IMPACT OF AUTONOMOUS VEHICLES ON LONG-DISTANCE TRAVEL MODE AND DESTINATION CHOICE IN TEXAS

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ABSTRACT

Privately owned and shared autonomous passenger vehicles (AVs and SAVs) and automated heavy-duty trucks (ATrucks) are expected to one day be widely available across the US and other nations. This study extends Texas' Statewide Analysis Model (SAM) to compare scenarios with and without AVs, SAVs, and ATrucks. Results suggest that, on average, individuals are likely to choose more remote destinations, as seen by an 18% rise in average trip length of long-distance (50-400 miles) business travel (from 121 to 142 miles) and 13% for non-business travel (135 to 151 miles). AVs and SAVs collectively accounted for 14% of one-person long-distance trips across Texas, contributing to a 17 percentage-point reduction in trips over 50 miles made by human-driven vehicles. For trips between 50 to 400 miles, SAVs carrying 3+ passengers accounted for 14.4% of the total 310 million person-miles traveled, two-passenger SAVs made up 7.8%, and one-person AV trips represented 10.7%. In the freight sector, ATrucks were the preferred mode, handling 35% of freight ton-miles, surpassing rail at 24% and human-driven trucks at 16% (vs 52% and 33% via HTrucks and rail, respectively, before the inclusion of ATrucks). Results suggest serious congestion issues if travel demand management measures are not implemented, with statewide daily VMT rising 24% (from 1.10 to 1.36 billion vehicle-miles) and weighted average speeds falling 37% (from 25.8 to 18.9 miles per hour).

Keywords: Long-Distance Travel, Autonomous Vehicles, Mode Choice, Autonomous Trucks, Freight.

BACKGROUND

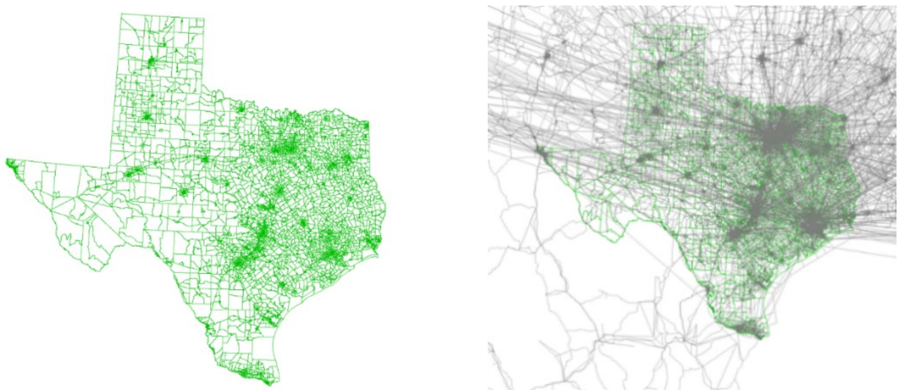
The rise of automated vehicles (AVs) is leading to significant developments in passenger and freight travel across urban and regional landscapes. As traditional barriers like the burden of driving and the hefty, fixed costs of vehicle ownership diminish, distant destinations and ground-based travel alternatives become more appealing, fundamentally altering mode choice (Zhao and Kockelman, 2018; Perrine et al., 2020; LaMondia et al., 2016). ATrucks free operators from driving duties and increase truck use by enabling rest breaks during the trip (Lee et al., 2023; Engholm and Pernestål, 2021). Currently, trucks dominate US inland freight transport (64% of the weight of annual shipments), moving 13,139 million tons in 2023 after pipeline and rail (5,297 million tons) (FAF5, 2021). Future integration of truck platooning via low-latency vehicle-to-vehicle communication will also improve freight efficiency (Huang et al., 2020). The possibility of ATrucks performing additional tasks, such as autonomous freight pickups and deliveries, may also improve supply chains.

While AVs may dramatically lower crash counts, improving access for the elderly, disabled, and others (Harper et al., 2016; Fagnant and Kockelman 2015; Gurumurthy and Kockelman, 2018), their introduction will also change how people travel. AVs are projected to increase vehicle-miles traveled (VMT) and attract passengers away from public transit. LaMondia et al. (2016) and Perrine et al. (2020) estimated 50% shifts away from airlines and driving, and toward AVs and SAVs (especially for trips under 500 miles each way). The availability of SAVs is also expected to reduce US car ownership (Gurumurthy and Kockelman, 2018). This study not only integrates AVs and SAVs but also considers the effects of different vehicle occupancies of AVs and SAVs on transportation networks. Numerous recent studies have explored how SAVs may impact car ownership. In their study, Mamdoohi et al. (2023) showed that approximately 26% of participants were willing to reduce their private car ownership in favor of SAVs. Fonzone et al. (2024) also did similar research and showed that 7.3% of respondents were willing to use an autonomous bus (AB) as soon as it became available (indicating early adoption), while 13.3% of respondents expressed willingness to use an AB soon after they are available. The numbers showed a cautious but substantial interest in using ABs when integrated into the transportation network.

Hamadneh et al. (2023) found that men and high-income individuals are more inclined to use privately owned SAVs than women and lower-income groups. However, a notable gap exists in understanding how these vehicles are used across different party sizes. The ride-hailing service providers with SAV fleets have the potential to streamline passenger flow, reducing wait times and enhancing connectivity between various modes of transportation. Furthermore, these providers improve fleet usage by optimizing routes and schedules based on real-time data, thus minimizing idle times and boosting the operational efficiency of transport services (Xu et al., 2024). Despite numerous studies investigating public preferences for AVs across various travel distances and purposes (e.g., Maleki and Arani, 2021; Ashkrof et al., 2019; Truong et al., 2017; Haboucha and Shiftan, 2017), there remains a notable gap in the application of studies across realistic settings. This study fills this gap by integrating AVs, SAVs, and ATrucks into Texas' statewide demand model (SAM) and evaluating their impacts on freight and long-distance passenger travel. The following sections describe the model briefly, detail changes to the mode choice modules, provide simulation results, and then deliver conclusions.

