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Implementation of Understanding the Impact of Autonomous Vehicles on Long-Distance Travel Mode and Destination Choice in Texas

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16. Abstract
Privately owned and shared autonomous vehicles (AVs and SAVs) and automated trucks (ATrucks) are coming to the US and Texas. This project updated TxDOT's Statewide Analysis Model (SAM) to integrate AVs, SAVs, and ATrucks as added transportation modes. For passenger trips over 50 miles (one way), the nested logit model was modified to include household-owned AVs and fleet-managed SAVs, under the drive-alone and shared-ride options (i.e., DA, SR2, and SR3+ persons). SAM applies fixed mode shares for all passenger trips under 50-miles one way (based on transit availability for different trip purposes and income groups), so a variety of fixed splits were assumed there. This study presents a comparative analysis of 7 distinct AV scenarios (for the year 2040) against the base "No AVs" scenario (with default SAM settings). The long-distance passenger-trip model assumes personal AVs cost \$0.6 per mile, SAVs \$1 per mile, and ATrucks cost 50% more than HTrucks with 25% reduction in VOTT while AVs and SAVs are assumed to have 20% reduction in VOTT as compared to HVs. 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 miles to 142 miles) and 13% for non-business travel purposes (135 miles to 151 miles). AVs + SAVs will have a combined mode share of 14% for "drive alone" LD trips, leading to a 17 percentage-point decline in the human-driven mode share for trips over 50 miles. AVs + SAVs made up 9% of all person trips carrying two passengers and 15% when carrying three passengers. ATrucks emerged as the dominant choice, carrying 43% of commodity tons, while human-driven truck (HTruck) tonnage fell by 39% point compared to NO-AV case. Without travel demand management (like credit-based congestion pricing), congestion issues will grow, thanks to an average VMT rise of 24% (from 1.10 to 1.36 billion miles), while daily average speeds fell by 44%. The base AV model was then modified to develop 6 more AV scenarios, each examining the effects of different factors on transportation choices and network characteristics. These scenarios include more expensive AVs, SAVs, and ATrucks, then more affordable SAVs, a reduced VOTT for AV use, unavailability of human-driven vehicles, pricey personal AVs, and increased empty AV driving. This study also provides a thorough evaluation of different "probe vehicle" (RITIS/INRIX) and loop-detector (PTR) datasets to compare to SAM's 2019 base-case flow predictions, to illuminate how demand for travel varies across days of the year, and by vehicle type (light-, medium- and heavy-duty vehicles). RITIS's light-duty vehicle (LDV) trip table averaged over 31 weekdays from 2021 aligned well with SAM's "typical day" prediction. However, heavy-duty vehicle (HDV) tables were not as consistent, and medium-duty vehicle (MDV) trip tables were not comparable at all. Furthermore, INRIX/RITIS data offer unexplained spikes in demand across all vehicle types and times of day for certain days of the 2021 year, so one must use those with care. The permanent traffic recorder (PTR) dataset demonstrated a regular demand pattern over multiple years, presenting a valuable opportunity to introduce demand variations to SAM.

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Products

5-7081-01: Research Report (R1B)

Table of Contents

List of Tables

List of Figures

Executive Summary

The emergence of privately owned and shared autonomous vehicles (AVs and SAVs), and automated trucks (ATrucks) is expected to reduce crashes, increase access for the elderly and impaired, and reduce emissions. AVs and ATrucks are expected to increase vehicle-miles traveled (VMT) by making driving “easier” and improving travel access, while also lowering private vehicle ownership (Gurumurthy and Kockelman, 2018). ATrucks extend operating hours and distances per day by reducing operator burden and enabling rest en route. This project work makes significant additions to TxDOT’s Statewide Analysis Model (SAM) via its mode choice options in order to predict the travel and traffic impacts of AVs, SAVs, and ATrucks on passenger and freight flows across Texas and beyond. Total statewide trip production in 2040 is predicted to rise 15% if AVs, SAVs, and ATrucks are available for all trip type, particularly among those with mobility constraints (Huang et al. 2020). For passenger trips over 50 miles (one way), SAM’s logit model was modified to include AV, and SAV. The modes are nested under the drive-alone and shared-ride options (i.e., DA, SR2, and SR3+ persons).

Two distinct SAM-V4 model specifications were used to compare travel predictions in the year 2040. The first specification, referred to as “No AV/ATruck Scenario”, has TxDOT’s default SAM settings without any modifications. The second model allows for AV, SAV, and ATruck modes. The “No AV/ATruck Scenario” model serves as a benchmark against which six different AV/ATruck scenarios are evaluated, allowing for a comprehensive analysis of the changes and benefits associated with the introduction of these advanced transportation technologies. For both models, a typical weekday was selected as the basis for the analysis, using SAM's weekday module. Feedback loops iterating from Traffic Assignment’s equilibrium travel times back to Trip Distribution’s destination choices were not included in these model runs due to extremely long (24+ hours per scenario) run times.

The value of travel time (VOTT) for AVs and SAVs was assumed to be 20% less than traditional human-driven vehicles (HVs), with operating costs of $0.60 and $1.00 per mile, respectively. The operating costs for ATrucks were assumed to be 1.5 times those of HTrucks to account for automation equipment cost and additional training expenses for humans supervising the truck) with a 25% reduction in VOTT for all AV scenarios (except for scenario 3 which assumes 50% reduction in VOTT). No rest time is 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 to reflect HTruckility 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 & time. For trips that are less 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.

Results show that, for trips that are longer than 50 miles, AVs + SAVs (personal) captured a 14% of market share, accompanied by a 17 percentage-point decline in human-driven "drive alone" mode. This shift can be attributed to a 25% reduction in Vehicle VOTT, allowing individuals to use their time more effectively. Personal AV driving with two or more occupants had share of 7% and 11%, respectively. SAV driving captured mode share of 3% and 4% when used with three or more occupants, while human-driven shared rides saw fall of 5% and 10% points with same party size. 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 exceeding 50 miles but less than 400 miles.

Average trip length rose across all vehicle categories, with light, medium, and heavy-duty trucks experienced rise of 35%, 32%, and 28%, in their mean trip distance travelled. This trend indicates an inclination for covering greater distances, likely due to the removal of 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% comes from more driving, longer trips, less flying, and a shift to ATrucks. Due to much higher VMT loads on the Texas network (as encoded in SAM, which is about 80% of centerline miles in the State of Texas), travel speeds are estimated to fall by about 35% on average (for the coded network). The VHT jumped by about 304%, largely thanks to passenger travel favoring the AM and PM peaks and mid-day, where travel speeds fell by 68%, 67%, and 40%. Speeds during night-time remained steady. Scenario analyses reveal that predicted mode shares of AVs, SAVs, and ATrucks are sensitive to cost variations.

The integration of ATrucks into the transportation system shifts the distribution of consumer manufacturing goods, with ATrucks emerging as the dominant choice, occupying approximately 43% of tons moved, while tonnage moved with HTruck fell by 39 percentage point across all commodities. This shift was found particularly in trips involving metallic and nonmetallic materials, consumer manufacturing, paper, petroleum, and food, which witness a decline of over 40 percentage-point in trips made by Htrucks, consequently leading to a rise in the share of trips made by ATrucks. The study presents six distinct scenarios, each examining the effects of different factors on transportation choices and network characteristics. In the first scenario, SAVs are made 40% less expensive, ATrucks costing 20% more than HTrucks, and personal AVs remaining cost-neutral. These changes triggered a shift towards ground travel, particularly in the drive-alone mode.

Business long-distance person trips ranging from 50 to 400 miles saw a 10% rise, while non-business trips within the same distance range have experienced a 15% rise. Conversely, air travel has saw a decline of 20% in business trips and 15% in non-business person trips within this distance bracket. On the other hand, inter-city rail' market share fell by 15% and 13% for business and non-business long-distance trips, respectively.

The second scenario, the operational costs of personal AVs was increased by 33%, while SAV costs were kept unchanged. The findings suggest a that as the cost of AVs rises, whether for personal or shared use, there is a notable reluctance to adopt them. While the market shares of "drive alone" long-distance trips remain relatively stable across all trip purposes, there is a significant 41 percentage point decline in drive-alone trips exceeding 400 miles. This shift shows a preference for more cost-effective ground travel options while still meeting travel needs.

The third scenario deals effects of further reduction in perception of travel time for AV passengers and their inclination towards undertaking LD trips by reducing their VOTT by 50%. These changes led to rise in VMT across all types of roads. Specifically, expressways, arterials, interstates, and other freeways experienced 23% surge in their VMT. This shift in travel behavior is mirrored in reduced airport boarding across various airports in Texas, driven by individuals' preference for AVs, primarily due to cost-savings and the more productive use of travel time. The major state airports such as Dallas/Fort Worth International Airport, George Bush International Airport, and San Antonio Airport saw declines in passenger volumes (over 5%), showing the growing preference for AVs. Similarly, while the decline was less pronounced (3%) at Austin-Bergstrom Airport, it still reflected a negative trend in passenger boarding.

The fourth scenario introduces parameters that incentivize choosing AVs over HVs. The findings show that in large urban areas, where despite the availability of AVs, a considerable portion of LD trips (38%) still involve traditional HVs. However, the removal of HVs caused a 10% rise in “drive-alone” AV trips. Additionally, SAVs trips saw a rise of 10% for two occupants and a 21% rise for three or more occupants. The fifth scenario explores the impact of high costs associated with personal ownership of AVs, leading individuals to favor SAVs and shifting back to HVs. As a result, a preference for SAVs led to an 11% mode share for “drive alone” SAVs in case of business trips, and a rise from 3% to 5% for non-business trips within the 50 to 400-mile range compared to the base-AV scenario. Mode share of SAVs with two occupants for business trips covering distances between 50 and 400 miles Saw rise from 2% to 12% and a 10% in SAVs with three or more occupants for non-business trips covering the same distance range.

Final scenario considers empty SAVs driving within the transportation network, included by a 20% fall in average passenger occupancy. The findings show rise in average VMT across all road types: 10% during morning peak hours, 9% during evening peak hours, and 8% during afternoon peak hours. Local streets saw the spike of 53% in VMT during morning peak hours and 37% rise during evening peak hours, closely followed by collector and local street roads. As the consideration of empty driving is considered into the network, congestion levels rose across all segments, as shown by the average speed reduction observed.. The results show an average 25% reduction in speed on expressways, interstates, and other freeways. This research project provides a thorough evaluation of different datasets that the TxDOT has access to. The main focus is on determining the most appropriate source for verifying the results of the Statewide Analysis Model (SAM) travel demand model. The study assesses the effectiveness of INRIX's Traffic Message Channel (TMC) segments, which cover a large part of the on-system network. This evaluation takes into account the extensive duties of TxDOT in managing and fixing more than 80,000 centerline-miles of highways, which facilitate over 70% of the State's yearly vehicle-miles traveled. TxDOT, which serves a population of 29 million and many visitors, can gain advantages from the research team's comprehensive datasets that are specifically focused on Texas. These datasets have been collected over many years of expertise in transportation design, planning, and operations.

These datasets include multiple probe data sources, including RITIS' National Performance Management Research Data Set (NPMRDS), INRIX's historical and real-time speed data, and Replica's simulated datasets. The vendor-neutral nature of RITIS NPMRDS allows for the indexing of roadway segments using Traveler Information Services Association (TISA) traffic message channel identification. The study also shows the use of INRIX data to analyze speed distributions, revealing significant variations in real-time speeds across the major metropolitan regions of Texas. In addition, it provides a visual comparison between INRIX segments and the routes managed by TxDOT, as well as public roadways in the Austin area, showing broad coverage in the region. The base 2019 SAM results were compared against several alternative data sources. The RITIS Nextgen Trip Analytics V4 can generate sample statewide origin-destination (OD) matrices using vehicle GPS data provided by INRIX. Analyses so far has focused on heavy-duty vehicle (HDV) data from 2021, revealing several key differences between the RITIS data and SAM estimates. First, although the RITIS data reveals some patterns for HDV travel over the course of a week, there are some unexplained variations in the total number of trips and VMT in the data, such as a decreasing trend over the available months and some sudden spikes (over 2x the normal levels).

Additionally, the average weekday HDV trip distance in RITIS is 10 miles shorter than that in the SAM forecast, suggesting that RITIS is breaking up trips for driver breaks. There are also spatial sampling biases in RITIS with trips distributed more unevenly compared to SAM. Chiefly, it is missing flows to and from west Texas and the Houston area. Furthermore, ordinary least squares regression was used to compare the OD trip counts between RITIS and SAM. Regression at the TAZ level provided an extremely poor fit, and while aggregating to the county level improved the fit, the slope was heavily controlled by a few outliers with very high flows. In addition, regression was performed on permanent traffic recorder (PTR) data from 2023 through 2022 to reveal demand variations. The daily total traffic counts at each station were standardized to z-scores. Results reveal that on average, traffic volumes fluctuate by 1.63 std dev over the course of a week, with Sundays being the least busy and Fridays being the busiest. Results also show that January is the quietest month, while June and July are the busiest. Furthermore, demand variations around a few select holidays were studied in detail in the regression, revealing that Wednesday before Thanksgiving and Christmas see the largest increase and decrease, respectively, from a regular comparable day in the same month.

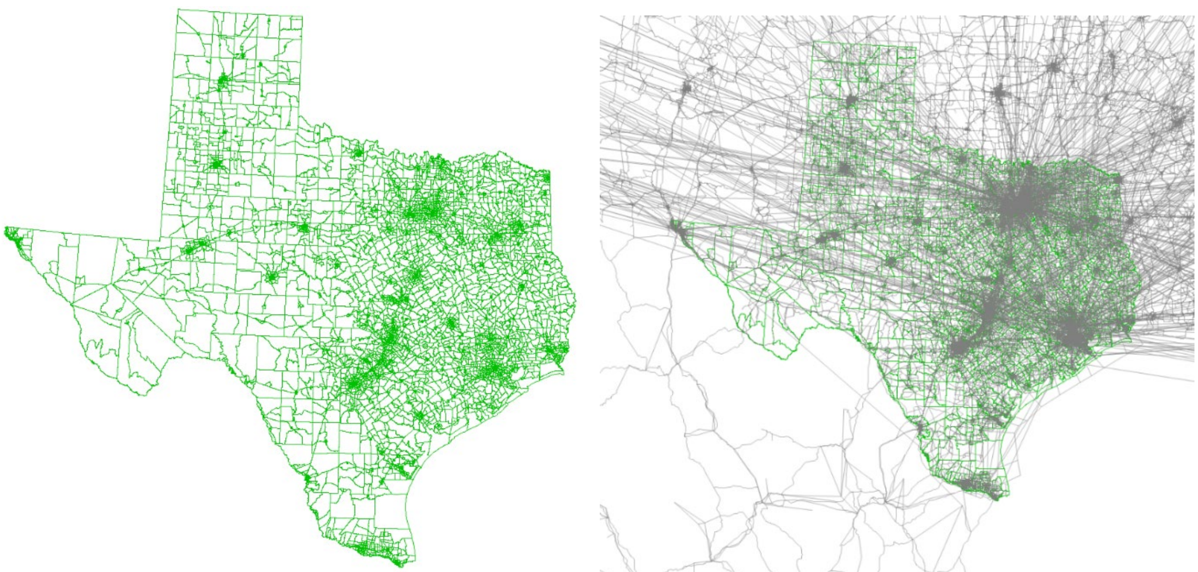
The study also includes an algorithm developed to detect intermediary "trips" that function as quick breaks within longer travel chains using the National Household Travel Survey (NHTS) and its

TRIP data file (trippub.csv). The TRIP data file treats each trip segment as a separate journey, even includes brief breaks made on the way to a main destination. The algorithm uses travel coordinates, dwell times at destinations, and trip purposes to differentiate between intentional and accidental stops. Upon implementing the method on the NHTS 2016/17 sample, the number of LD trips undergoes a little reduction of 3.4%. The algorithm initially relies on the coordinates and goals of journeys, and then takes into account the successive segments of the trips to detect changes in direction. It also identifies return trips and distinguishes between shifts in transportation mode and actual destinations.

This 5-7081-01 Research Report (R1B) 5-7081-01 provides analysis of the integration of AVs into the SAM model, considering seven different AV scenarios, focusing on the Year 2040. The study also investigates the process of aggregating data to compare the movement of journeys between origins and destinations (OD) utilizing datasets such as INRIX and RITIS. Additionally, it presents an analysis of long-distance trip chaining using the NHTS-2017 dataset. It includes a comprehensive evaluation of various datasets available to the TxDOT.

