto and bus modes are available to travelers, to all other scenarios, with CAV and SAV alternatives, results in over 20% more vehicle-miles traveled (VMT), during the AM peak.

Table 3 Regional VMT forecasts during AM peak period

Scenario	Parameter value assumptions				VMT per day			% Base Case	% Change relative to Scenario 1 values		
	VOTTs of CAVs & SAVs (as %of Auto)	Parking costs of CAVs as % of Auto	Operating costs of CAVs ($/mile)	Operating costs of SAVs ($/mile)	Auto	CAV	SAV		Auto	CAV	SAV
Base					5,823,350 mi	-	-				
1	50%	100%	$1/mi	$1.5/mi	1,562,157	3,926,846	1,820,202	126%			
2	25%	100%	1	1.5	803,487	5,116,016	2,298,955	141%	51.4%	130.3%	126.3%
3	75%	100%	1	1.5	2,212,197	3,149,242	1,488,724	118%	141.6%	80.2%	81.8%
4	50%	50%	1	1.5	1,561,185	3,931,598	1,817,080	126%	99.9%	100.1%	99.8%
5	50%	0%	1	1.5	1,560,335	3,937,089	1,814,158	126%	99.9%	100.3%	99.7%
6	50%	100%	1	1	1,478,870	3,805,329	2,181,801	128%	94.7%	96.9%	119.9%
7	50%	100%	1.5	1.5	1,751,416	3,660,881	2,099,617	129%	112.1%	93.2%	115.4%

The implementation of CAVs and SAVs is predicted to move car-owners from conventional vehicles to AVs, assuming they would enjoy the in-vehicle time and reduce their VOTTs. Scenario 2 suggests that if the VOTTs of AVs are reduced to 25% of autos, about 50% additional auto traffic will shift to AVs, compared to Scenario 1 where VOTTs of AVs are 50% of autos. On the other hand, if the VOTTs of AVs are 75% of autos, as shown in Scenario 3, auto traffic will obtain about 40% from AVs. These tests suggest that how people evaluate their in-vehicle travel time in the AVs is the key for the shifts between autos and AVs. That is, the comfort, convenience, and safety of the AVs are important to travelers to spend even more time on the AVs.

Parking costs appear to be a good traffic management tool to control AVs, assuming that CAVs can find lower-cost parking lots away from their destinations and that SAVs will not need any paid parking. Scenarios 4 and 5 assume parking costs of CAVs will be half that of conventional vehicles autos, and potentially even free, resulting in a marginal increase on CAV VMTs. However, since parking is only not free in downtown areas in most cities in Texas (and the U.S.), it is necessary to take a close look at Austin's CBD parking costs, as shown in Figure 4. This downtown area's model results for Scenarios 1, 4, and 5 are shown in Table 6. When CAVs' parking costs are assumed to be half the cost of storing regular automobiles (due to self-parking in lower-cost locations, away from the actual destination), the model predicts a roughly 4% increase in CAVs' VMT or use; and, when CAV parking carries zero cost, the increase is about 8%, versus the scenerious where CAV parking costs equal those of conventional automobiles. Of course, CAV self-parking does carry other costs, that are not simulated here: driving to a new location, to park at low or zero cost, carries operating costs, as well as added system VMT that is neglected here. Unfortunately, conventional models of travel demand are not designed to accommodate self-driving or shared vehicles: essentially, vehicles become travelers in their own right. Shared vehicles also pick new destinations and routes in a very dynamic way, so agent-based simulation (as done in Fagnant et al. 2015, Chen et al. 2016, Loeb et al. 2016, Liu et al. 2016, and other papers) is the best way to reflect such settings, but is much more computationally intensive than various approximate modifications to existing software packages, like TransCAD.