DATA SET

This study centers on travel demand modeling using TransCAD software, which supports a four-step travel demand model called SAM. SAM is a multi-modal travel tool maintained by the Texas Department of Transportation (TxDOT) and developed by the Alliance Transportation Group (ATG). SAM covers North America, focusing on regions in and around Texas. Figure 1 represents the state's extensive network of highways, railways, and airline routes, with 228,562 links, 166,039 nodes, and 6,860 traffic analysis zones (TAZs). It has passenger and freight models, which follow a four-step structure (from trip generation to destination, mode, and route choices, with feedback). Passenger vehicles and freight trucks are combined for network loading in the highway assignment step. The SAM simulation comprehensively analyzes travel patterns involving a substantial population of 40.2 million individuals distributed across 13.5 million households within Texas. These households have an average size of 2.98 individuals, and the population-to-employment ratio is 2.1.



a. Texas TAZs b. Network

Figure 1. SAM-V4 TAZ and Network File

Passenger Model

The passenger model in SAM-V4 uses destination choice models to distribute most short-distance trips (less than 50 miles) and all long-distance trips (50 miles or greater). In contrast, gravity models are applied for other short-distance trips such as home-based K-12 school trips, non-home-based visitor trips, and non-freight truck trips. The model time-of-day step categorizes highway passenger trips and freight truck trips into four time periods: morning (AM) peak period, mid-day (MD) period, afternoon (PM) peak period, and night (NT) period, for final assignment according to these periods. Mode share factors, which vary based on the transit accessibility of a TAZ, are applied for short-distance trips. A four-level nested-logit mode choice model is used for long-distance trips, including auto, intercity rail, high-speed rail, and air travel.

The passenger model reflects three trip types: short-distance, long-distance, and non-freight truck trips. Short-distance passenger trips are those under 50 miles one-way, including home-based work trips (HBW), home-based other trips (HBO), home-based K-12 school trips (HBS), non-home-based other trips (NHBO), and non-home-based visitor trips (NHBV) trips. Long-distance trips are those over 50 miles (one-way) within Texas or between Texas and the continental US (and may take more than 24 hours). SAM-V4 distinguishes these by purpose and distance: infrequent long-distance business and non-business/other trips are between 50 and 400 miles (ILDB and ILDO), while infrequent and very long- (or "long long") distance trips (400+ miles) for business and non-business/other purposes are ILLB and ILLO. Non-freight truck trips are short-distance trips not captured by the freight model, serving local areas with purposes like contractors delivering goods and services to households. Fixed mode-split factors were applied to estimate the mode split for short-distance trips, while a nested logit (Figure 2) was used for trips over 50 miles.

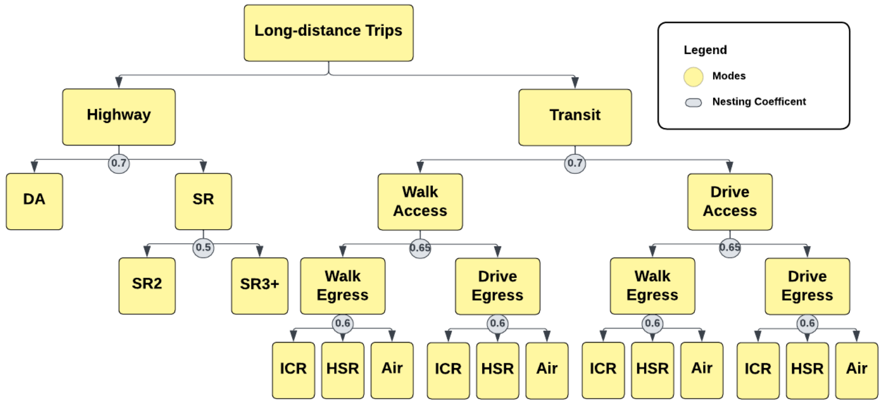


Figure 2. SAM-V4 Passenger Long-Distance Mode Choice Nested-Logit Structure and Nesting Coefficients (Source: Alliance Transportation Group, 2019)
Note: DA = Drive Alone, SR = Share Ride, ICR = Intercity Rail, HSR = High-Speed Rail

Freight Model

The SAM-V4 freight models were developed using 2015 TranSearch data, classifying goods into 15 distinct groups, as shown in Table 1. A four-step travel demand model combines freight trips with passenger travel in the final step of traffic assignment. The freight mode choice model consists of truck, carload rail, intermodal rail, water, and air, as shown in Figure 3. An incremental logit choice method pivots off existing mode shares (as found in the base scenario) as time and cost parameters change. The freight model's coefficients were estimated using Texas 2015 TranSearch commodities flow data, with results shown in Table 2. After mode splits are produced, SAM's tonnage estimates (by commodity) are divided into separate truck trips and loaded on the roadway network. Interestingly, the freight model has just 348 TAZs: 254 Texas counties plus 48 US states (all but Hawaii), the District of Columbia, 32 Mexico states, and 13 Canadian provinces.

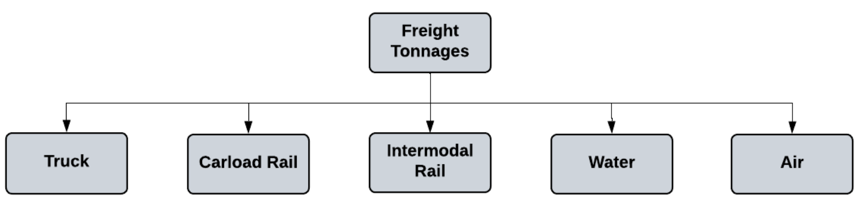


Figure 3. SAM-V4 Freight Mode Choice Structure (Source: ATG, 2019)

Table 1. SAM-V4 Freight Mode Choice Coefficients (Source: ATG, 2019)

#	Commodity Name	Carload Constant	IMX Constant	Cost Coef.	Time Coef.	# of IMX Coef.

1	Agriculture	5.481	-4.277	-0.0063	0	0.0469
2	Metallic Ore & Coal Mining	4.124	-3.1	-0.0032	-0.0584	0
3	Crude Petroleum or Nat. Gas	3.549	0	0	-0.0162	0
4	Nonmetallic Minerals	-0.679	-8.4338	-0.0061	0	0.0998
5	Food	-3.279	-2.7486	-0.0058	0	0.0406
6	Consumer Manufacturing	0	0	-0.0019	-0.042	0.0409
7	Non-Durable Manufacturing	-3.757	-6.5606	-0.0059	0	0.0279
8	Lumber	-4.016	-8.0001	-0.0011	-0.0131	0.0461
9	Durable Manufacturing	-2.860	-6.4946	-0.0017	0	0.0317
10	Paper	-0.619	-3.0581	-0.009	0	0.0414
11	Chemicals	-2.341	-6.0239	-0.0045	0	0
12	Petroleum	-3.092	-8.4885	-0.0056	0	0.0854
13	Clay, Concrete, Glass	-3.336	-7.1387	-0.0064	0	0.0368
14	Primary Metal	-1.887	-4.321	-0.006	0	0
15	Secondary & Misc. Mixed	-3.176	4.5037	-0.0077	0	0.0529

Table 2. SAV-V4 Mode Choice Parameters (Source: ATG, 2019)

Parameters	Mode		
	Truck	Carload	IMX
Cost rate ($/ton-mile)	0.1986	0.0191	0.0362
Time rate	1	1	1
Cost Constant	0	10.3	42.94
Drayage access	-	-	0.1986

METHODOLOGY

The mode choice models for passenger and freight transportation were updated to incorporate AVs, SAVs, and ATrucks. To account for the anticipated spike in vehicle-miles traveled due to the implementation of AVs, a 15% rise in trip production rates has been included. The rise acknowledges a potential growth in ground travel demand that would result from providing transportation for people who are elderly, those who do not have driver's licenses, or those with mobility limitations. These modifications align with research by Harper et al. (2016), which calculated a 14% rise in U.S. VMT due to non-driving individuals, senior citizens, and people with medical issues that hinder traditional modes of transportation.