Chapter 1. Prediction Of AV's Impacts on Texas Transportation

SAM is a multi-modal travel model maintained by the TxDOT and developed by the Alliance Transportation group. The latest version is SAM-V4, which is designed to operate on TransCAD 8.0 Build 22180 64-bit platform. It covers North America, focusing on regions in and around Texas. Figure 11b represents the vast network of highway, railway, and airline routes in the state, comprising 228,562 links and 166,039 nodes. In SAM-V4, there are 6,860 traffic analysis zones (TAZs) within Texas, as seen in Figure 1a.



a. Texas TAZs (n=6860) b. Network of highway, railway, and airline routes (n=228,562)

Figure 1. SAM-V4 TAZ and Network File

1.1. Travel Demand Model Methods

SAM-V4 comprises two components: a passenger model and a freight model, both of which follow a four-step model structure. The vehicle trips estimated from the passenger model and the freight trucks estimated from the freight model are combined in the highway assignment step and loaded onto the highway network. A four-step travel demand modeling process is used to model traffic patterns across the entire state of Texas. This includes trip generation, trip distribution, mode choice, and traffic assignment, as shown in Figure 2. The passenger model in SAM-V4 uses destination choice models for distributing most short-distance trips (less than 50 miles) and all long-distance trips (50 miles or greater). Gravity models are applied for other short-distance trips such as home-based K-12 school trips and non-home-based visitor trips, as well as 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, midday (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. For long-distance trips, SAM-V4 uses a four-level nesting logit mode choice model that includes options such as auto, intercity rail, high-speed rail, and air travel.

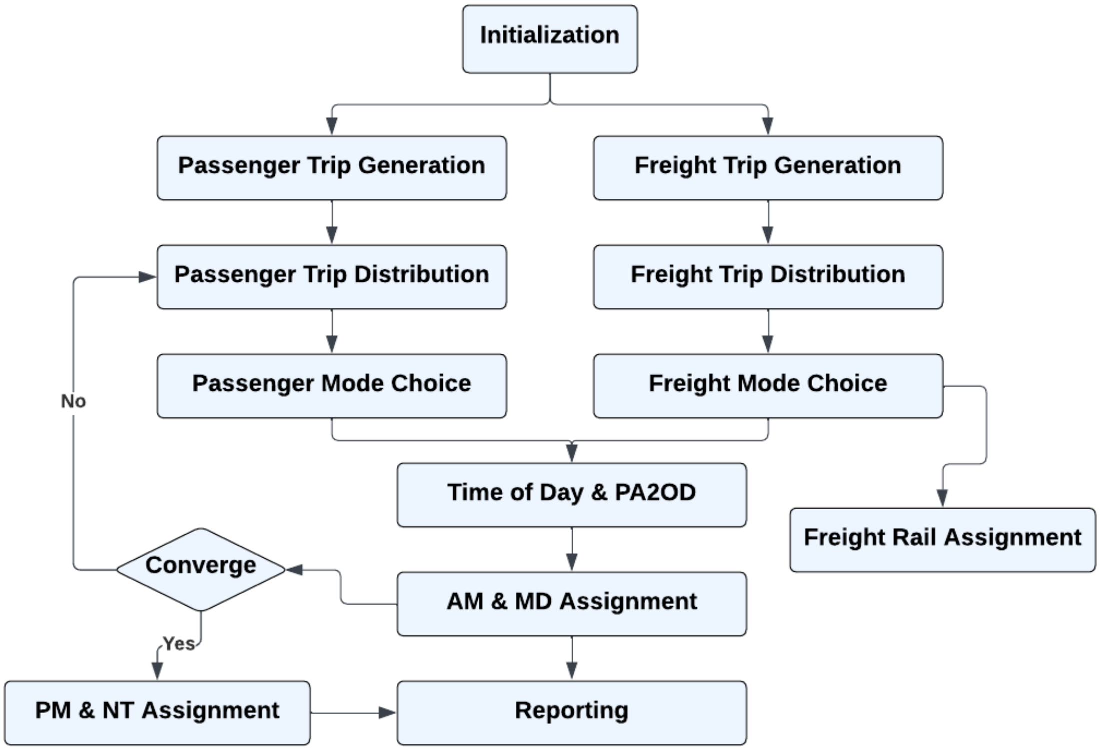
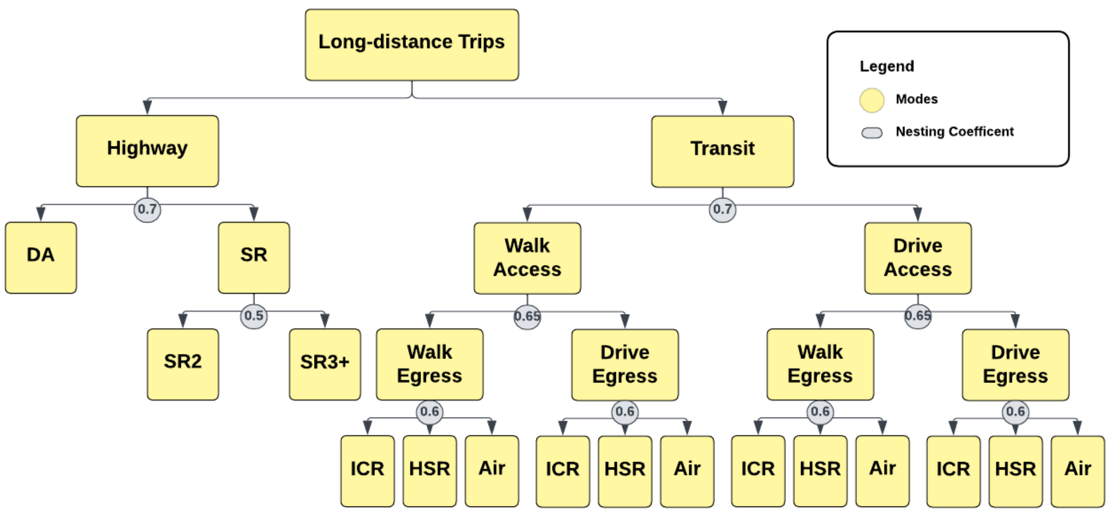


Figure 2. SAM-V4 Model Structure (Source: Alliance Transportation Group, 2019)

1.1.1. Passenger Model

The SAM-V4 passenger model comprises three types of trips, namely short-distance trips, long-distance trips, and non-freight truck trips. Short-distance trips are trips within 50 miles; these include 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 trips over 50 miles one-way and can occur within Texas or between Texas and the Continental United States over multiple days. SAM-V4 distinguishes long-distance trips into four types according to their purpose and distance: one, infrequent long-distance business trips (ILDB); two, infrequent long-distance other trips (ILDO) for trips that are 50 miles or greater and less than 400 miles; three, infrequent long long-distance business trips (ILLB); and four, infrequent long long-distance other trips (ILLO) for trips that are 400 miles or greater and are work or work-related. Non-freight truck trips are short-distance truck trips that are not captured by the freight model, serving local areas with purposes such as delivering goods and services. The SAM-V4 has a separate weekday and weekend module that analyzes and predicts weekday traffic conditions (typical day of Monday through Friday during non-summer months) and weekend traffic conditions (Saturday during the summer months of July through August), respectively, for the entire state of Texas. SAM-V4 passenger model applies different approaches to estimate the mode split for short-distance trips and long-distance trips based on their distinct trip characteristics and mode alternatives. For short-distance trips, mode-share factors are applied. On the other hand, the SAM-V4 long-distance mode choice module adopts a nested logit model structure. Figure 3 shows the nested logit structure for the passenger long-distance mode choice model. This model has four levels of nesting logit structure, with the highest level representing a choice between highway and transit travel. The second level includes a choice between drive-alone (DA) and shared-ride conditional on highway travel, and a choice between walk and drive access conditional on transit travel. The third level consists of a choice between shared-ride 2 (SR2) and shared-ride 3 or more (SR3) conditional on the choice of shared ride, a choice between walk egress and drive egress conditional on the choice of walk access, and conditional on the choice of drive access. The lowest level nest in the long-distance transit nest includes three transit modes: intercity rail (ICR), high-speed rail (HSR), and air.



*DA – Drive Alone, SR – Share Ride, ICR – Intercity Rail, HSR – High Speed Rail

Figure 3. SAM-V4 Passenger Long-Distance Mode Choice Nested-Logit Structure and Nesting Coefficients (Source: Alliance Transportation Group, 2019)

Table 1 shows SAM-V4's alternative-specific constants (ASCs) and parameters for passenger long-distance mode choice. These were estimated for each of the two long-distance trip purpose groups and for four different household income groups (dollar price in 2015): Category 1 is for household with incomes under $25,000 per year (dollar price in 2015, Category 2 is $25,000 to $49,999, Category 3 is $50,000 and $99,999, cand Category 4 is those having household incomes over $100,000 (SAMV4 Passenger Model, 2019).

Table 1. SAM-V4 Passenger Long-Distance Mode Choice Model Nesting Coefficients

Nest	Nesting Parameter (IV Coef)
Highway	0.70
Share Ride	0.50
Transit	0.70
Drive Access	0.65
Walk Access	0.65
Drive Access - Walk Access	0.60
Drive Access - Drive Access	0.60
Walk Access - Walk Access	0.60
Walk Access - Drive Access	0.60

(Source – SAM-V4 Passenger Model, 2019)

Table 2. SAM V4 Passenger Long-Distance Mode Choice Model Parameters: ASCs + Time & Cost Coefficients

		ILDB	ILDO	ILLB	ILLO
Drive Alone = Base Mode		N/A	N/A	N/A	N/A
Share Ride 2 ASCs		-1.5 utils	-0.1	-3.0	-0.8
Shared Ride 3+ ASCs		-2.0	-0.2	-4.2	-2.0
High Speed Rail ASCs		-1.1	-2.5	2.5	-0.4
Intercity Rail ASCs		-5.0	-3.8	-5.0	-2.5
Air ASCs		-1.1	-2.5	2.5	-0.4
IVTT Coefficient		-0.02 utils/hour	-0.01	-0.02	-0.01
OVTT Coefficient		-0.02	-0.01	-0.02	-0.01
Income 1	VOTT ($/hr)	$7.2/hr	5.4	7.2	5.4
	Travel Cost Coef.	-0.1664 utils/dollar	-0.1109	-0.1664	-0.1109
Income 2	VOTT ($/hr)	$21.6/hr	16.2	21.6	16.2
	Travel Cost Coef.	-0.0555	-0.0370	-0.0555	-0.0370
Income 3	VOTT ($/hr)	$43.3/hr	32.4	43.3	32.4
	Travel Cost Coef.	-0.0277	-0.0185	-0.0277	-0.0185
Income 4	VOTT ($/hr)	$72.3/hr	54.1	72.3	54.1
	Travel Cost Coef.	-0.0166	-0.0111	-0.0166	-0.0111

Note: ASC: alternative specific constants, OVTT out of vehicle travel time, IVTT in vehicle travel time, VOTT: value of travel time

(Source – SAM-V4 Passenger Model, 2019)

1.1.2. Freight Model

SAM-V4's freight module also follows a four-step framework consisting of trip generation, trip distribution, mode choice, and traffic assignment. In the final stage of traffic assignment, freight truck trips are merged with passenger trips. SAM-V4's freight models were developed based on 2015 TranSearch data. SAM-V4 commodity groups were grouped into 15 different categories based on 2015 TranSearch data. Table 3 shows the 15 commodity groups. The mode choice model for freight includes various modes like truck, carload rail, intermodal rail, water, and air, and it uses an incremental logit choice approach. Figure 4 shows the multi-logit structure for the freight mode choice model. The initial step in the incremental logit formulation involves the existing mode shares as a baseline and then makes adjustments to these values based on the variations in the explanatory variables' characteristics. Texas 2015 TranSearch commodity flow data is used to estimate the coefficients for the freight mode choice model. The mode choice coefficients used by SAM-V4 are presented in Table 2. After the mode choice step, the annual freight truck tonnage is used to estimate the number of daily freight truck trips, which are then input into the highway assignment process. The freight model uses a different zonal structure than the passenger model. It contains 348 TAZs, 254 Texas counties, 49 US states and the District of Columbia, 32 Mexican states, and 13 Canadian provinces. These are disaggregated to the 6860-passenger model TAZs before assignment.

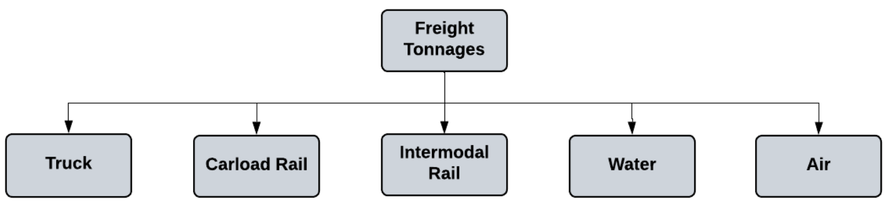


Figure 4. SAM-V4 Freight Mode Choice Structure (Source – Alliance Transportation Group, 2019)

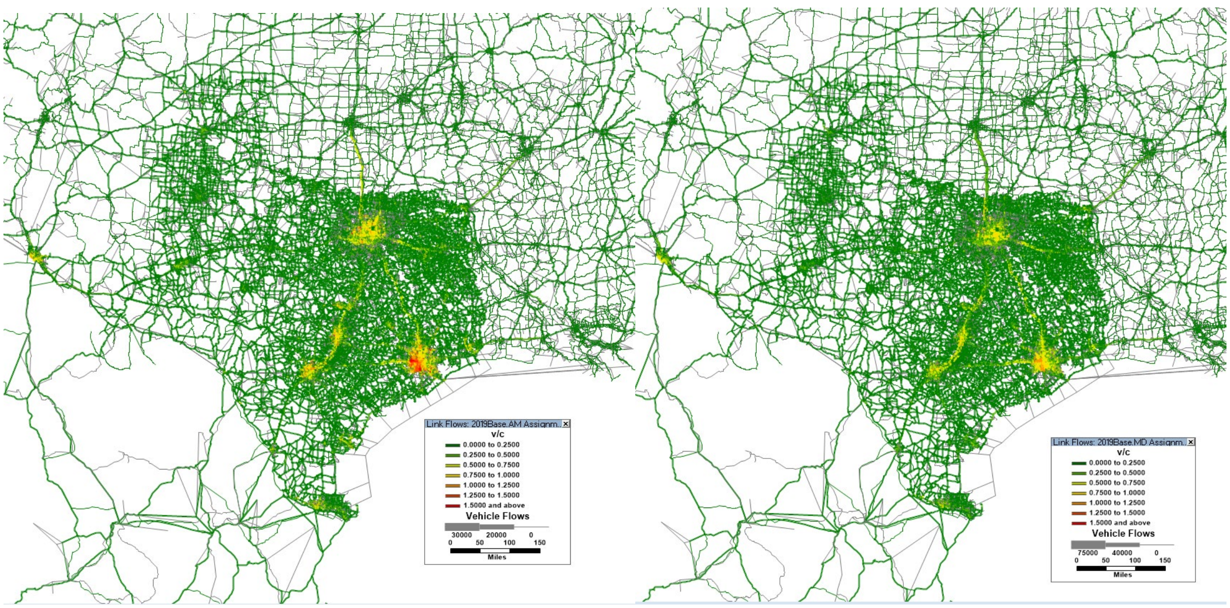
Table 3. SAM-V4 Freight Mode Choice Coefficients (Source – Alliance Transportation Group, 2019)

#	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

1.2. SAM Base Validation Scenario 2019

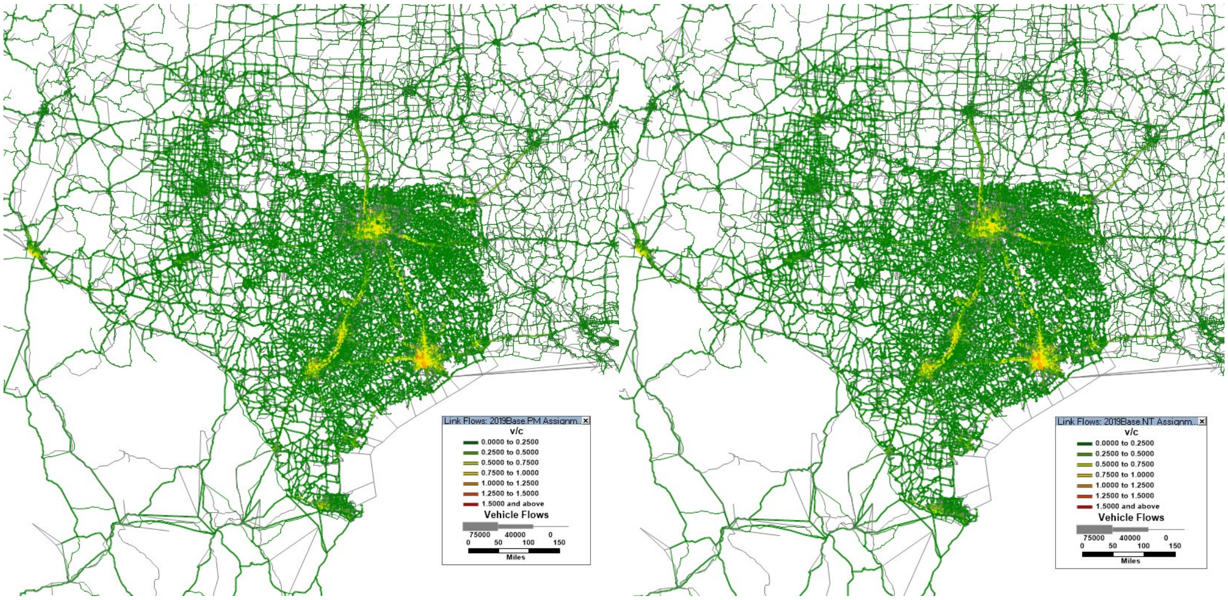
TransCAD Version 8.0, Build 22180 64-bit was used to operate SAM-V4. A 2019 scenario with default SAM-V4 inputs and parameters was run as the base model. It should be noted that SAM-

V4 is not compatible with a different version or build. The default scenarios included in the SAM-V4 package are 2015, 2025, 2035, and 2045. The 2019 scenario was created by using the Scenario Year Interpolation function. This uses the closest subsequent default year scenario (2025 in this case) inputs to estimate the non-default year parameters. The following discussion looks at model results such as network congestion, passenger LD trip travel time and distance, freight trip lengths and freight mode splits. The network congestion for AM (6-8 AM), MD (8 AM - 2 PM), PM (2-6 PM), and NT (6 PM - 6 PM) time periods is presented below. Figure 5 shows the volume-to-capacity ratio across the Texas region for the four times of days analyzed. Congestion (v/c > 1.25) in all periods occurs mostly among the major cities across Texas, especially Dallas-Fort Worth, Houston, and San Antonio. Congestion is also observed in a few other cities - like El Paso and Corpus Christi, and in southern Texas near McAllen and Harlingen.



a. AM

b. Midday (MD)



c. PM d. Nighttime (NT)

Note: These results are for an average weekday when school is in session. (SAM also allows weekend-day simulation, but not specific days of the year.)