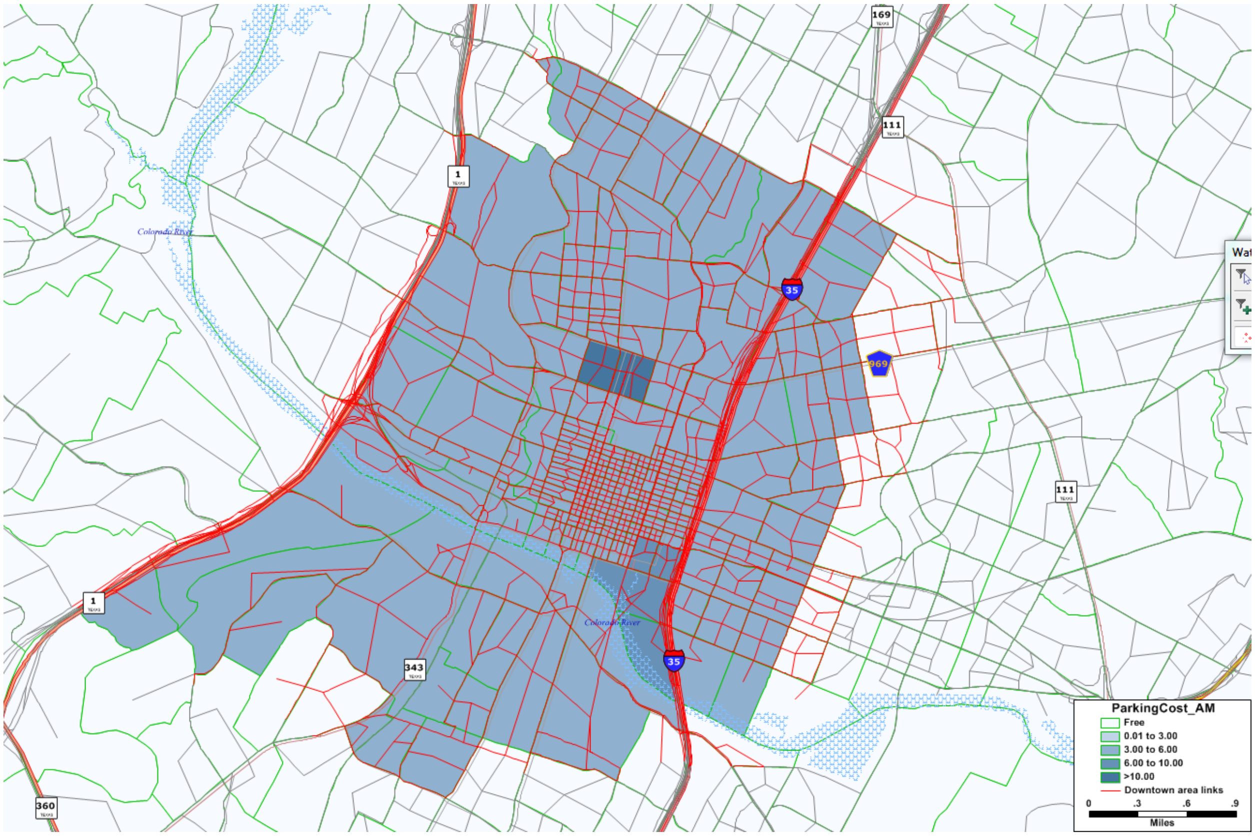

FIGURE 4 Map of downtown Austin with AM period parking costs

TABLE 6 Downtown Austin VMT during AM Peak Period

Scenario	Downtown Austin VMT			% Change, relative to Scenario 1		
	Auto	CAV	SAV	Auto	CAV	SAV
1	22,288	71,850	46,525	N/A	N/A	N/A
4	21,532	74,751	44,451	96.6%	104.0%	95.5%
5	20,736	77,596	42,304	93.0%	108.0%	90.9%

Finally, AVs' assumed operating costs play an important role in travelers' choices, as shownin Table 6. For example, when SAVs' operating costs (as perceived by the users) fall to that of CAVs (about $1/mile, which is still higher than a standard automobile's assumed $0.6/mile), VMT levels by SAV are predicted to rise 20%, relative to the $1.5-per-SAV-mile scenario. However, if CAVs' operating costs are increased from $1/mile to $1.5/mile (reaching SAVs' same cost level), CAV VMT values are predicted to fall about 7%.

CONCLUSIONS AND FUTURE WORK

This study illustrates potential traffic impacts of CAVs and SAVs on regional metropolitan areas, using a case study of Austin, Texas and the regional travel demand model. The model results suggest that with reduced VOTTs, operating costs, and parking costs, more travelers will choose AVs over the conventional vehicles and buses, resulting in more than a 20% rise in VMT around the region, with associated congestion delays. The sensitivity analysis of the different assumptions of VOTT, operating costs, and parking costs indicated significant impacts arising from the use of AVs and SAVs.

If people want to embrace advanced transportation technologies without increasing current traffic congestion, dynamic ride-sharing would be a feasible alternative for the local DOT. The exact impacts of dynamic ride-sharing, however, are difficult to investigate in the regional travel demand model, particularly based on the trip-based model. The traditional travel demand model also cannot directly model the travel of AVs when there are no passengers in the vehicles, such as when CAVs look for parking lots and SAVs drive emptily.

More advanced travel demand modeling, such as activity-based and agent-based modeling, should be developed. For future work, the research team recommends adding a vehicle ownership model to the travel demand model to evaluate the impacts of CAVs and SAVs. Creating and analyzing more scenarios will help us understand how CAVs and SAVs will increase the network burden and bring heavier traffic congestion. The activity-based model has other benefits, such as a disaggregate level of travel behavior, compared with the trip-based model. Further exploration of the activity-based model would present another interesting aspect for future work. Toll policy may play a role in controlling the total VMT and VHT, which, in turn, may reduce traffic congestion. Increasing operating costs may also make carpooling a more attractive alternative for travelers who want to minimize their travel costs.

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