Short-Distance Passenger Mode Choice

SAM uses mode shares determined by transit availability for various trip purposes and income brackets for short-distance trips. Four different options are being evaluated for short travels, including Drive-alone (DA), Shared-Ride 2 (SR2), Shared-Ride 3 or more people (SR3+), and "Other" modes. The "Other" category includes transportation modes such as buses, urban rail, ferries, and other modes not specified in the survey questionnaire. It uses several parameters depending on three sorts of areas: "No Transit Available Area," "Bus Available Area," and "Urban Rail Available Area." In areas without transit, DA, SR2, and SR3+ values of 40% for HVs, 40% for AVs, and 20% for SAVs were assumed. Similarly, in areas with transit availability (bus and urban rail available areas), 40% for HVs, 40% for AVs, and 20% for SAVs were assumed for DA, SR2, and SR3+, mirroring the previous case with a 50% reduction in the mode shares of "Other" modes. Zhao et al. (2018) predicted that 66% of all automobile users will choose AVs or SAVs. Litman (2020) predicted that AVs will make up 30% of the U.S. fleet by 2040, while other research suggests that AVs might range from 25% to 87% of the U.S. fleet by 2045, depending on various assumptions (Bansal and Kockelman, 2016). Huang et al. (2021) found that for trips between 75 and 500 miles, business trips were split approximately 23% HV, 28% AV, and 17% SAV, whereas non-business trips were split 37% HV, 15% AV, and 34% SAV.

Long-Distance Passenger Mode Choice

SAM's nested logit model was adjusted to include HV, AV, and SAV for trips exceeding 50 miles. The modes were categorized under DA, SR2, and SR3+. The nesting order was established based on individuals' tendency to choose a transportation mode depending on party size. Figure 4 shows the revised nesting structure along with the assumed nesting coefficients. Table 3 presents the mode choice constants (ASCs), explanatory variable coefficients used in the model, and the default values established in the base. The parameters were chosen using the SAM-V4 base model and a comparable model adjusted by Huang et al. (2020). Individual trips generated at the mode choice stage are converted into vehicle trips before traffic assignment. Auto occupancy rates for SR3+ trips in SAM were determined according to trip purpose and income group using NHTS data. These rates ranged from 3 to 4.79, except for a rate of 7.57 for ILLO trips by those in income group 3. This 7.57 seems relatively high, especially since the long-distance mode choice model does not include bus modes. This could be a potential error in SAM, where a small sample of bus modes in the NHTS was accidentally considered while estimating these rates.

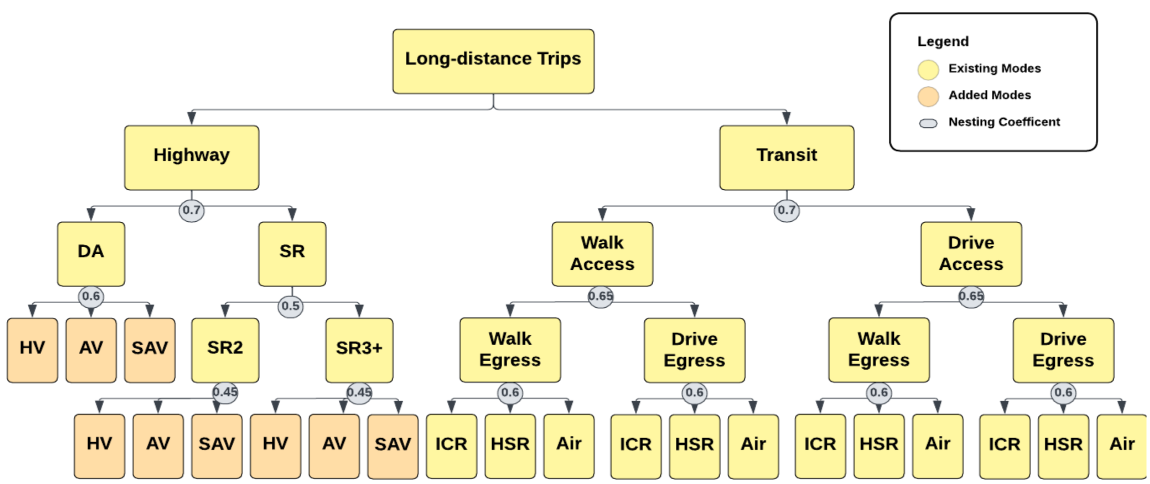


Figure 4. AV/ATruck Scenario Long-Distance Mode Choice Nested-Logit Structure and Nesting Coefficients (DA – Drive Alone, SR – Share Ride, ICR – Intercity Rail, HSR – High-Speed Rail)