Figure 5. V/C Ratios predicted by SAM in 2019 across four Times of Day

Table 4 shows the average trip and travel time and distances for long-distance trips based on the four trip purposes. The average travel time and distance for trips below 400 miles (ILDB and ILDO) are approximately 12% lower for business trips than for other trips. However, for business trips over 400 miles, the average travel time and distance are about 7% higher relative to others.

Table 4. LD Trip Length by Purpose

Trip Purpose	Average travel time (minutes)	Average travel distance (miles)
ILDB	113.2 min	113.3 miles
ILDO	128.1	128.5
ILLB	942.0	1011.0
ILLO	879.6	943.2

Table 5 outlines the average length of freight trips based on commodity groups. The results reveals that the Oil and Gas and Consumer Manufacturing sectors have longer average trip lengths than others. Table 6 shows the mode share of freight transportation for different industry sectors, as determined by SAM4's mode choice specification. According to the table, trucks are the primary mode of transportation for goods, accounting for 65.4% of the total goods transported. Carload rail follows at 20.7%; water, intermodal rail, and air make up the remaining 8.4%, 5.3%, and 0.2%, respectively.

Table 5. Freight Trip Length by Commodity Group

Commodity Group #	Commodity Group Name	Average Trip Length (Miles)
1	Agriculture	587.83 mi
2	Other Mining	959.06
3	Oil and Gas	1,018.91
4	Nonmetallic Minerals	240.54
5	Food	767.49
6	Consumer Manufacturing	1,130.02
7	Non-Durable Manufacturing	799.06
8	Lumber	841.93
9	Durable Manufacturing	771.45
10	Paper	819.38
11	Chemicals	704.04
12	Petroleum	323.35
13	Clay, Concrete, Glass	265.97
14	Primary Metal	804.54
15	Secondary & Misc. Mixed	495.85

Table 6. Freight Mode Split by Commodity Groups

Commodity Group	Commod. Group #	Truck Share (%)	Carload Rail Share (%)	Intermodal Rail Share (%)	Air Share (%)	Water Share (%)
Agriculture	1	64.97%	30.47%	3.7%	0.08%	0.77%
Other Mining	2	18.54%	80.77%	0.51%	0.04%	0.14%
Oil and Gas	3	0.56%	11.54%	0.46%	0%	87.44%
Nonmetallic Minerals	4	86.47%	11.93%	0.03%	0.21%	1.36%
Food	5	68.49%	27.06%	4.21%	0.02%	0.22%
Consumer Manufacturing	6	69.4%	1.24%	28.51%	0.83%	0.03%
Non-Durable Manufacturing	7	90.48%	3.17%	6.09%	0.25%	0.01%
Lumber	8	80.85%	18.22%	0.74%	0.03%	0.16%
Durable Manufacturing	9	72.28%	21.67%	5.25%	0.65%	0.16%
Paper	10	57.73%	34.59%	7.63%	0.03%	0.01%
Chemicals	11	64.51%	28.4%	1.13%	0.2%	5.76%
Petroleum	12	64.32%	7.32%	0.1%	0.1%	28.16%
Clay, Concrete, Glass	13	94.61%	4.96%	0.23%	0.02%	0.18%
Primary Metal	14	69.55%	27.42%	0.97%	0.14%	1.93%
Secondary & Misc. Mixed	15	77.76%	1.32%	20.31%	0.34%	0.27%

Chapter 2. Integration of AVS, SAVS, AND A-TRUCKS in SAMV4 (AV Base Scenario)

To integrate AVs, SAVs, and ATrucks as additional transportation modes within SAM, significant modifications were made to the mode choice component of the model. Specifically, the AV/ATruck scenario underwent substantial adjustments using the GISDK within the TransCAD software. Within SAM, a comprehensive set of 38 scripts guides the four-step process. For this particular scenario, the scripts pertaining to trip generation, skim creation, mode choice (includes passenger short-distance and long-distance mode choice, as well as freight mode choice), traffic assignment, and report generation were carefully edited. These modifications are discussed in further detail in the subsequent sections.

2.1. Passenger Model

To accommodate the anticipated rise in VMT resulting from the introduction of AVs and SAVs, a 15% increase in trip production rates has been incorporated. This augmentation acknowledges the potential growth in travel demand facilitated by AVs, which will grant access to elderly individuals, those without driver's licenses, and people with mobility impairments. This adjustment pertains specifically to trip generation rates in the year 2040, encompassing both trip productions and attractions, as enabled by AV technologies. This assumption aligns with findings from Harper et al. (2016), which estimated a 14% surge in U.S. VMT attributable to non-driving Americans, elderly citizens, and individuals with medical conditions that impede conventional travel. As previously discussed, our passenger model in the SAM employs distinct approaches for short-distance and long-distance trips. The following sections elucidate the modifications made to accommodate this scenario.

2.1.1. Short-Distance Mode Choice

For short-distance trips, SAM applies mode shares based on transit availability for different trip purposes and income groups. Within SAM-V4, four distinct modes are considered for short distance trips: Drive-alone (DA), Shared-Ride 2 (SR2) and Shared-Ride 3 or more people (SR3+) and “Other” modes. The “Other” category includes modes such as bus, urban rail, ferries, and any other transportation modes not captured by the survey questionnaire. SAM-V4 applies different factors based on three area types: "No Transit Available area", "Bus Available Area", and "Urban Rail Available Area". Figure 6 highlights TAZs according to their transit availability. Zone pairs where one of the zones has no transit access is considered a “No Transit Available Area”. When both zones have urban rail access, it is classified as “Urban Rail Available Area”. Similarly, for zone pairs where both have transit access but at least one zone has only bus access, it is considered “Bus Available Area”.

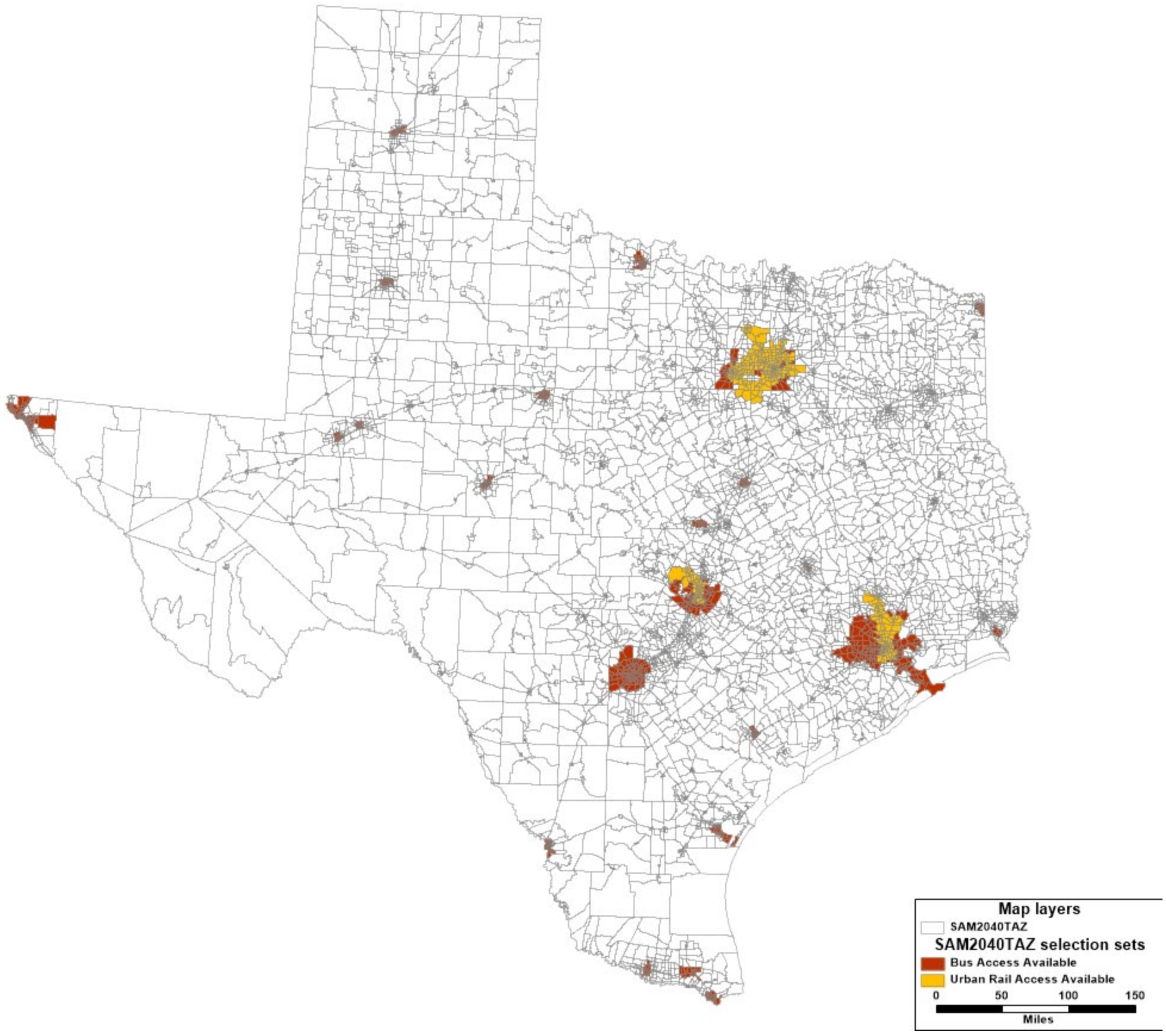


Figure 6. 2040 SAM-V4 Transit Availability by TAZ

In areas where no transit is available, a distribution of 40% for human-driven vehicles (HV), 40% for AVs, and 20% for SAVs was assumed for DA, SR2, and SR3+. Similarly, in areas with transit availability (bus and urban rail available areas), the distribution of 40% for HVs, 40% for AVs, and 20% for SAVs was assumed for DA, SR2, and SR3+, mirroring the previous case. Additionally, a 50% reduction in the mode shares of "Other" modes was considered in these areas. Zhao et al. (2018) forecasted two-thirds of all auto users opting for AV or SAV. Litman (2020) forecasts predicted 30% U.S. fleet in 2040 to be AVs, while other research predicts AVs comprising anywhere from 25% to 87% (based on different assumptions) of U.S fleet in 2045 (Bansal and Kockelman, 2016). Huang et al. (2021) survey results for trips between 75 and 500 miles indicate approximately a 23%, 28%, and 17% split for HV, AV, and SAV for business trips, and a 37%, 15% and 34% split for HV, AV, and SAV for non-business trips. These studies were used as reference for developing the assumptions outlined above. For further details and the comprehensive set of applied mode shares, please refer to the Appendix, which includes the corresponding table.

2.1.2. Long-Distance Mode Choice

For trips greater than 50 miles, SAM's nested logit model was modified to include HV, AV, and SAV. These modes were nested under DA, SR2 and SR3+. The nesting order was determined so because individuals are more inclined to determine the mode of transportation based on the size of their party, rather than selecting a mode first and then considering the number of people traveling with them. Figure 7 presents the updated nesting structure with the assumed nesting coefficients. The specific mode choice constants (ASCs) and explanatory variable coefficients assumed for the model, along with those set by default in the base model, are presented in Table 7.

These parameters were selected based on the SAM-V4 base model and a similar model calibrated in the Huang et al. (2020) Texas megaregion study. Person-trips produced in the mode choice step are converted to vehicle trips before traffic assignment. Auto occupancy factors are fixed for different modes for this step. DA and SR2 have occupancy of 1 and 2, respectively. Auto occupancy rates for SR3+ trips are applied in SAM based on trip purpose and income group, based on the National Household Travel Survey (NHTS). These rates range from 3 to 4.79, with an exception of 7.57 for ILLO trips of income group 3. This 7.57 seems quite high, especially since long-distance mode choice model does not include bus modes. This could potentially be an error in SAM, where a small sample of bus modes in the NHTS were accidently considered while estimating these rates.

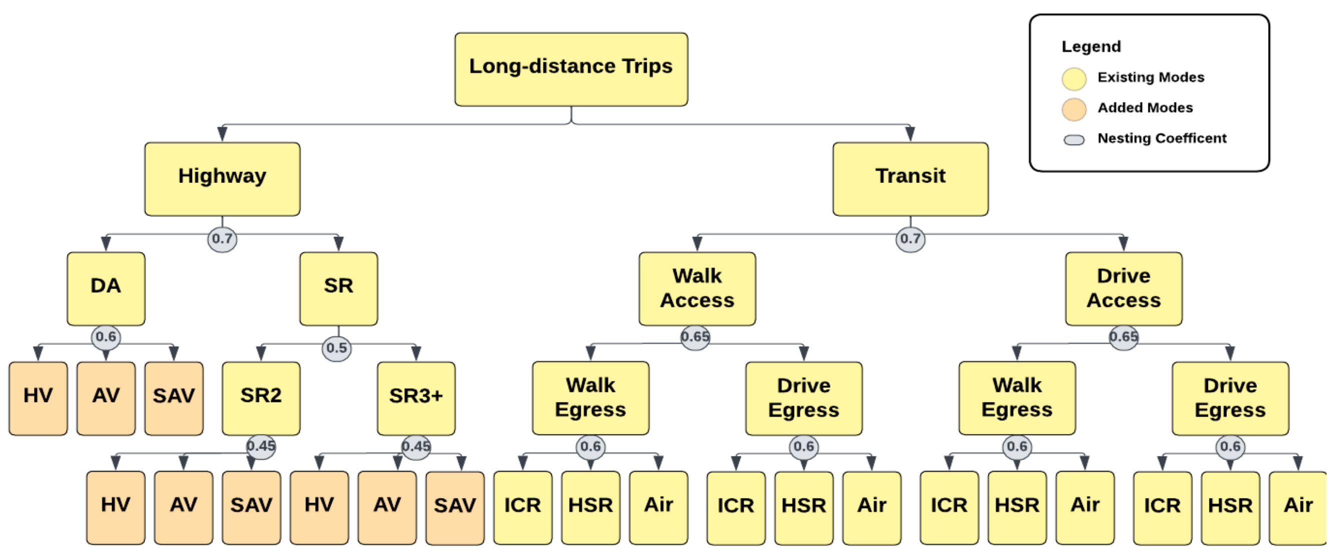


Figure 7. AV/ATruck Scenario Long-Distance Mode Choice Nested-Logit Structure and Nesting Coefficients

*DA – Drive Alone, SR – Share Ride, ICR – Intercity Rail, HSR – High Speed Rail

Table 7. Passenger Model Parameters

No AV/ATRUCK 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

Note: ILD = infrequent, long-distance (>50 mile) passenger trips. under 400 miles. ILL = extra-long trips (> 400 miles each way). B = business trips, and O = non-business or "other" trips.

2.1.3. 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 ATrucks from HTruck. The Texas megaregion study conducted by Huang et al. (2020) is again used as a starting point for the model parameters, assuming a nesting coefficient of 0.7 for HTruck to reflect the relative substitutability between the two modes. The operating costs for ATrucks were assumed to be 1.5 times those of HTrucks to account for automation equipment cost and additional training expenses for humans supervising the truck). The ATruck travel time skim was assumed to be 0.42 times that of HTruck to reflect HTruckility of automated trucks to drive 24 hours a day. As shown in Table 3, the time coefficient for 11 out of 15 commodities in SAM-V4 are 0. Therefore, for these groups, only the operating cost is increased. The updated mode choice structure for this scenario, along with the nesting coefficient, is shown in Figure 8. As previously mentioned, 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.

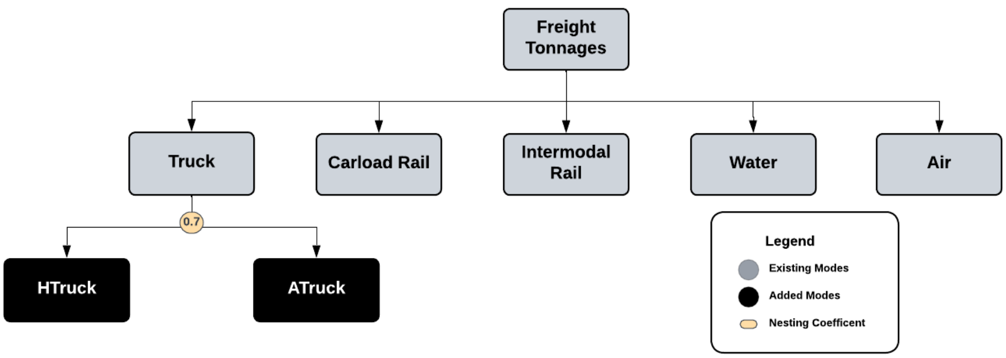


Figure 8. AV/ATruck Scenario Mode Choice Structure and Nesting Coefficient

To begin, the utilities of HTruck and ATruck for every commodity group and zone pair were computed using the explanatory variables 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 logsum of the utilities of HTruck and ATruck, taking the nesting coefficient into consideration. 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 logsum of HTruck and ATruck, with the previous utility of the truck mode, before introduction of new mode (and nest). The shares of ATruck and HTruck 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:

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

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

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

2.2. Comparative Analysis Between Base Scenarios and AV Scenario

This study examines and compares two distinct SAM-V4 models to analyze travel patterns in the year 2040. The first model, referred to as “No AV/ATruck Scenario”, has the default SAM settings without any modifications. The second model, “AV/ATruck Scenario”, includes AV, SAV and ATruck modes. By developing these two models, the study aims to assess the potential impacts and differences brought about by the integration of AVs, SAVs, and ATrucks into the transportation system. The “No AV/ATruck Scenario” model serves as the benchmark against which the AV/ATruck scenario is evaluated, allowing for a comprehensive analysis of the changes and benefits associated with the introduction of these advanced transportation technologies. For both models, a typical weekday was selected as the basis for the analysis, using SAM’s weekday module. Feedback loops involving iteration from Traffic Assignment to Trip Distribution were not included in these model runs due to the very long model run times. Further modifications in the scenarios involving AVs that were not previously specified encompass changes to the occupancy of SAVs. The occupancy of SAV was reduced by 20% after the mode choice stage to ensure the appropriate inclusion of empty VMT (eVMT).

The simulation model used in this study provides a comprehensive analysis of travel patterns involving a substantial population of 40,217,918 individuals who are distributed across 13,509,343 households within the state of Texas. These households have an average size of 2.98 individuals, which is an essential demographic factor that significantly influences transportation behavior and infrastructure demands. Furthermore, the population-to-employment ratio stands at 2.1, highlighting the critical relationship between workforce distribution and transportation requirements. In order to develop a more detailed understanding of the economic environment and its impact on travel patterns, it is crucial to examine the distributions of different job prospects. The distributions, depicted in Figure 9 below, offer useful insights into the sector-based spread of employment within the region. This is especially important in the domain of transportation planning and policy structure, as it influences the patterns of everyday travel, urban movement, and the need for different modes of transportation.

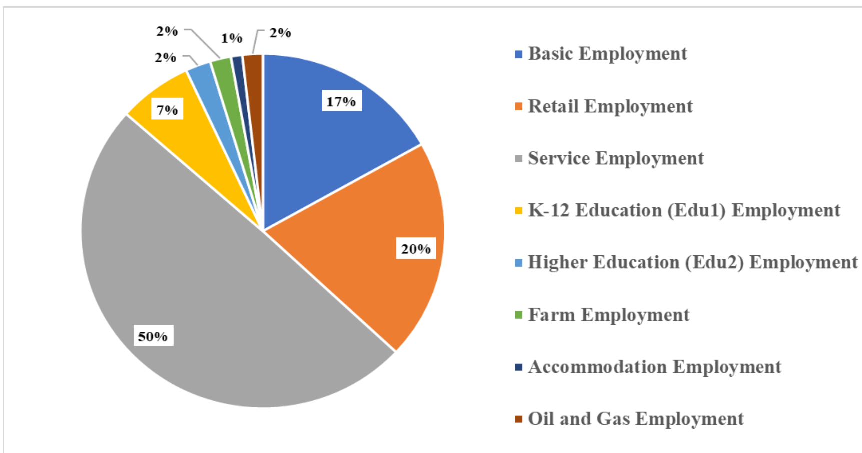


Figure 9. Employment Distributions by Sector (Total: 19,170,201)

The mode splits for short-distance trips remain consistent even with the introduction of AVs, as they stick to a fixed distribution unaffected by changes in mode choice model parameters. However, subsequent analysis focuses on the shifts in mode split patterns following the integration of AVs in passenger and freight transportation for long-distance trips exceeding 50 miles. Integrating AVs into the mode choice model for long-distance passenger travel, for those exceeding 50 miles, revealed that personal AVs captured a 14% market share, while 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. In Figure 12, it's evident that the introduction of AVs has led to 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.

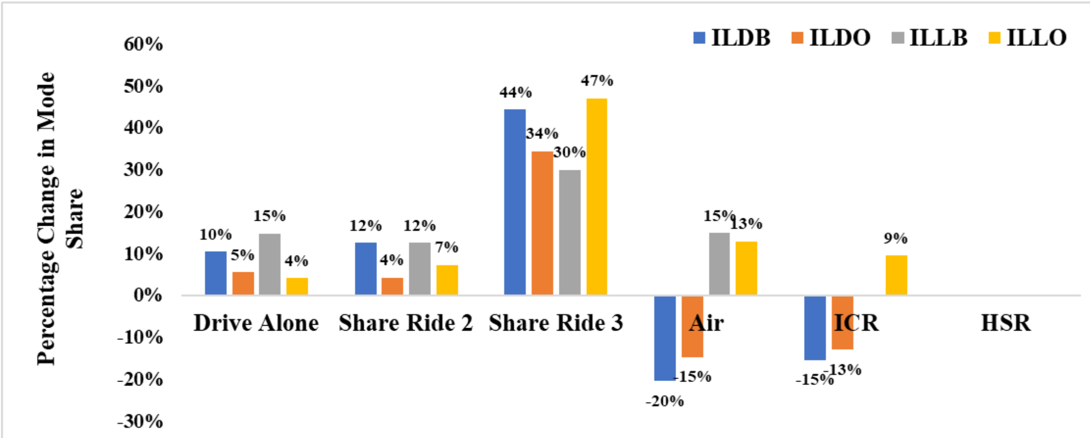


Figure 10. Percentage Change in Mode Shares of Ground Travel vs Air vs Transit for No-AV Vs AV Base Scenario

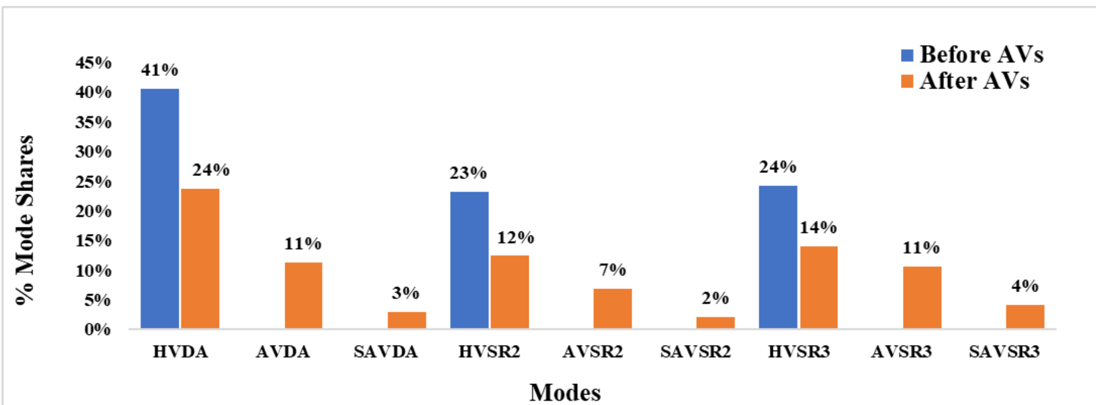


Figure 11. Percentage Change in Mode Shares for Ground Travel: No-AV Vs AV Base Scenario (HV = human-driven vehicle, DA = drive alone, SR2/3 = shared ride with 2/3 persons)

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 12, the AV inclusion into the transportation system has led travelers to opt for more distant locations as compared to their previous choices. Additionally, the ability to use time while inside AVs has increased the possibility of making trips, particularly for work-related trips that were previously deemed too far. And 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 13, 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 for covering greater distances, likely due to the removal of driving burdens in AV modes. Furthermore, the increase in the number of hours vehicles spent on the road on all types of roads also indicate fall in average speeds. Arterial roads, collector roads, and interstate highways were significantly impacted, with average speeds falling by more than 60%. 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 as shown in Figure 14.

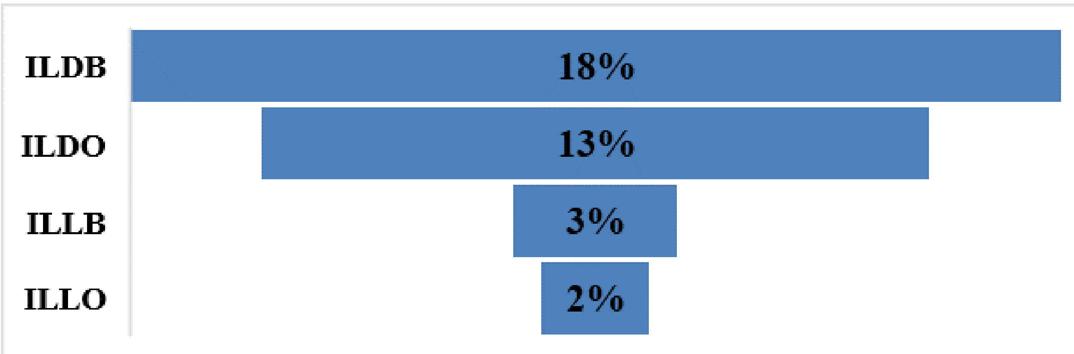


Figure 12 Percentage Change in Average Trip Length: No-AV vs AV Base Scenario

(ILDB: infrequent long-distance business trips; ILDO: infrequent long-distance other trips for trips that are 50 miles or greater and less than 400 miles; ILLB: infrequent long long-distance business trips; ILLO: infrequent long long-distance other trips for trips that are 400 miles or greater and are work or work-related)

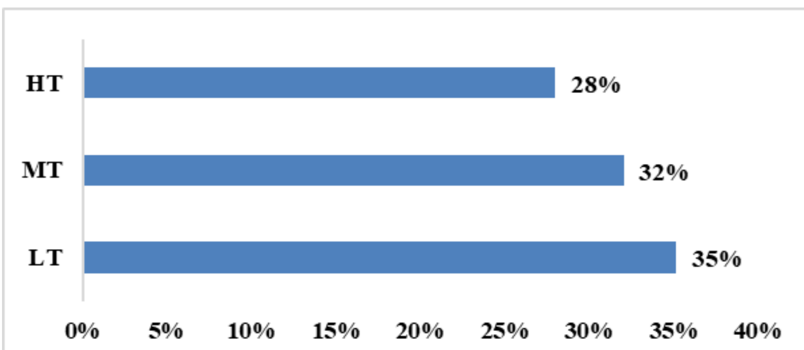


Figure 13 Percentage Change in Average Trip Length of Trips Exceeding 50 Miles: No-AV vs AV Base Scenario

(HT: heavy-duty trucks; MT: medium-duty trucks; LT: passenger vehicles, light-duty trucks (non-freight))

VMT experienced a notable increase across all time periods, as shown in Figure 14. During the AM and PM periods, VMT rose by more than 28%, followed by a 22% rise during the afternoon periods. Passenger VMT saw a 26% rise, while truck VMT rose by 7%. This upward trend in VMT due to ATrucks is expected to further increase as they become more cost-effective compared to human-driven trucks. Expressways and freeways witnessed a significant rise of over 20% in passenger VMT, as shown in Figure 15. Furthermore, the increase in the number of hours vehicles spent on the road on all types of roads (Figure 16) also indicate 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 17. 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.

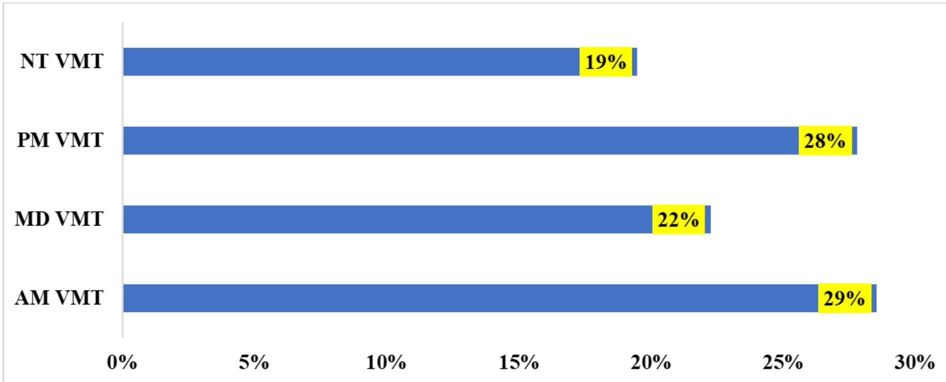


Figure 14 Percentage Change in VMT in Trips Exceeding 50 Miles: No-AV vs AV Base Scenario

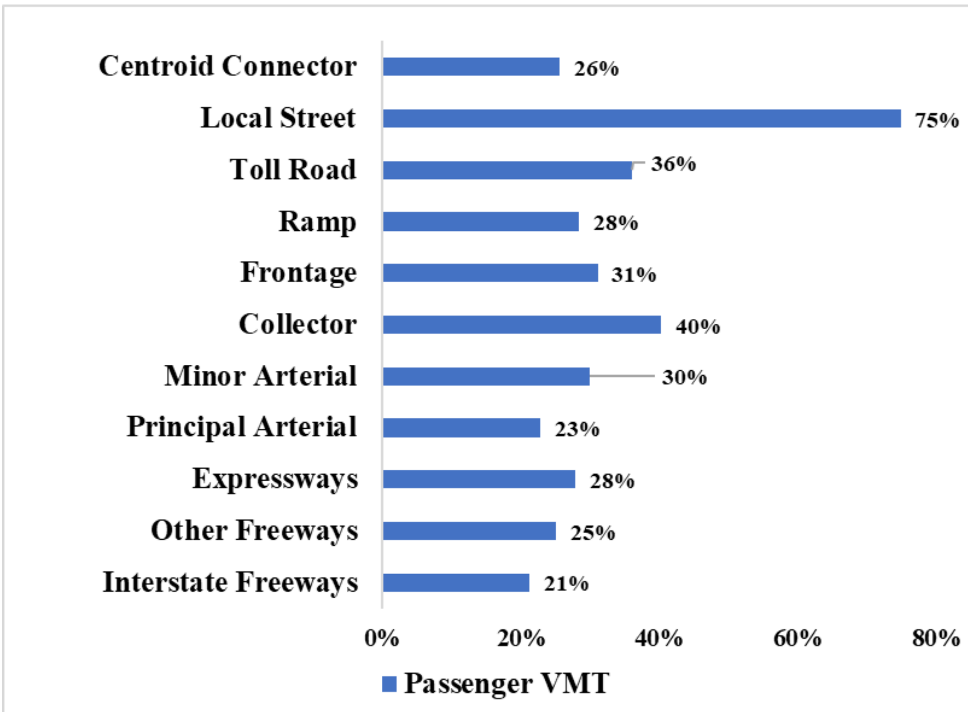


Figure 15 Percentage Change in Passenger VMT across Road Types: No-AV vs AV Base Scenario

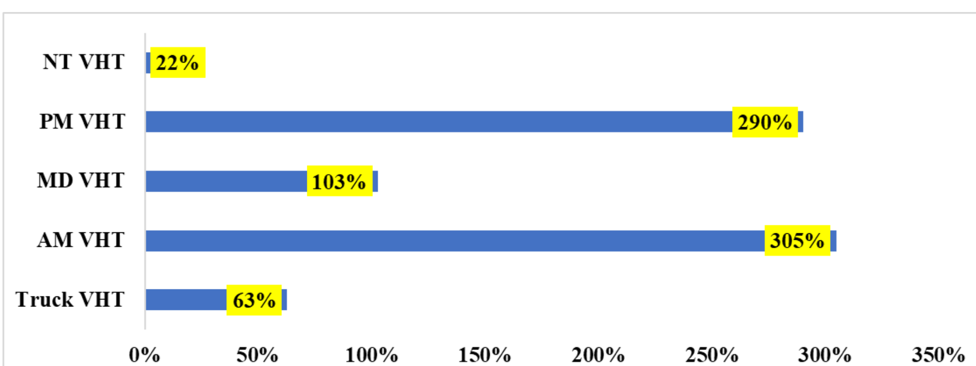


Figure 16 Percentage Change in VHT in Trips Exceeding 50 Miles: No-AV vs AV Base Scenario

As shown in Figure 18, the integration of ATrucks into the transportation system brings about significant changes in the distribution of consumer manufacturing goods. ATrucks emerged as the prevailing preference, accounting for around 43% of the transportation of goods, while trucks operated by human drivers have witnessed a significant decline of 39% in their market share across all the commodities. Trips involving the transportation of metallic and nonmetallic materials, consumer manufacturing, paper, petroleum and food experience a decline of over 40% in the proportion of trips made by Htrucks. This decline subsequently leads to an rise in the proportion of trips made by ATrucks.