Table 3. Passenger Model Parameters

NO-AV SCENARIO

Mode		ILDB	ILDO	ILLB	ILLO
Drive Alone (DA)		N/A	N/A	N/A	N/A
Shared-Ride 2 (SR2)		-1.5	-0.1	-3	-0.8
SR 3+ (SR3+)		-2	-0.2	-4.2	-2
High-Speed Rail (HSR)		-1.1	-2.5	2.5	-0.4
Intercity Rail (ICR)		-5	-3.8	-5	-2.5
Air		-1.1	-2.5	2.5	0
Auto Operating Cost ($/mile)		0.346	0.17	0.346	0.17
In-Vehicle Time Coefficient		-0.02	-0.01	-0.02	-0.01
Out-of-Vehicle Time Coefficient		-0.02	-0.01	-0.02	-0.01
Travel Cost Coefficient	Income I	-0.1664	-0.1109	-0.1664	-0.1109
	Income II	-0.0555	-0.037	-0.0555	-0.037
	Income III	-0.0277	-0.0185	-0.0277	-0.0185
	Income IV	-0.0166	-0.0111	-0.0166	-0.0111
AV/ATRUCK SCENARIO					
Mode		***ILDB***	***ILDO***	***ILLB***	***ILLO***
DA	Human-Driven Vehicles (HV)	N/A	N/A	N/A	N/A
	Autonomous Vehicles (AV)	-0.05	-0.05	-0.05	-0.05
	Shared Autonomous Vehicles (SAV)	-0.2	-0.2	-0.2	-0.2
SR2	HV	-1.5	-0.1	-3	-0.8
	AV	-1.55	-0.15	-3.05	-0.85
	SAV	-1.7	-0.3	-3.2	-1
SR3+	HV	-2	-0.2	-4.2	-2
	AV	-2.05	-0.25	-4.25	-2.05
	SAV	-2.2	-0.4	-4.4	-2.2
High-Speed Rail (HSR)		-1.10	-2.50	2.50	-0.40
Intercity Rail (ICR)		-5	-3.8	-5	-2.5
Air		-1.1	-2.5	2.5	-0.4
HV Operating Cost ($/mile)		0.346	0.17	0.346	0.17
AV Operating Cost ($/mile)		0.6	0.6	0.6	0.6
SAV Operating Cost ($/mile)		1	1	1	1
In-vehicle Time Coefficient		-0.02	-0.01	-0.02	-0.01
Out-of-vehicle Time Coefficient		-0.02	-0.01	-0.02	-0.01
Travel Cost Coefficient	Income I	-0.1664	-0.1109	-0.1664	-0.1109
	Income II	-0.0555	-0.037	-0.0555	-0.037
	Income III	-0.0277	-0.0185	-0.0277	-0.0185
	Income IV	-0.0166	-0.0111	-0.0166	-0.0111

Freight Mode Choice

The freight mode choice was updated to include ATrucks as a new category. These ATrucks are nested under the broader truck mode, separating automated trucks (ATrucks) from human-driven trucks (HTrucks). The Texas megaregion study by Huang et al. (2020) was again used as a starting point for the model parameters, assuming a nesting coefficient of 0.7 for HTrucks to reflect the relative substitutability between the two modes. The operating costs for ATrucks were assumed to be 50% more than those of HTrucks to account for automation equipment costs and additional training expenses for humans supervising the truck, with a 25% reduction in VOTT. No rest time was assumed for ATrucks (as opposed to the 13 hours of rest accounted for HTrucks after every 11 hours of driving). The ATruck travel time skim was assumed to be 0.42 times that of HTruck, reflecting the ability of automated trucks to drive 24 hours a day. The time coefficient for 11 of 15 commodities in SAM-V4 is 0.00 (Table 4). Therefore, time and cost coefficients were re-estimated for the 11 commodities by halving the beta of cost and choosing the beta time coefficients carefully so those newly added multiples would make up for the reduction in the beta cost*cost terms. This was done by taking half the cost coefficients and selecting 11-time coefficients to minimize errors in hitting current rail/truck splits (no AV scenario) for each commodity's top 50+ OD pairs. This process was repeated for 11 commodities. Table 4 shows the updated coefficients for all the commodities.

Table 4 Freight Mode Choice Coefficients

Commodity Group #	Original		Modified		Original		
	Time Coeff.	Cost Coeff.	Time Coeff.	Cost Coeff.	Carload Constant	IMX Constant	IMX # Coeff.
1	0	-0.0063	-0.01843	-0.00315	5.4809	-0.4277	0.0469
2	-0.0584	-0.0032	-0.0584	-0.0032	4.1237	-3.1	0
3	-0.0162	0	-0.0162	0	3.549	0	0
4	0	-0.0061	-0.18701	-0.00305	-0.6799	-8.4338	0.0998
5	0	-0.0058	-0.01368	-0.0029	-3.2788	-2.7486	0.0406
6	-0.042	-0.0019	-0.042	-0.0019	0	0	0.0409
7	0	-0.0059	-0.05899	-0.00295	-3.7565	-6.5606	0.0279
8	-0.0131	-0.0011	-0.0131	-0.0011	-4.0162	-8.0001	0.0461
9	0	-0.0017	-0.00595	-0.00085	-2.8602	-6.4946	0.0317
10	0	-0.009	-0.0365	-0.0045	-0.6198	-3.0581	0.0414
11	0	-0.0045	-0.04677	-0.00225	-2.3405	-6.0239	0
12	0	-0.0056	-0.36019	-0.0028	-3.0916	-8.4885	0.0854
13	0	-0.0064	-0.41205	-0.0032	-3.3361	-7.1387	0.0368
14	0	-0.006	-0.0098	-0.003	-1.8875	-4.321	0
15	0	-0.0077	-0.02697	-0.00385	-3.1761	4.5037	0.0529

As mentioned, the SAM-V4 freight mode choice model uses an incremental logit structure that builds upon existing base share. However, with the introduction of ATruck and the associated changes in the model structure, the calculations for mode shares needed to be updated.

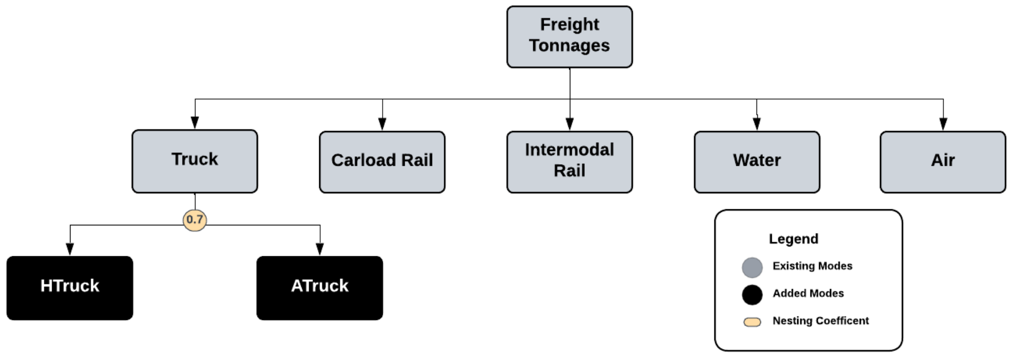


Figure 5. AV/ATruck Scenario Mode Choice Structure and Nesting Coefficient

The utilities of HTruck and ATruck for every commodity group and zone pair were computed using travel time, cost, and modal constant terms, similar to the approach followed in the base model. The utility calculation for ATruck is shown as an example below:

$$U_{ij}^{ATruck,k} = ASC^{ATruck,k} + \beta_t^{ATruck} * Travel\ Time_{ij} + \beta_c^{ATruck} * (Cost\ Rate\ per\ ton - mile * Distance_{ij})$$

where $ASC^{ATruck,k}$ is the alternate specific constant, β_t^{ATruck} is the time coefficient, and β_c^{ATruck} is the cost coefficient for ATrucks, for commodity k from zone i to j. Next, the utility of the truck mode was determined by calculating the log sum of the utilities of HTruck and ATruck, considering the nesting coefficient. The formula for this calculation is expressed below:

$$U_{ij}^{Truck,k} = \theta *log\ log\left(e^{\left(\frac{U_{ij}^{HTruck,k}}{\theta}\right)} + e^{\left(\frac{U_{ij}^{ATruck,k}}{\theta}\right)}\right)$$

where θ = Nesting Coefficient and U_{ij} = Utility for specified mode for commodity k from zone i to j. Following this, the new truck share or probability was calculated using the same methodology as before, using the base mode shares. The incremental logit model form as followed in the AV base or no AV scenario model is shown below: For every mode m, in commodity group k, from zone i to j:

$$New\ Mode\ Share_{ij}^{m,k} = \frac{Existing\ Mode\ Share_{ij}^{m,k} * e^{\Delta U_{ij}^{m,k}}}{\sum\left(Existing\ Mode\ Share_{ij}^{m,k} * e^{\Delta U_{ij}^{m,k}}\right) for\ all\ m\ in\ k}$$

where $\Delta U_{ij}^{m,k}$ = Change in Utility

For Truck mode, the change in utility is determined by comparing the newly calculated utility of the truck mode, which involves taking the log sum of HTruck and ATruck with the previous utility of the truck mode before introducing the new mode (and nest). The shares of ATruck and HTruck in every zone pair) were then derived from the total number of truck trips (which is calculated by multiplying the new truck share with the total number of trips from each zone i to zone j) as shown below:

$$ATruhare_{ij}^{k} = Total\ Truck\ Trips * \frac{e^{(\frac{U_{ij}^{ATruck,k}}{\theta})}}{e^{(\frac{U_{ij}^{HTruck,k}}{\theta})} + e^{(\frac{U_{ij}^{ATruck,k}}{\theta})}} HTruck\ Share_{ij}^{k}$$

$$= Total\ Truck\ Trips * \frac{e^{(\frac{U_{ij}^{HTruck,k}}{\theta})}}{e^{(\frac{U_{ij}^{HTruck,k}}{\theta})} + e^{(\frac{U_{ij}^{ATruck,k}}{\theta})}}$$

where θ = Nesting Coefficient and U_{ij} = Utility for specified mode for commodity k from zone i to j.

RESULTS

The “No-AV/ATruck Scenario” model serves as a benchmark for assessing the impacts of AV/ATruck inclusion in the network. For both models, SAM's weekday module selected a typical weekday as the basis for the analysis. Feedback loops iterating from traffic assignment’s equilibrium travel times to trip distribution’s destination choices were not included in these model runs because run times were extremely long (24+ hours per scenario). SAV occupancy was reduced by 20% after the mode choice stage to ensure the appropriate inclusion of empty VMT (eVMT). The VOTT for AVs and SAVs was assumed to be 20% less than traditional HVs (HVs), and ATrucks were assumed to have a 25% reduced VOTT compared to HTrucks. No rest time was assumed for ATrucks (as opposed to the 13 hours of rest accounted for HTrucks after every 11 hours of driving). The ATruck travel time skim was assumed to be 0.42 times that of HTruck, reflecting the ability of automated trucks to drive 24 hours a day. Previously, the time coefficient for 11 out of 15 commodities in SAM-V4 was 0. Therefore, time and cost coefficients were re-estimated for these commodities by adjusting betas of cost and time.

The mode splits for short-distance trips (<50 miles) remained fixed even with the introduction of AVs. Integrating AVs into the mode choice model for long-distance (> 50 miles) passenger travel revealed that personal AVs captured a 14% market share. At the same time, the human-driven "drive alone" mode experienced a 17% fall as individuals shifted to AVs. This shift may be attributed to a 25% reduction in VOTT, allowing individuals to use their time more effectively with AVs. Additionally, mode shares showed a 7% rise in AV driving with two occupants and an 11% in AV driving with three or more occupants, as shown in Figure 11. Figure 12 shows that the introduction of AVs has led to a rise in business trips, with SAVs spanning 50-400 miles and non-business trips exceeding 400 miles by 44% and 47%, respectively. At the same time, air mode lost 20% of business trips and 15% of non-business trips within 400 miles. The surge in air travel within the 400-mile range can be attributed to the assumption of a 15% rise in trip frequency following the introduction of AVs. Inter-city rail, too, witnessed a decline in market share by 15% and 13% for business and non-business long-distance trips, respectively.

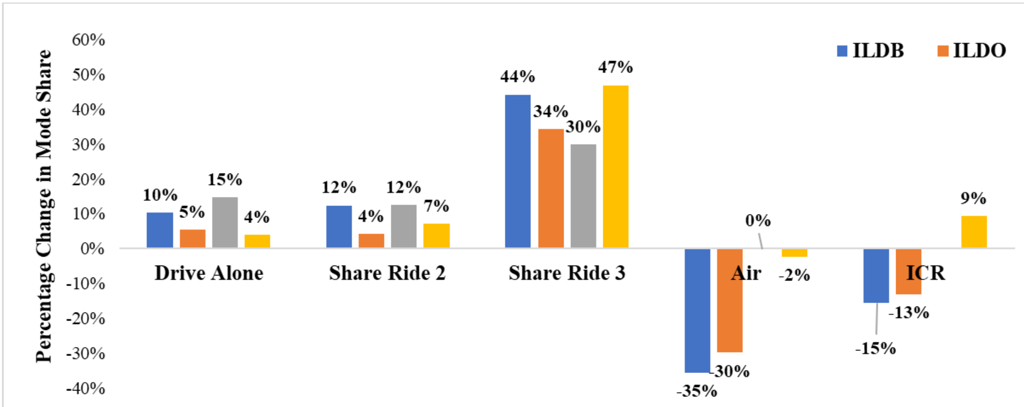


Figure 6. Percentage Change in Person Trips of Long-Distance Travel (> 50 miles one way) No-AV vs AV Base Scenario