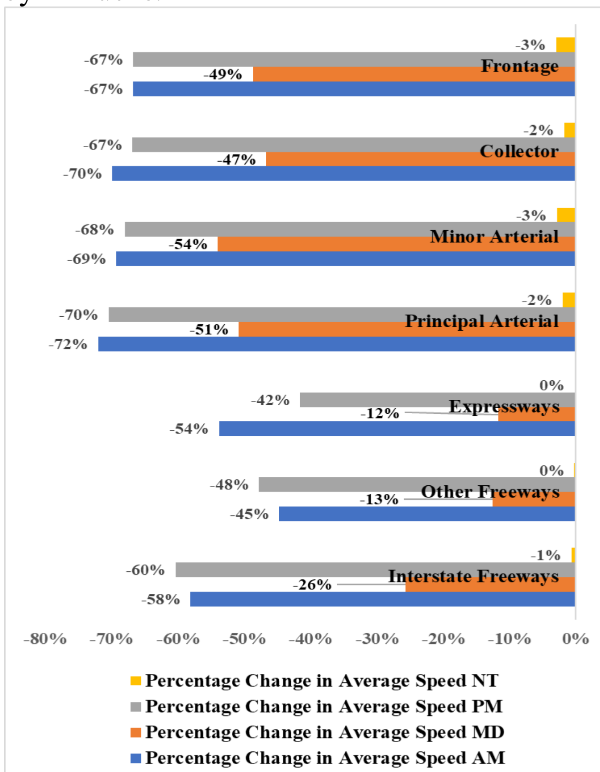


Figure 17 Percentage Change in Average Speed Across Road Types: No-AV vs AV Base Scenario

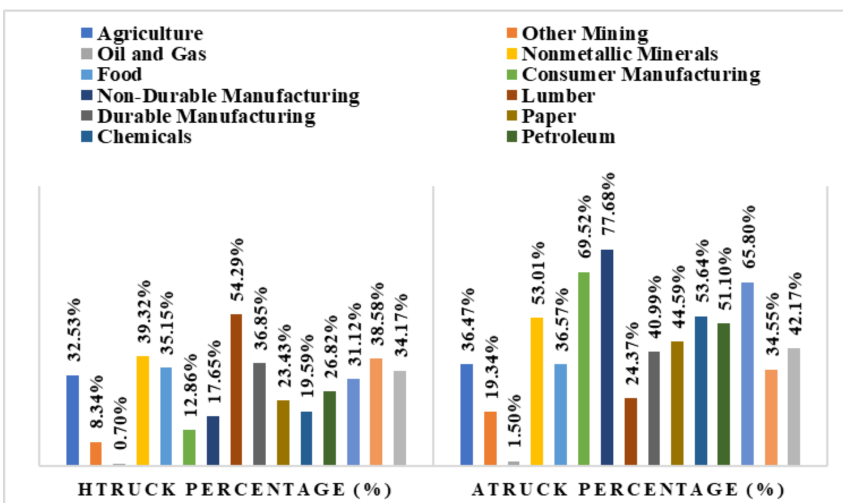


Figure 18 Percentage Mode Shares of HTrucks vs ATrucks across Commodities

Chapter 3. Developed Scenarios

The initial AV model under the SAM framework was subsequently subjected to six distinct scenarios, wherein the parameters of AVs, SAVs, and ATrucks were modified. The present study conducted an analysis of several situations in order to examine the potential changes in long-distance travel, namely trips beyond a distance of 50 miles. Scenario 1 investigates the effects on network features that arise from the decrease in the cost of AVs in comparison to vehicles operated by humans. The operating costs of personal AVs have remained constant, but SAVs have been found to be 40% less expensive than previously estimated in the basic scenario and The operating costs for ATrucks were assumed to be 1.5 times those of HTrucks to account for automation equipment cost and additional training expenses for humans supervising the truck with a 25% reduction in VOTT for all AV scenarios (except for scenario 3 which assumes 50% reduction in VOTT) as shown in Table 7.

Scenario 2 centers on the examination of the effects resulting from the escalation of expenses associated with AVs in comparison to those of human-driven vehicles, specifically in relation to network characteristics. In this particular scenario, the operational expenses for personal AVs experienced a 33% rise but the costs associated with SAVs remained unchanged. Consequently, the operating costs for AVs and SAVs have been adjusted to 0.8 dollars per mile and 1 dollar per mile, respectively. No rest time is 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 to reflect HTruckility of automated trucks to drive 24 hours a day.

As shown in Table 3, the time coefficient for 11 out of 15 commodities in SAM-V4 are 0. Therefore, time and cost coefficients were re-estimated for the 11 commodities by lowering (by half) beta of cost & choosing the beta time coefficients carefully so that those newly added multiples will make up for the reducing in the beta cost*cost terms. This was done by taking the half of the cost coefficients & selecting 11-time coefficients to minimize errors in hitting current rail/truck splits (no AV scenario) for the top 50+ OD pairs for each commodity. This process was repeated for 11 commodities. The updated coefficients are shown in Table 8.

The impacts of these adjustments are subsequently analyzed in relation to travels exceeding 50 miles. In accordance with microeconomic theory, individuals are expected to make decisions regarding transportation while operating under the assumption that their daily time budget is limited. Hence, individuals make decisions on the allocation of their time between different activities, as well as by the valuation they place on reducing the time spent on a specific activity. The subjective VOTT savings can be defined as the willingness to pay (WTP) in order to decrease the amount of time spent on travel. The variability of Vehicle Travel Time Savings is typically contingent upon the purpose and duration of a trip. It also exhibits variation across different modes of transportation.

Thus, Scenario 3 analyzes the effect of a reduction in the perceived VOTT as they will be able to use the time for other purposes they like. In this case, we have assumed that VOTT for AVs will decrease by 50% across all the income groups. The scenario aims to examine the link between lower values of trip time for AV passengers and their tendency to engage in longer distance travel while reducing their reliance on public transit systems. Table 9 presents the revised cost coefficients corresponding to specific income groups.

Table 8 Freight Mode Choice Coefficients

Commodity Group No.	Original		Modified		Original		
	Time Coefficient	Cost Coefficient	Time Coefficient	Cost Coefficient	Carload Constant	IMX Constant	No. of IMX Coefficient
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

Table 9. SAM-V4 Long Distance Model VOTT (Dollar/Hour)

	ILDB	ILDO	ILLB	ILLO
Income 1	7.2	5.4	7.2	5.4
Income 2	21.6	16.2	21.6	16.2
Income 3	43.3	32.4	43.3	32.4
Income 4	72.3	54.1	72.3	54

Scenario 4 explores the implications that follow from the complete absence of human-operated vehicles in passenger and freight transportation. The parameters of the nested logit model used in the base scenario were modified to simulate the alternatives. Scenario 5, on the other hand, addresses the situation in which individuals may find owning a personal AV costly, leading them to consider SAVs and human-driven vehicles as more favorable options. Similar to Scenario 4, the nested logit model for mode choice was adapted to replicate these particular choices. Scenario 6 investigates the impact of empty SAVs in the network through a reduction of 20% in average passenger occupancy. The study assumes that if occupancy is decreased, there is a likelihood of a substantial 25% rise in the distance covered by unoccupied SAVs.

3.1. Scenario 1 (Less Expensive AVs)

Scenario 1 examines the implications for network characteristics that result from AVs becoming less expensive than human-driven cars. Personal AVs' operational costs have not changed; however, SAVs expenses have been discovered to be 40% lower than those of the baseline scenario. and ATrucks will be 20% more expensive than HTrucks with 25% reduction in VOTT as shown in Table 9. The assumptions include a cost of $0.60 per mile for both personal and SAVs.

Table 10. Scenario 1 Model Parameters

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 ($/mile)		0.6	0.6	0.6	0.6
ATruck Operating Cost ($/mile)		1.2*HTruck (for all commodities)			
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

In Figure 19, it is evident that further reducing the cost of SAVs did not significantly alter their mode shares compared to the Base AV scenario. However, there was a substantial shift from HTrucks to ATrucks across all commodity transportation sectors. HTrucks experienced a loss of 41.6% in mode shares across all commody transportation, while ATrucks gained 46% in shares after their integration into the mode choice model for freight. As depicted in Figure 20, consumer manufacturing and non-durable manufacturing, saw over 70% of goods transported via ATrucks, and for paper, chemicals, petroleum, and non-metallic minerals, more than half of their transportation will be facilitated by ATrucks.

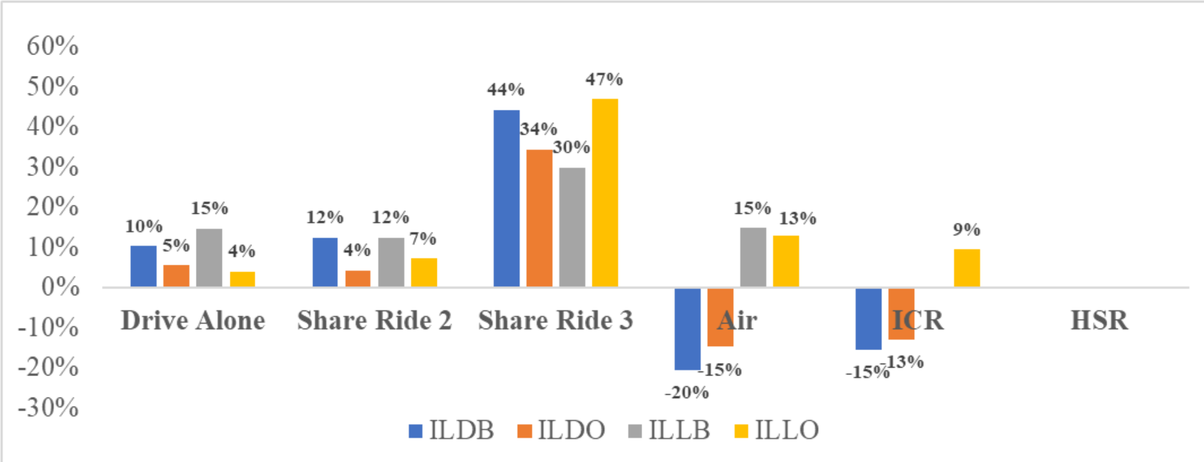


Figure 19. Mode Distribution as per Trip Purpose: No-AV vs AV Base Scenario

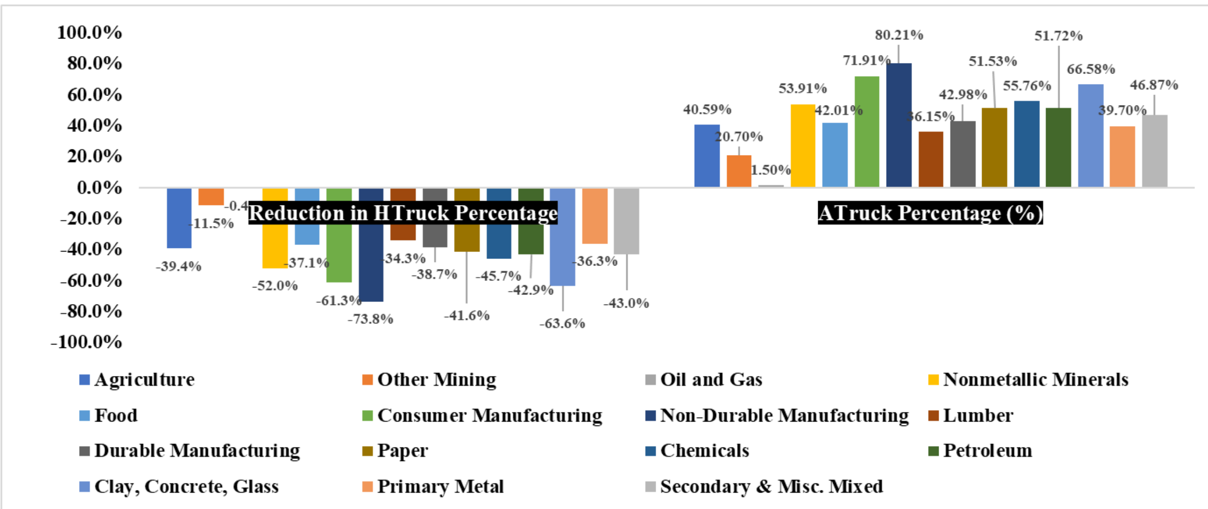


Figure 20. Mode Shift to ATrucks: AV Base Scenario

3.2. Scenario 2 (Increased AV Costs)

This scenario explores the consequences that arise in transportation networks when AVs become more expensive than HVs. The objective of this scenario is to highlight the challenges of this transition, specifically with regard to the economic dynamics of AVs and their influence on different vehicle classifications. During the simulation, operational expenses of individual AVs were rose by 67% compared to the standard AV scenario. In addition, the operational costs of SAVs increased by a substantial 50% compared to the baseline scenario of AVs. Furthermore, the study assumes that ATrucks are twice as high as that of HTrucks with 25% reduction in VOTT. This difference is crucial in evaluating the cost-effectiveness and practicality of self-driving trucks for different freight transportation purposes. The assumptions include that the cost for individual AVs is $1.00 per mile, while SAVs have a slightly higher cost of $1.50 per mile, as shown in Table

11. The results show a clear trend: as the cost of AVs, whether for personal or shared use, rises, there's a noticeable hesitancy to adopt them, as shown in Figure 22. While the market shares of "drive alone" long-distance trips (ranging from 40 miles to 500 miles) remain relatively stable across all trip purposes, there's a significant 41% fall in drive-alone trips exceeding 400 miles. This decline shows a rise in shared rides with two or more occupants, witnessing a significant rise of over 200% in both business and non-business trips. This shift reflects a preference for more economical ground travel options while still meeting travel needs. There was not change in shares of air, intercity rail, however, people shifted to shared rides to save money.