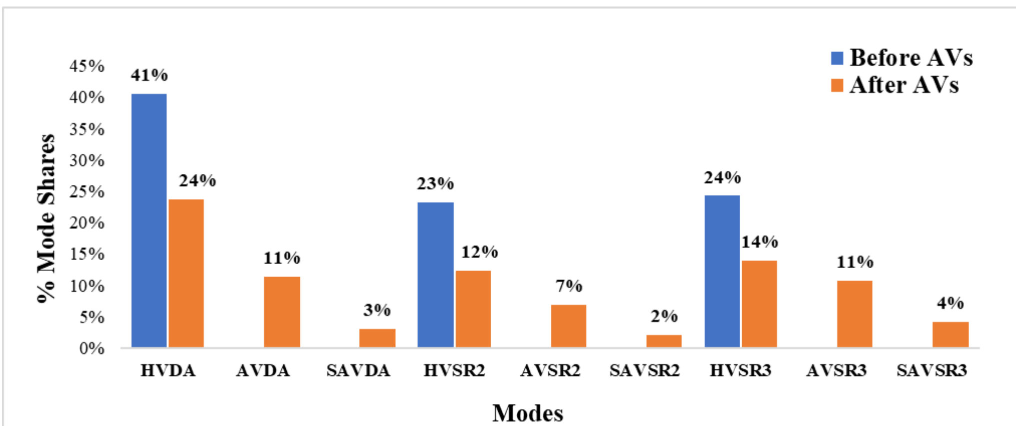


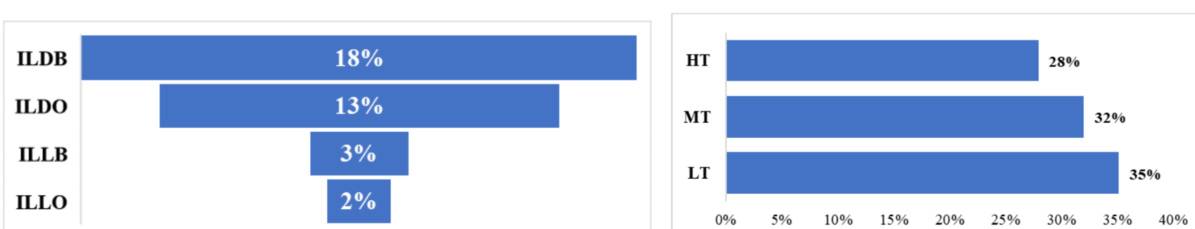
Figure 7. Percentage Change in Person Trips for Ground Travel: No-AV vs AV Base Scenario (HV = human-driven vehicle, DA = drive alone, SR2/3 = shared ride with 2/3 persons)

In the case of SAV driving, there was a modest 3% rise in AV driving with two occupants and a 4% rise with three or more occupants. On the other hand, there was a 5% and 10% decrease in human-driven shared rides with two occupants and shared human driving with three or more occupants, respectively. As shown in Figure 8 (a), incorporating AVs into the transportation system has led travelers to opt for more distant locations than their previous choices. Additionally, the ability to spend time in alternative ways while inside AVs has increased the possibility of making trips, particularly for work-related trips that were previously deemed too far. Hence, we observed an 18% rise in average trip length for infrequent long-distance business trips and a 13% rise for non-business trips exceeding 50 miles but less than 400 miles. As shown in Figure 8 (b), there was a substantial rise in average trip length across various vehicle categories, with light-duty, medium-duty, and heavy-duty trucks witnessing rises of 35%, 32%, and 28%, respectively. This trend suggests a tendency to cover greater distances, likely due to removing driving burdens in AV modes. Furthermore, the rise in the number of hours vehicles spend on all types of roads also indicates a fall in average speeds.

Figure 10 illustrates the PMT in ton-miles for business and non-business travel ranging from 50 to 400 miles, across passenger cars in the AV scenario. AV inclusion has impacted the person-miles traveled (PMT) across various travel and trip purposes. Specifically for business trips, the PMT for 'drive alone' and ‘shared rides with two passengers’ rose by 7.6% and 12.2%, respectively. Additionally, there was a substantial 49% rise in shared rides with three passengers. The results show a 37% rise in shared rides with three passengers for non-business trips. Business trips indicate a strong dependence on conventional vehicles (HVs). Solo drivers using HVs compromise the most PMT at 35.7 million (0.89 miles/day/capita), while AVs have a decent level of acceptance for individual business trips, covering 0.516 miles/day/capita (Figure 10). On the other hand, SAVs are used very little, with only 3.8 million person-miles traveled. This could suggest that SAVs are not widely available or that people are not very interested in using them, even when not sharing a car with others. Regarding shared rides, HVs with two passengers had a 14.6% share in total PMT (vs. 27% before AVs), and HVs with 3+ passengers made up 18% as opposed to 33% before AVs.

AV use for non-business individual travel resulted in 0.36 PMT per capita, accounting for 6% of total PMT, while HVs comprised 20%. AVs constituted 8% of the total PMT for trips with two passengers, while HVs represented 18%. Trips with three or more passengers saw AVs covering 16% of the PMT, lower than HVs at 22%. In shared rides, high-occupancy HVs performed better than AVs and single-occupancy shared autonomous vehicles (SAVs). HVs with multiple passengers covered 37.25 million person-miles, or 18% of total PMT, which is significantly higher than the 8% for AVs and 2% for SAVs. Traditional vehicles remain the favored option for leisure travel, with a 3+ party size covering 1.2 PMT per capita. Prior to the implementation of AVs, HTrucks were the leading competitor in the freight market, accounting for 1326.9 billion freight ton-miles (Figure 11). Rail transport was extensively employed, with 827.7 billion ton-miles recorded. Water and Intermodal (IMX) transport accounted for 108.19 and 263.51 billion ton-miles, respectively. Despite its high speed, air transport was used sparingly due to its high expenses, as seen by its modest ton-miles of 5.24 billion. This mode of transportation is suitable mainly for valued or time-sensitive shipments.

ATrucks do not require a driver, so they are not constrained by fixed schedules related to drivers’ availability. Thus, results show an overall 15% rise in ton-miles transported after their introduction. Additionally, freight distribution saw significant shifts: traditional trucking, air freight, rail, and water transport experienced reductions of 65%, 25%, and 17% in ton-miles, respectively, compared to the period before the introduction of ATrucks. Meanwhile, ATrucks accounted for 35% of the total ton-miles following their deployment.



(a) (b)

Figure 8. Percentage Change in Average Trip Length Across Trip Types (a) and Vehicle Types (b)

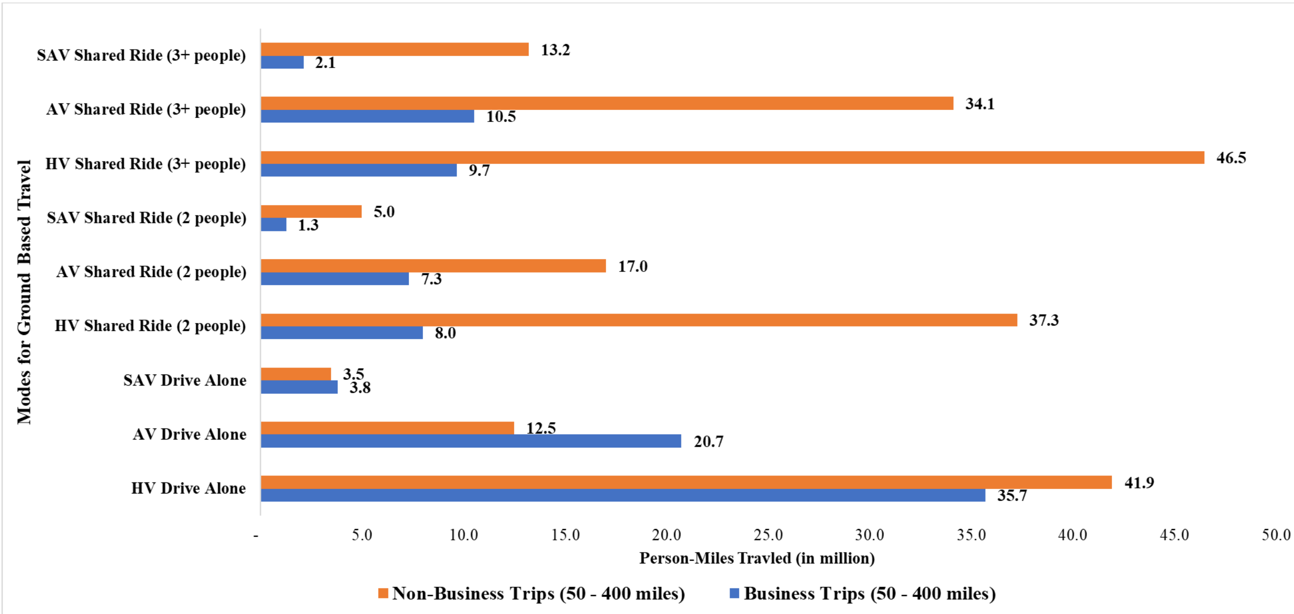


Figure 10. Person-miles Travelled for Trips Exceeding 50 miles: No-AV vs AV Base Scenario

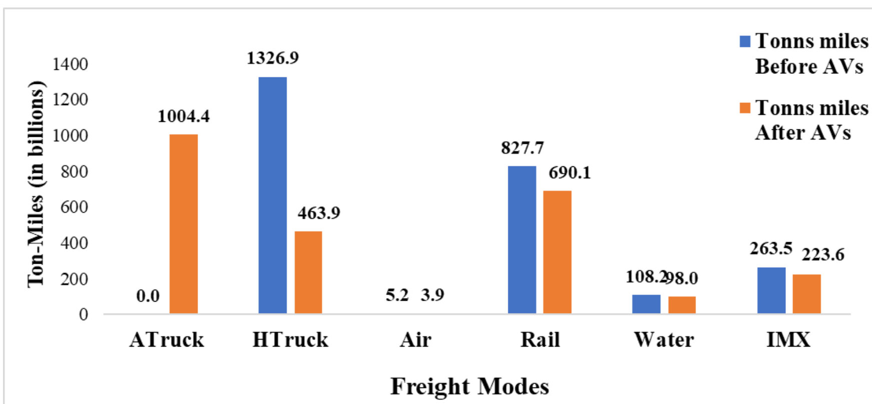


Figure 11. Ton miles Moved across Commodities: No-AV vs AV Scenario

VMT experienced a notable rise across all time periods, as shown in Figure 12. During the AM and PM periods, VMT rose by more than 28%, followed by a 22% rise during the afternoon. Passenger VMT saw a 26% rise, while truck VMT rose 7%. This upward trend in VMT due to ATrucks is expected to increase further as they become more cost-effective than HTrucks. Expressways and freeways witnessed a significant rise of over 20% in passenger VMT, as shown in Figure 13. Furthermore, the rise in the number of hours vehicles spent on all types of roads (Figure 14) also indicates decreases in average speeds. Arterial roads, collector roads, and interstate highways were significantly impacted, with average speeds decreasing by more than 60%, as shown in Figure 15. The results suggest that there is increased traffic congestion in AV scenarios. The most significant reductions in speed are observed during morning and evening hours, followed by afternoons, and then nights.

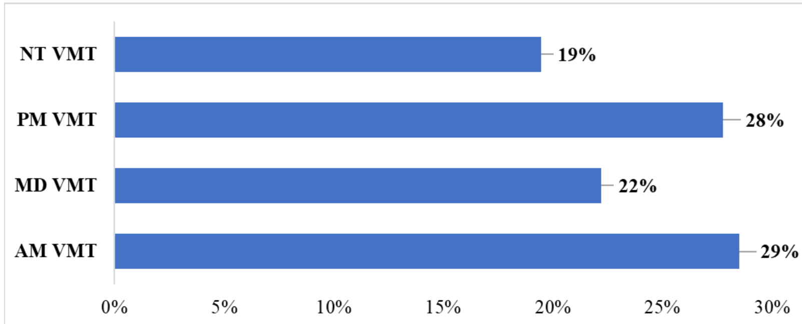


Figure 12. Percentage Change in VMT for Trips Exceeding 50 Miles: No-AV vs AV Base Scenario

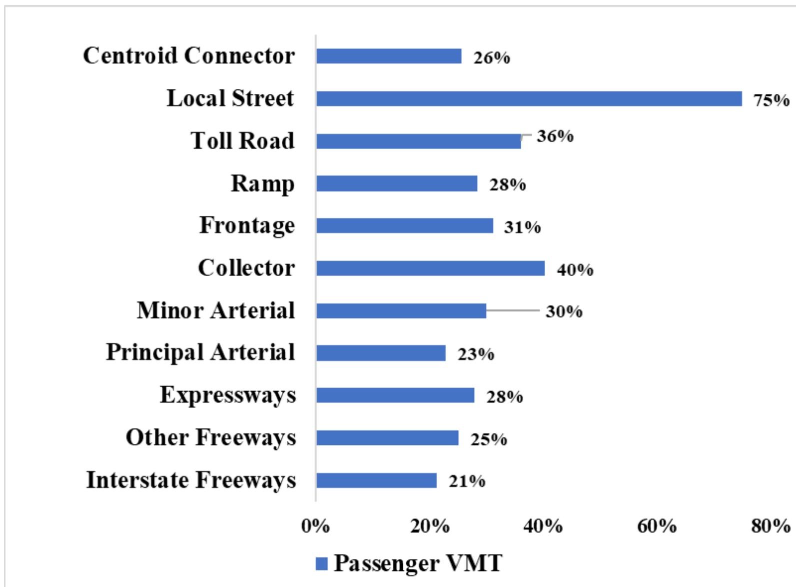


Figure 13. Percentage Change in Passenger VMT across Road Types: No-AV vs AV Base Scenario