Table 11. Scenario 2 Nested Logit Model Parameters

Mode		**ILDB**	**ILDO**	**ILLB**	**ILLO**
DA	Human-Driven Vehicles (HVs)	N/A	N/A	N/A	N/A
	Autonomous Vehicles (AVs)	-0.05	-0.05	-0.05	-0.05
	Shared Autonomous Vehicles (SAVs)	-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)		1	1	1	1
SAV Operating Cost ($/mile)		1.5	1.5	1.5	1.5
In-vehicle Time Coefficient		-0.02	-0.01	-0.02	-0.01
Out-of-vehicle Time Coefficient		-0.02	-0.01	-0.02	-0.01
ATruck Operating Cost ($/mile)		2*HTruck (for all commodities)			
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

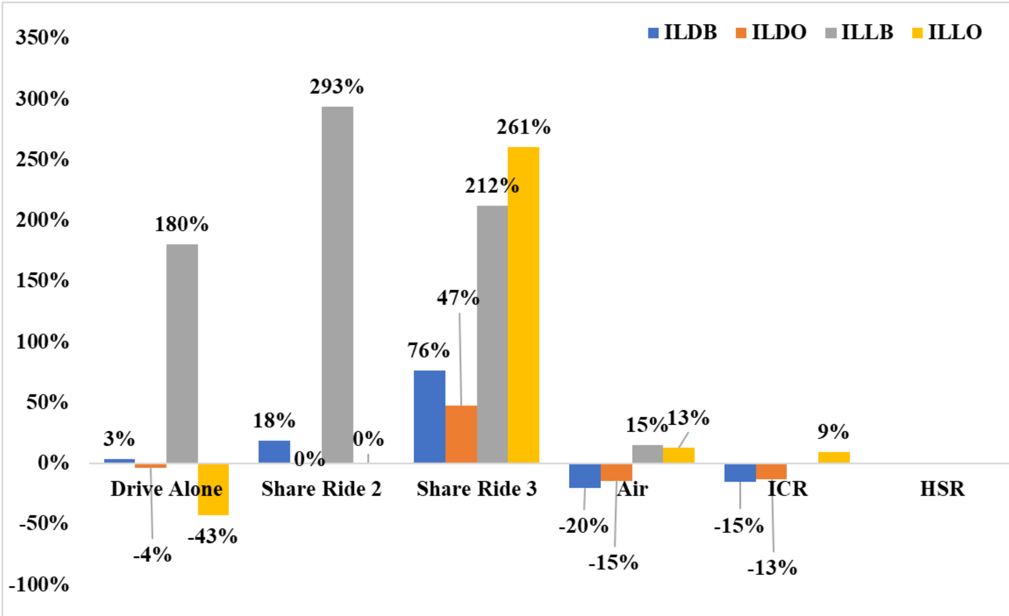


Figure 21. Mode Distribution as per Trip Purpose: No-AV vs AV Base Scenario

3.3. Scenario 3 (Reduced Value of Travel Time)

This scenario examines the consequences resulting from a decrease in the perceived cost of travel time. In this case, we assume that the VOTT for AVs decreases significantly by 50% across various income classes. This scenario aims to analyze the complex relationship between the reduced perception of travel time for AV passengers and their tendency to undertake long-distance trips, potentially reducing their dependence on personal human-driven vehicles. This scenario examines the consequences resulting from a decrease in the perceived cost of travel time. In this case, we assume that the VOTT for AVs decreases significantly by 50% across various income classes. It analyzes the complex relationship between the reduced perception of travel time for AV passengers and their tendency to undertake long-distance trips, potentially reducing their dependence on personal human-driven vehicles.

The results show that people are more likely to choose longer trips, leading to an increase VMT on all types of roads. Specifically, roads like expressways, arterials, interstates, and other freeways see a 23% rise in travel as shown in Figure 23. Expressways and freeways make up 7% of the lane-miles, while arterials and collector roads make up 45% of the lane-miles. The reduced in VOTT in case of AVs also impacts airport boarding patterns across various airports. This shift is driven by individuals' inclination towards AVs, primarily motivated by cost-saving opportunities and the ability to use travel time more productively for other activities.

With the elimination of the need for manual driving, travelers can allocate their time on the road more efficiently, engaging in a diverse range of tasks, thereby reducing the perceived value of their time. The consequences of this shift are seen through an analysis of airport boarding trends in the state of Texas. Results presented in Figure 24, showing the percentage change in passenger boarding at Texas Airports, reveals a slight decline in the number of passengers initiating their journeys from major state airports. Dallas/Fort Worth International Airport and George Bush

International Airport both witnessed a decrease of over 5% in passenger volumes, highlighting the growing preference for AVs. Similarly, San Antonio Airport displayed a comparable pattern, with a 5% decline in boarding numbers, as shown in the figure below. While the magnitude of change was somewhat less pronounced at Austin-Bergstrom Airport, it nonetheless showed a negative trend, with a -3% decline in passenger boarding.

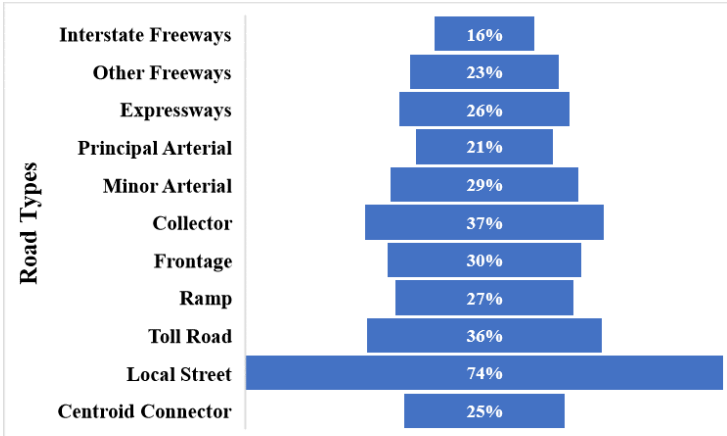


Figure 22. Change in Percentage VMT Change across Road Types: No-AV vs AV Base Scenario

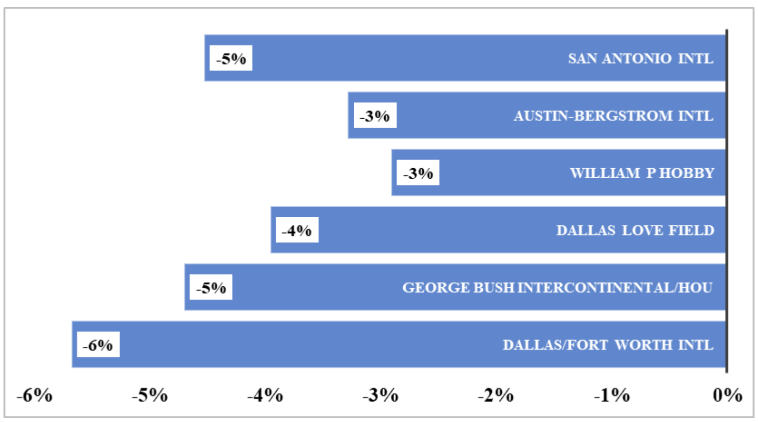


Figure 23. Percentage Changes in Passenger Boarding Counts at Major Texas Airports as Compared to Base No AV Scenario

Scenario 4 (AV Mode Preference Over Humans)

This scenario investigates the effects of eliminating human-operated vehicles from both passenger and freight transportation. We adjusted the parameters of a nested logit model to force people to choose AVs over traditional vehicles. The findings show significant changes, especially in large urban areas. Despite AVs being available, a significant portion of long-distance trips (38%) still involve traditional human-driven vehicles. However, when human-operated vehicles are removed, there's a 10% rise in people choosing drive-alone AV trips. SAV trips with two occupants also rose by 10%, and those with three or more occupants see a significant 21% rise.

These results highlight the potential of AVs to reshape urban transportation and alleviate congestion. As individuals increasingly opt for Avs specifically SAVs for their transportation needs, a notable impact is observed in the airport boardings across major airports in the state of Texas. Figure 26 shows the trends, revealing a marked fall in airport boardings following the surge in AV use. The significant airports including Dallas/Fort Worth International, George Bush Intercontinental, Dallas Love Field, William P Hobby, Austin-Bergstrom International, and San Antonio International, collectively representing a substantial portion, accounting for 53% of total airport boardings in the region. Each of these airports has experienced an average fall of 22% in their boarding numbers. This decline shows the profound impact of AV adoption on traditional travel patterns, with individuals increasingly favoring AVs over conventional transportation options.

Moreover, this shift in travel behavior reflects broader preferences, showing the evolving consumer choices. These results also offer valuable insights for policymakers, urban planners, and industry stakeholders navigating the transition towards AV technologies.

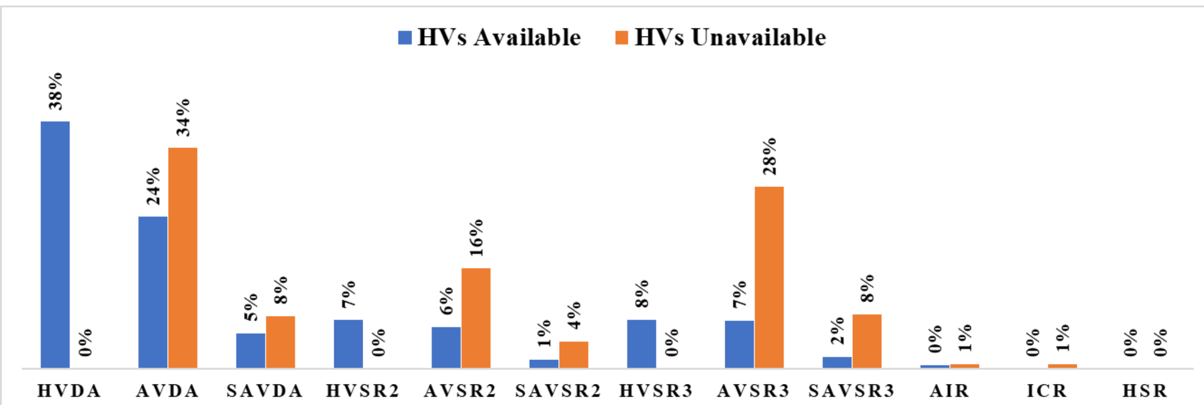


Figure 24. Percentage Change in Airport Boardings at Major Texas Airports: No-AV vs AV Base Scenario

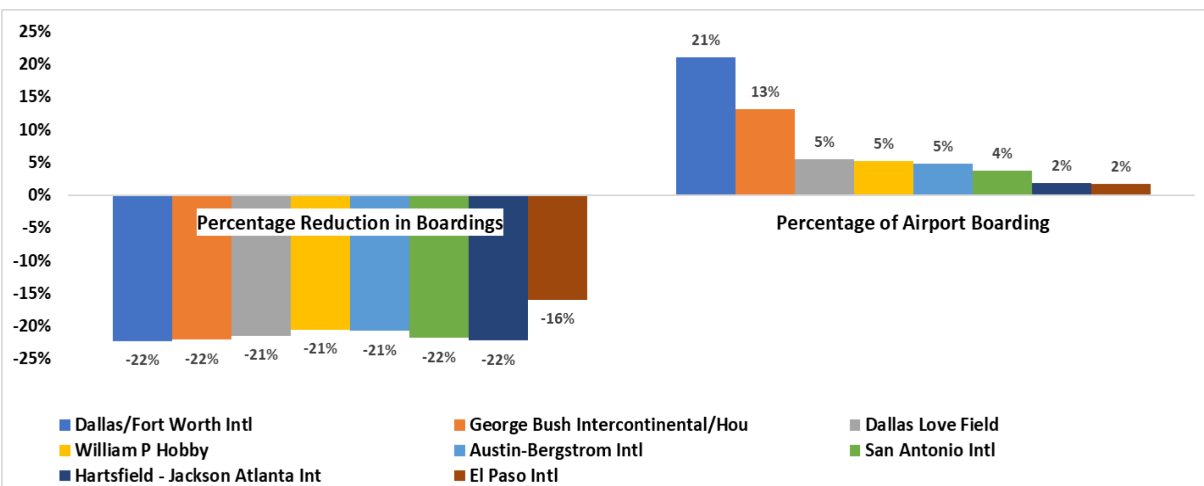


Figure 25. Percentage Change in Airport Boardings at Major Texas Airports: No-AV vs AV Base Scenario

Scenario 5 (Personal AVs Are No Longer Available)

This scenario examines a scenario where individuals perceive personal ownership of AVs as costly, leading them to find SAVs and human-driven vehicles more appealing. The nested logit model for mode choice was adjusted to mirror these preferences, just like it was done in Scenario 4. Consequently, people opted for HVs over AVs for long-distance trips. Additionally, they showed a preference for SAVs. This resulted in an 11% rise in the use of SAVs (drive alone mode) for business trips, and for non-business trips within the 50 to 400-mile range, it rose from 3% to 5% compared to the base-AV scenario.

For SAVs where two or more individuals travel together, there was no change in mode share across all trip purposes, as shown in Figure 27 and Figure 28. However, there was a significant increase from 2% to 12% in the mode share of SAVs with three or more occupants for business trips covering distances between 50 and 400 miles, and a 12% rise in the mode share of SAVs with three or more occupants for non-business trips covering the same distance range, as illustrated in Figure 28. However, these altercations did not bring any change in trips by air, ICR, HSR.

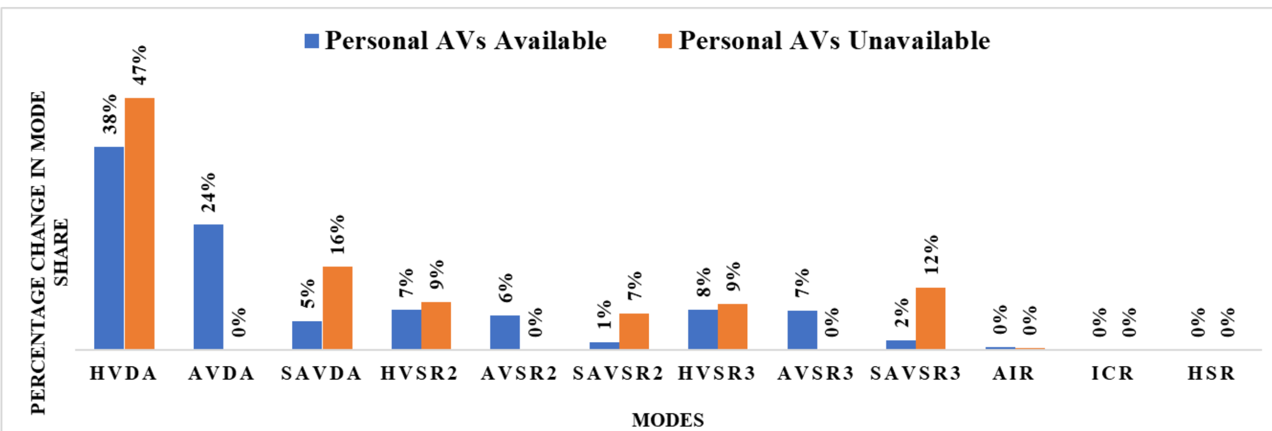


Figure 26. Percentage Change in Mode Share (ILDB): No-AV vs AV Base Scenario

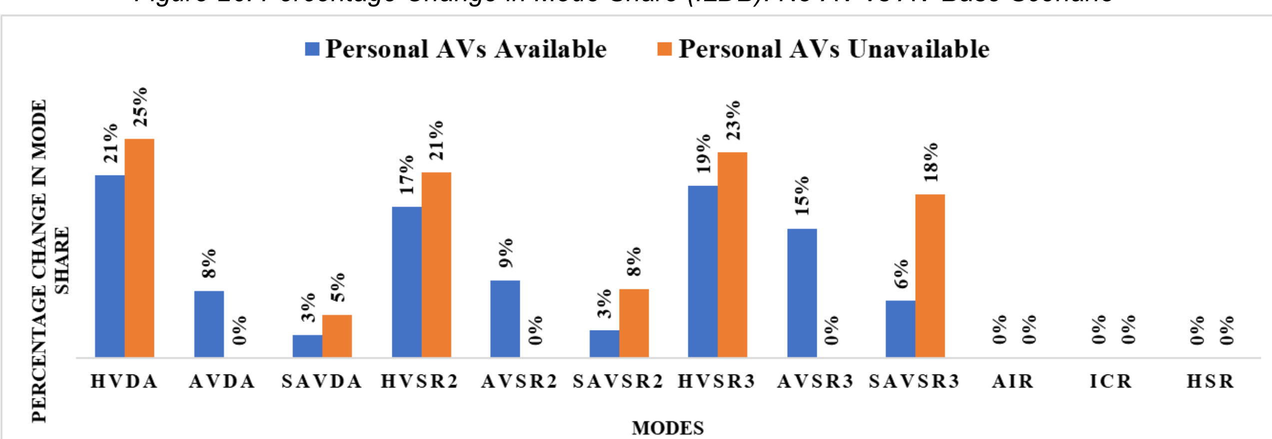


Figure 27. Percentage Change in Mode Share (ILDO): No-AV vs AV Base Scenario

Scenario 6 (Increased VMT due to Empty SAVs)

Scenario 6 looks into the effects of considering empty SAVs within the transportation network, achieved through a 20% decrease in average passenger occupancy. The study assumes that this reduction in occupancy could result in a rise of approximately 25% in the distance traveled by empty SAVs. These changes brought a significant rise in average VMT and VHT within the transportation system. In the coded SAM network, expressways and freeways collectively constitute 7% of lane-miles, while arterials and collector roads comprise a more substantial 45% of lane-miles. As shown in figure 23, the average VMT experienced a notable rise: 10% during morning peak hours, 9% during evening peak hours, and 8% during afternoon peak hours across all road types. Additionally, there was an average 11% rise in VMT across all road types.

Local streets experienced the most significant surge in VMT, with a rise of 53% rise during morning peak hours and a substantial 37% rise during evening peak hours, closely followed by collector and local street roads. As empty driving is taken into account within the network, it inevitably impacts congestion levels across all segments, as shown by the average speed reduction observed on these roads, shown in Figure 24. The findings indicate an average 25% reduction in speed on expressways, interstates, and other freeways. Evening peak hours exhibited the highest congestion levels, as illustrated in the figure. Interestingly, nighttime congestion levels remained relatively unchanged, with minimal fluctuations in speeds observed across all road types during nighttime hours.

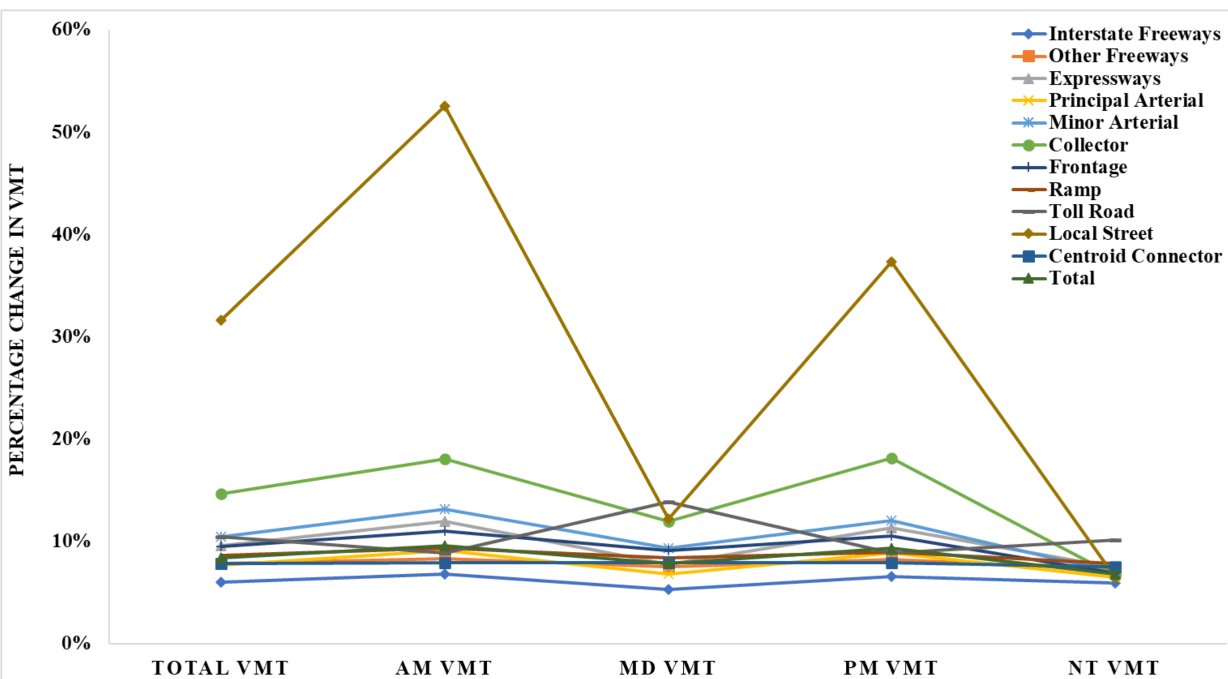


Figure 28. Percentage Change in VMT across all Road Types: No-AV vs AV Base Scenario

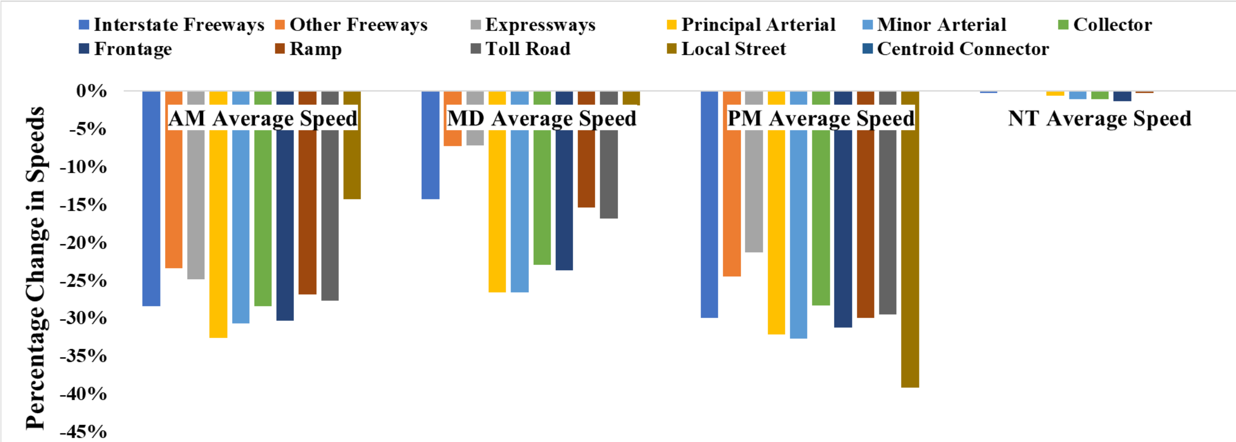


Figure 29. Percentage Change in Avg Speeds across all Road Types: No-AV vs AV Base Scenario

Chapter 4. Long-distance Trip Chaining

The NHTS contains four files: HOUSEHOLD, PERSON, VEHICLE and TRIP data files. We use the TRIP data file for this study (trippub.csv). It considers every trip segment as an individual trip: even those segments that are quick stops en route to one's main destination. For example, a 150-mile trip from Austin to Houston that involves a refueling stop shows as two separate trips (one for "shopping" midway, and one for the true purpose of the trip at the final destination). Long-distance (LD) trips are defined as those with the real destination (not an en-route "pit stop" for gas or food) more than 75-miles away (on the travel network). To address the limitation in segments vs true trips, we developed an algorithm to identify intermediate "trips" that are really just pit stops in a longer-distance trip chain en route to a final destination (resulting in fewer true LD trips). The algorithm is also designed to fuse "short" (less than 75-mile one-way) trip segments into long-distance (LD) trips (more than 75 miles one-way) as well as "long" (>75 miles) and "short" (<75 miles) trip segments with each other when they can be considered part of chain to the final destination. Thus, the number of LD trips may rise or fall, relative to a simple counting of segments that are 75-miles or longer (which is the technique that most analysts use). The algorithm reflects trip coordinates (to appreciate trip direction, thereby avoiding back-and-forth trips or tours to many true destinations [like delivery chains]), *dwell times* at "destinations" (at the end of every trip segment, to avoid counting relatively short "pitstops"), and trip *purpose* (to distinguish refueling and meals en route, for example, from a longer-duration final-destination activity).

After applying the algorithm's many rules, the NHTS 2016/17 sample's LD trips (i.e., those more than 75 miles one-way) fell by just 3.4% (from 1.84 one-way LD trips per American per month to 1.78). This brings the total number of NHTS person-trips down by 0.88%, with the average American making 3.47 trips per day instead of the previously estimated 3.50 trips. Notably, the algorithm was only applied to trips or chains of trips that met the criteria for long-distance travel (those segments more than 75 miles each or a series of related segments adding to more than 75 miles one-way), ensuring that it did not impact shorter trips. The best predictor in distinguishing pit stops are the coordinates (latitude and longitude) of stopping points. Followed by the purpose of the trip. Successive trip segments by each NHTS respondent were used to discern whether distance from the origin kept rising in a directed way, or started pivoting (or even falling), indicating changes in direction. If the Euclidean distance from the chain origin started falling (after rising after earlier stops), it indicated a return trip. Combined with other factors (including mode changes, site activity/trip-end purpose, and short-activity durations), these falling distances or changes in direction helped distinguish trip chains. Mode shifts (like driving to or taking a bus to an airport and changing planes at a hub airport) are not real destinations. Additionally, stopping away from the origin during a long-distance trip, to purchase food or gasoline, is often not a true destination - especially when the stop is short and trip direction unchanged. NHTS trip purposes are as follows in Table 12.

Table 12. NHTS Trip Purposes (WHYTO variable)

WHY TO variable ID	NHTS Trip Purposes
1	Regular home activities (chores, sleep)
2	Work from home (paid), 3 Work, & 4 Work-related meeting / trip
5	Volunteer activities (not paid)
6	Drop off /pick up someone
7	Change type (mode) of transportation
8	Attend school as a student, 9 Attend childcare, 10 Attend adult care
11	Buy goods (groceries, clothes, appliances, gas)
12	Buy services (dry cleaners, banking, service a car, pet care)
13	Buy meals (go out for a meal, snack, carry-out)
14	Other general errands (like post office and library)
15	Recreational activities (e.g., visit parks, movies, bars, & museums)
16	Exercise (e.g., go for a jog, walk, walk the dog, go to the gym)
17	Visit friends or relatives
18	Health care visit (including medical, dental, & physical therapy)
19	Religious or other community activities
97	Something else, -9 Not ascertained, -8 I don't know, & -7 I prefer not to answer

Meal and carry-out stops shorter than 90 minutes and general errand stop (like to a post office) shorter than 15 minutes are assumed to be part of a longer trip. While the algorithm is designed to identify and classify long-distance trips more accurately, there are limitations to pitstop inference. For example, it is challenging to determine whether a person stopped to purchase gas or a breakfast coffee when setting out on a long-distance trip. The NHTS “WHYTO” purpose categories (shown above) do not distinguish fuel stops from grocery or clothing-shop stops, and do not distinguish errand types (like a visit to the post office versus a library), making it difficult to categorize these as true destinations or pit stops along the way. To address this challenge, a destination dwell time threshold of 30 minutes (for fuel/shopping) and 15 minutes (for errands) is assumed to help identify longer stops that may indicate a true purpose. Some of these stops should be considered as necessary, separate, or true destinations that would have been made regardless of the longer trip that day. Similarly, stops near the end of a long-distance trip may be trips that would have been made anyway upon arrival at the destination. Travelers have many options in how they chain trips, and some important destinations may be along one's long-distance trip route.

When "pit stops" (short stops, typically to eat, refuel, change modes, etc.) on long-distance trips are no longer counted as destinations (thanks to the algorithm's application), only the attributes of the final leg of a trip chain (variables of travel day trip purpose [WHYTRP90] and trip purpose summary [WHYTRP1S]) are used to determine the LD trip purpose. This approach reduces the shares of LD trips taken for commutes plus work trips, shopping, meals/food, and other volunteer activities/change in mode (indicated by the "97= Something else" purpose) by 12.5, 35.5, 74.2, and 54.9 percentage points, respectively. Removing such pit stops raises the shares of (1) school plus religious trips, (2) medical trips, (3) transporting someone, and (4) social trips (visiting friends and relatives) plus recreational trips, by 14.8, 16.7, 20.8 and 21.0 percentage points, respectively. Average and median LD person-trip lengths also rise (after applying the algorithm), by about 10 percent: from 268.5 to 289.9 (average LD trip) miles and from 129.2 to 138.5 (median) miles, respectively. See Table 13.

Table 13. Trip Purposes Before and After Applying the Trip Chaining Algorithm

		Without Trip Chaining (Previous Method)		With Trip Chaining		% Change
		# of trips	% of Total	# of trips	% of Total	
# of LD Trips (> 75 miles one-way) in NHTS Sample		15,972	1.73%	15,434	1.69%	-3.37%
# of Person-Trips in NHTS Sample		923,573		915,457		-0.88%
# Trips per Day per American		3.495		3.465		
WHYTRP90 (Travel Day trip purpose)	01=To/From Work	1146	7.2%	1342	8.7%	17.1%
	02=Work-Related Business	809	5.1%	941	6.1%	16.3%
	03=Shopping	2350	14.7%	1562	10.1%	-33.5%
	04=Other Family/Personal Business	1368	8.6%	1609	10.4%	17.6%
	05=School/Church	421	2.6%	506	3.3%	20.2%
	06=Medical/Dental	351	2.2%	421	2.7%	19.9%

	08=Visit Friends/Relatives	2534	15.9%	3025	19.6%	19.4%
	10=Other Social/Recreational	3900	24.4%	3594	23.3%	-7.8%
	11=Other (such as change of mode)	3083	19.3%	2423	15.7%	-21.4%
	99=Refused / Don't Know	10	0.1%	11	0.1%	10.0%
WHYTRP1S (Trip purpose summary)	01=Home	4537	28.4%	6010	38.9%	32.5%
	10=Work (and work-related business)	2138	13.4%	1870	12.1%	-12.5%
	20=School/Daycare/Religious activity	271	1.7%	311	2.0%	14.8%
	30=Medical/Dental Services	228	1.4%	266	1.7%	16.7%
	40=Shopping/Errands	1854	11.6%	1196	7.7%	-35.5%
	50=Social/Recreational	3316	20.8%	4013	26.0%	21.0%
	70=Transport Someone	607	3.8%	733	4.7%	20.8%
	80=Meals	1693	10.6%	436	2.8%	-74.2%
	97=Something Else (like unpaid volunteer activities & change of mode)	1328	8.3%	599	3.9%	-54.9%

Note: NHTS samples exclude Americans under 5 years of age.

This algorithm considers the location, timing, and sequence features of sample “trips” to infer the real reasons behind long-distance travels (where many “long” [> 75-mile] and/or “short” [< 75-mile] segments may be describing a single long-distance trip). Figure 30 illustrates how 8-segment and 3-segment trip chains have just three and two true destinations away from home (for business/work or visiting friends). The second example in this image highlights one of the limitations of the algorithm that was pointed out in the earlier sections. Here it is difficult to determine if the second stop is a true destination or an intermediate pit stop. Since the stop occurs at the beginning of a long trip, it is possible that it could be considered a true destination and would have warranted a separate trip regardless of whether or not a long-distance trip was planned that day. As elaborated in the earlier sections, looking at sequences of trip segments by the same person (over the 24-hour sample day), trip chains were determined based on coordinates, dwell time at destination (time at destination) and trip purpose. The logic used to determine this is as follows:

If Trip destination purpose = "Change type of transportation"
 then part of chain
else if Trip destination purpose = "Buy goods (groceries, clothes, appliances, gas)" & Dwell time < 30 min & Next trip distances from origin of increases
 then part of chain

else if Trip destination purpose = "Buy meals (go out for a meal, snack, carry-out)" & < 90 min & Next trip distance from origin of increases

then part of chain

else if Trip destination purpose = "Other general errands (post office, library)" & Dwell time < 15 min & Next trip distances from origin of increases

then part of chain

else if Trip destination purpose = "Something else" & Dwell time < 30 min & Next trip distances from origin of increases

then part of chain

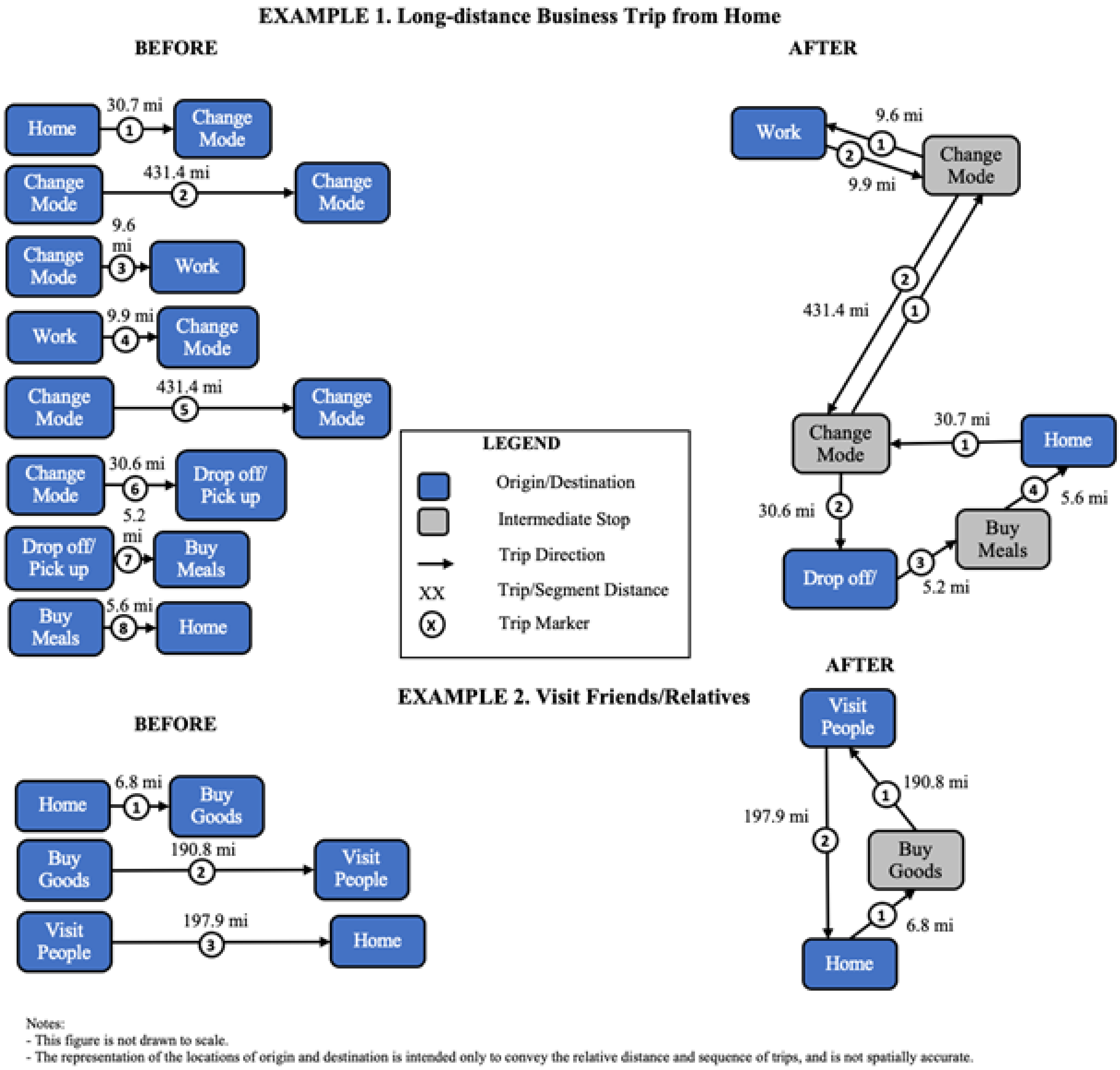


Figure 30. Examples of Long-distance Trip Chaining (from Home, on Single day)

Figure 31 displays maps with a LD trip origins and paths, distinguishing for origins and paths that have been considered part of a longer-distance trip. These maps offer a visual representation of the algorithm's impact on the classification of trips and stops. Overall, this algorithm provides a more accurate and comprehensive understanding of true long-distance travel patterns, accounting for the complex nature of multi-stop trips and ensuring that the resulting data is meaningful for transportation planning and policy.