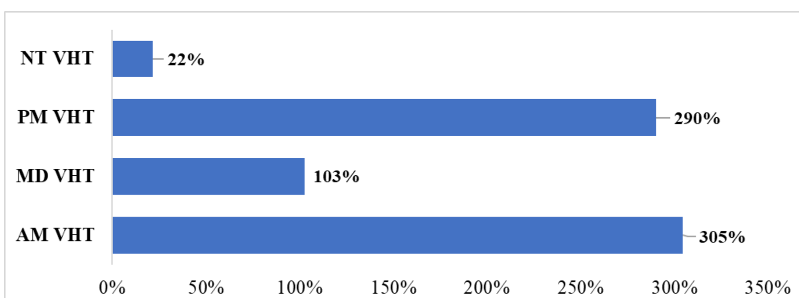


Figure 14. Percentage Change in VHT for Trips Exceeding 50 Miles: No-AV vs AV Base Scenario

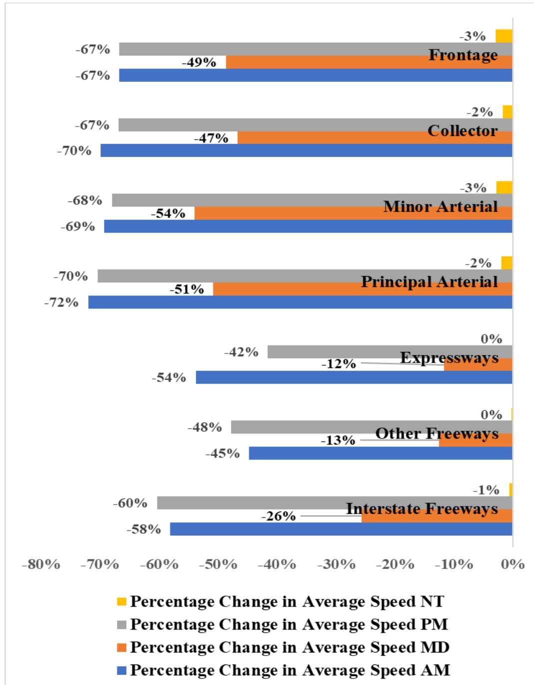


Figure 15 Percentage Change in Average Speed Across Road Types: No-AV vs AV Scenario

CONCLUSIONS

This study extends TxDOT's SAM model via its mode choice options to predict the travel and traffic impacts of AVs, SAVs, and ATrucks on passenger and freight flows across Texas and beyond. For passenger trips over 50 miles (one-way), SAM's logit model was modified to include AVs and SAVs. The "No AV/ATruck Scenario," has TxDOT's default SAM settings, while the second model allows for AV, SAV, and ATruck modes. The "No AV/ATruck Scenario" model serves as a benchmark against AV/ATruck scenarios, allowing for a comprehensive analysis of the changes and benefits of introducing these advanced transportation technologies. For both models, SAM's weekday module selected a typical weekday as the basis for the analysis. For trips that are shorter than 50 miles, the mode split stays the same. However, for trips that are longer than 50 miles, the nested logit model was modified to include AVs, SAVs, and ATrucks.

AV simulation revealed that AVs and SAVs (personal) captured 14% of the market share, accompanied by a 17 percentage-point decline in human-driven "drive alone" mode for trips over 50 miles. This shift can be attributed to a 25% reduction in Vehicle VOTT, allowing individuals to use their time more effectively. The ability to use time effectively in AVs has encouraged travelers to opt for more distant locations, resulting in an 18% rise in average trip length (from 121 miles to 142 miles) for infrequent long-distance business trips and a 13% rise (135 miles to 151 miles) for non-business trips within 50 to 400 miles. For business-related travels, PMT for driving alone and two-passenger shared rides increased by 7.6% and 12.2%, respectively, with a significant 49% rise in three-passenger shared rides. AVs and SAVs show lower adoption rates for leisure trips, with HVs dominating larger group travels and significantly leading in PMT, indicating a strong preference for conventional vehicles in recreational contexts.

In the freight sector, ATrucks were the preferred mode, handling 35% of freight ton-miles, surpassing rail at 24% and human-driven trucks at 16% (vs. 52% and 33% via HTrucks and rail, respectively, before the inclusion of ATrucks). Average trip length rose across all vehicle categories, with light, medium, and heavy-duty trucks experiencing a rise of 35%, 32%, and 28% in their mean trip distances traveled. This trend indicates an inclination to cover greater distances, likely due to removing driving burdens in AV modes. Without travel demand management (like credit-based congestion pricing), congestion issues will grow, thanks to an average VMT rise of 25.6% (from 1.09 to 1.37 billion miles per day). Of course, about 14% of this VMT rise is due to our starting assumption that AVs enable 15% more trip generation by passengers (for all trip purposes by all household types). The other 11% results from more driving, longer trips, less flying, and a shift to ATrucks. The AV inclusion influenced PMT distribution across modes for business and non-business trips.

Due to much higher VMT loads on the Texas network (as encoded in SAM, about 80% of centerline miles in the State of Texas), travel speeds are estimated to fall by about 36.9% on average (for the coded network). The VHT jumped by about 304%, largely due to passenger travel favoring the AM and PM peaks and mid-day. Speeds during night-time remained steady. Although AVs are gaining acceptance for business travel, HVs remain the preferred option for business and leisure purposes, especially for shared rides. This study's limitation is the scope of the modifications made for the AV scenario; integrating AVs, SAVs, and ATrucks was restricted to the mode choice step.

While these changes can predict shifts in trip distribution, mode splits, and trip assignments with feedback loops, they cannot predict the change in trip production. For a more realistic model, the enhancement of the trip generation step is required and will be the next step in future work planned. Due to their long run times, these models do not include full feedback loops from traffic assignment to trip distribution. This omission limits the ability to produce realistic travel times, which may affect the accuracy of the results. Another limitation comes from fixed mode share splits for short-distance trips. While SAM is primarily designed for large-scale studies and is not intended to replace urban models for city-level analyses, the reliance on fixed shares affects the ability to fully assess the impacts of AVs.

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AUTHOR CONTRIBUTION

The authors confirm their contributions to the paper as follows: conceptualization and methodology: Vellimana, M., and Kockelman, K.M.; data collection: Kockelman, K.M.; formal analysis and investigation: Paithankar, P., and Kockelman, K.M., Y.; writing—original draft: Paithankar, P., and Kockelman; All authors reviewed the results and approved the final version of the manuscript.

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