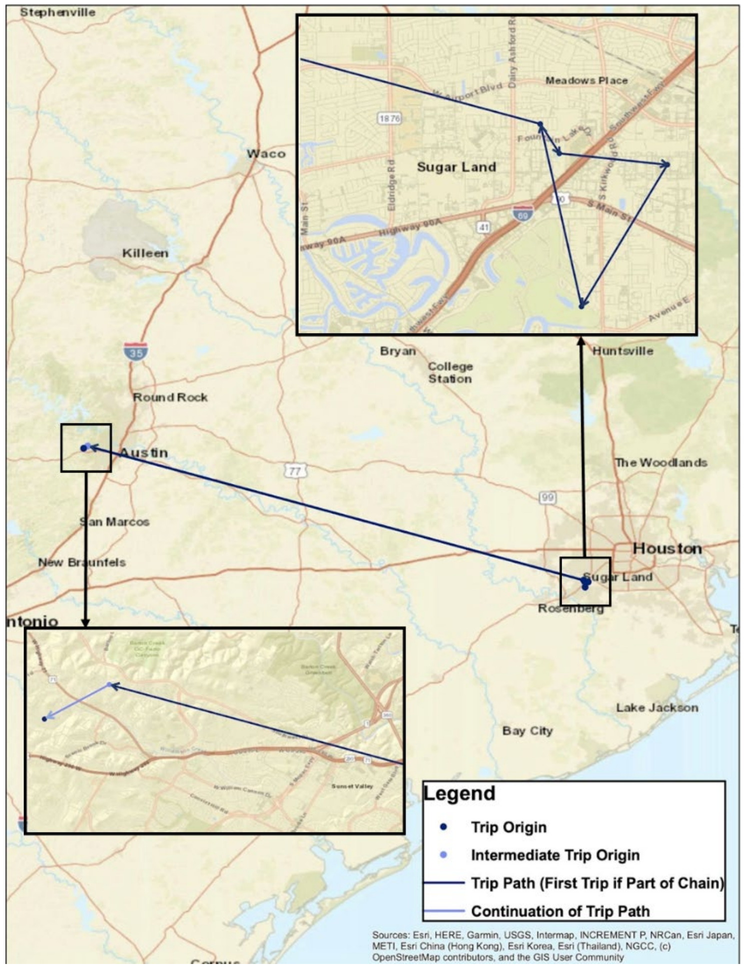


Figure 31. Map of a Long-Distance Trip and Intermediate Segment Origins in Texas

Chapter 5. Comparisons of Different Origin-Destination (OD) Travel Study Source

This section compares the various datasets available to TxDOT, with a particular focus on identifying the most suitable source for validating the outputs of the Statewide Analysis Model (SAM) travel demand model. By exploring and comparing the different options, we hope to determine which dataset will provide the most accurate and reliable information for this purpose.

Serving the nation's second largest state (in population and area), TxDOT is responsible for maintenance and repair of over 80,000 centerline-miles of highways, which carry over 70% of the State's annual 712 million vehicle-miles traveled (TxDOT 2022). INRIX's TMC (traffic message channel) segments currently cover 101,353 of those centerline-miles, containing roughly 25% of the on-system network's centerline-miles (and much higher coverage within metro areas), and 14.8% of the State's 686,658 total (reflecting all local streets [TxDOT 2021]). Serving a population of 29 million, plus millions of visitors every month and year, TxDOT can make excellent use of the research team's extensive Texas-focused data sets, developed over decades of transportation design, planning, and operations experience.

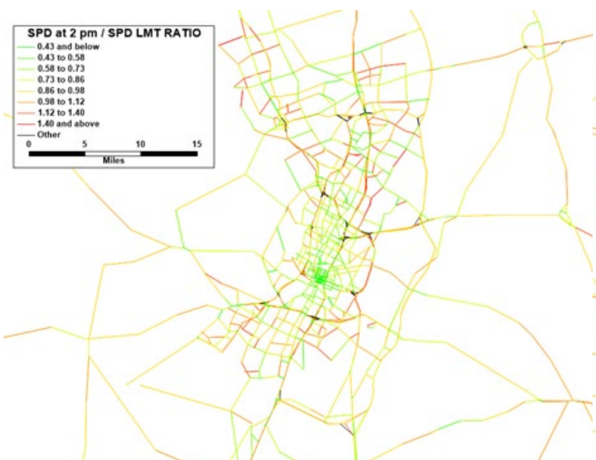
Several of Table 14's probe data are being leveraged, including those already accessible to the research team. They are RITIS' National Performance Management Research Data Set (NPMRDS) – containing flows and speed (by road segment), and now trip-count data (by zone pair), INRIX's historic and current/"live" speed data, and Replica's simulated datasets which produces disaggregate trip and population tables, hourly origin-destination (OD) and mode split tables (can be as recent as the prior week). RITIS NPMRDS is provided via pooled funds (from participating agencies [including TxDOT] that also sign a data-sharing agreement with INRIX). One advantage of RITIS NPMRDS is that it is vendor-neutral (i.e., not specific to INRIX) allowing for indexing of roadway segments by Traveler Information Services Association (TISA) traffic message channel (TMC) identifiers.

Table 14 Probe Data Sets

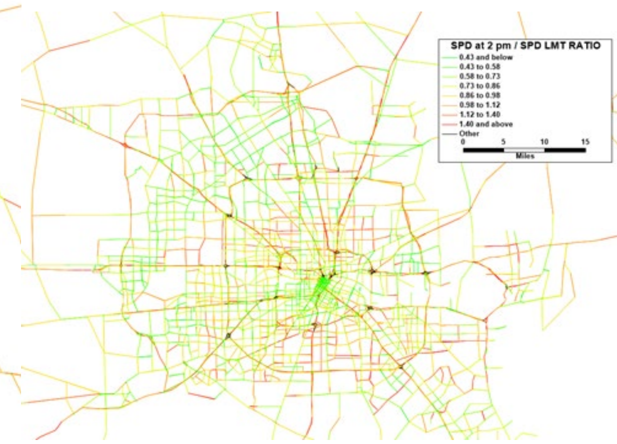
Product	Description
INRIX	Aggregates subsample of vehicles tracked by road network sensors, fleet vehicle devices, and mobile app users to estimate live and historic **segment speeds**. Provides origin-destinations analysis at regional level.
RITIS's NPMRDS Tool	Provides vendor-neutral historic **segment speeds** and traffic **origin-destination analyses** among others on a pooled-funded platform. Currently leverages INRIX speed data.
StreetLight	Analytics process trajectories of vehicles tracked by vehicle navigation devices and smartphones to deliver **traffic count** estimations and **origin-destination analyses**, among others. May be useful for congestion studies.
Replica	Uses various sources such as mobile location data, consumer/resident data, built environment data, economic activity data and ground truth data to produce

	simulations that mirror the movements and activities of residents, visitors, and commercial vehicle fleets in a given region and season on a typical day. Additionally, it can also generate mobility data including hourly nationwide OD table, mode splits and residential VMT.
Wejo	Connected-vehicle data (mostly GM vehicles, with OnStar-type connection) to provide high-frequency **vehicle movement** and **driving event** (e.g., hard braking) data. Can be used for speed and congestion studies.
Geotab	Collects connected-vehicle data to provide trip data, vehicle exception occurrences, hourly and daily traffic data, along with weather, urban infrastructure, and vehicle locations.
HERE	Offers third-party data services that include vehicle sensor info, weather, and **consumer behavior** data, mobility and smartphone data, and road + infrastructure data.

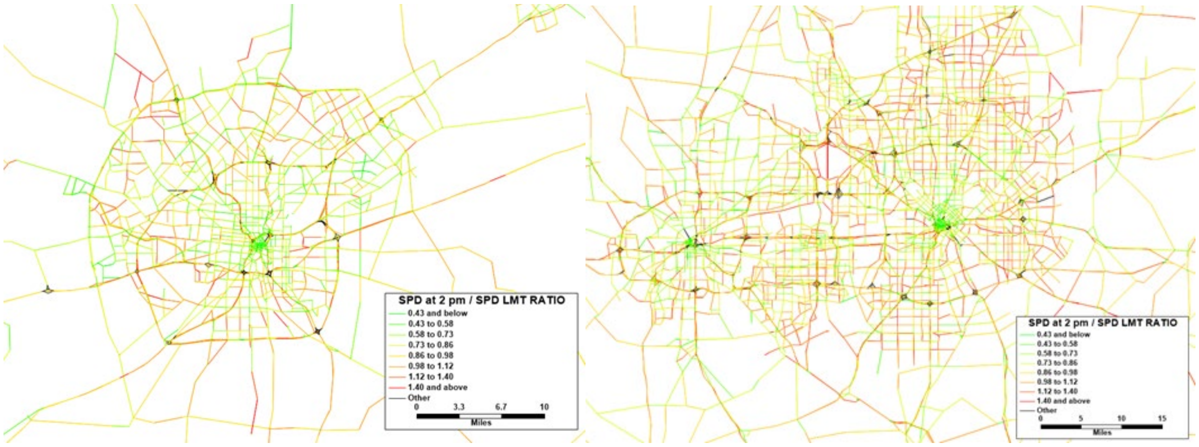
One example of INRIX data use is for speed distributions by link and time of day and day of year. A total of 90,883 TMC segments were successfully matched to TxDOT's speed limit inventory (which has 512,779 segments). Using INRIX's TMC segments at 2 pm on Tuesday, November 16, 2021 (as extracted through the RITIS platform), Figure 32 shows the ratios of real-time speeds to posted speed limits across Texas' four largest metro areas. Green-colored segments have ratios above 1.0, showing real-time (average) speeds that exceed the posted speed limit (across all TMC segments, state-wide). Figure 33's histogram of these ratios shows how 8.4% of the road segments have average speeds (at 2 pm on Nov. 16, 2021) that exceed the posted speed limits by at least 10 percent (i.e., 8.4% comes from summing the blue bars for x-axis values of 1.1 and up).



Austin



Houston



San Antonio **Dallas-Fort Worth**

Figure 32. Spatial Pattern of INRIX's Real-Time Speeds to Speed Limit Ratio Across Texas' 4 Largest Regions (at 2 pm on Tuesday, Nov 16, 2021)

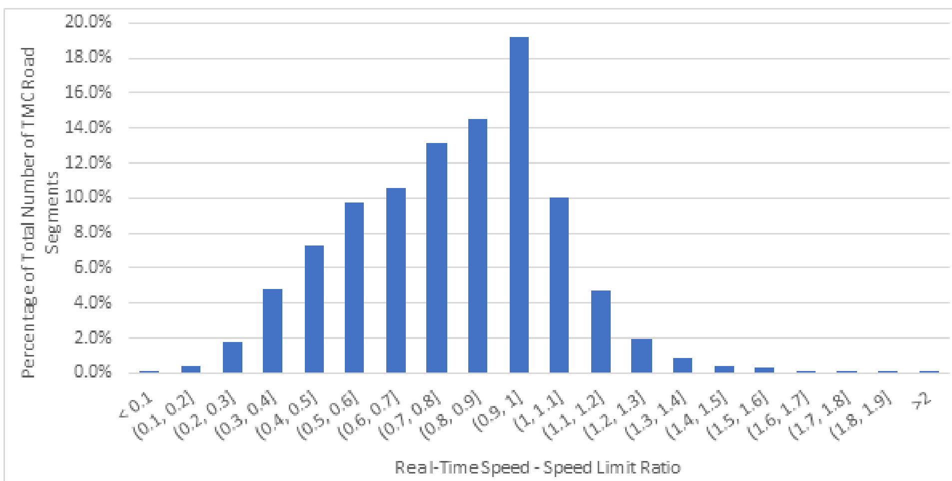
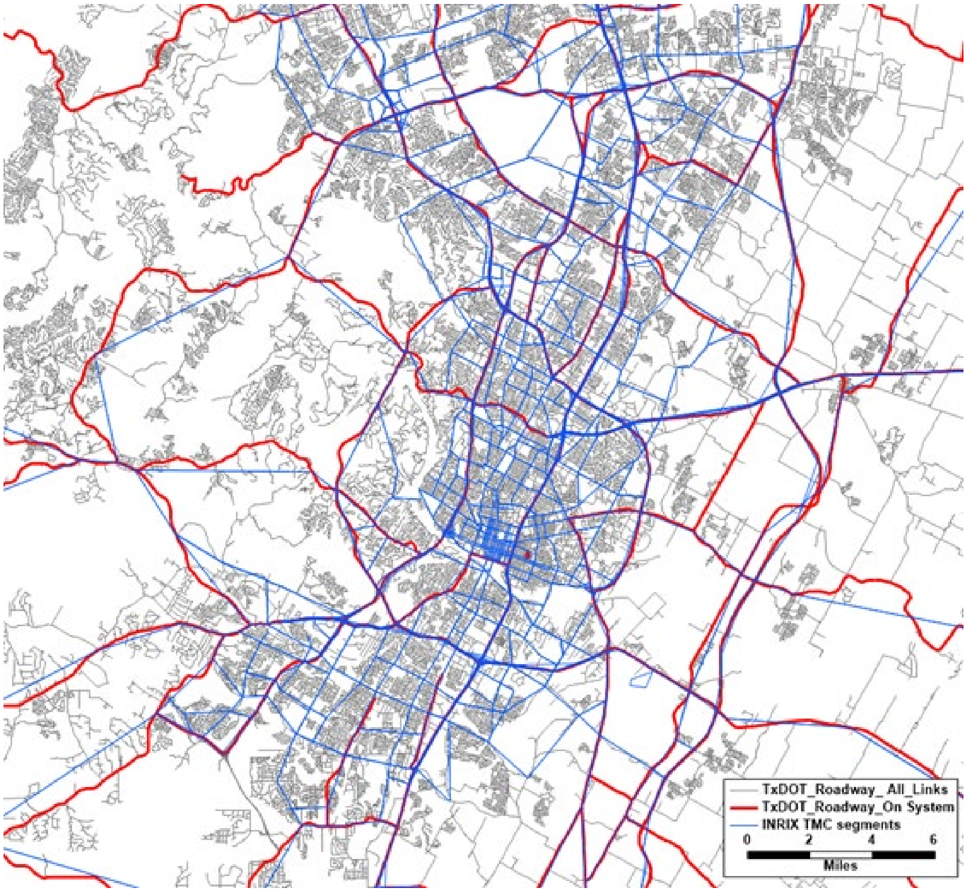


Figure 33. Histogram of INRIX's Real-Time (Average) Speeds Divided by Posted Speed Limits (Using Data at 2 pm on Tuesday, Nov 16, 2021)

Figure 34 illustrates the comparison between INRIX segments, TxDOT-maintained roadways, and all public roadways in Austin area. It is worth noting that INRIX has a relatively comprehensive coverage of TxDOT-maintained roadways in this region, as evidenced by the blue segments in Fig 29's map. Table 15 provides a sample (10 zones pairs) of RITIS trip tables (derived using the INRIX data) for passenger cars in the PM peak (3-6:30 PM) during a typical Monday in April. The OD columns follow the GEOID code convention provided by the US Census Bureau.



Note that INRIX TMCs are not GIS-encoded, so their positions are approximate.

Figure 34. INRIX Segments (in blue) vs. TxDOT-maintained Roadways (in blue + red) and All Public Roadways (in grey/black).

Table 15. Partial View of RITIS Trip Table Data for Dallas for the PM Peak

Origin	Destination	Trips
5021	5016	25
5021	5017	12
5021	5018	7
5021	5019	182
5021	5020	43
5021	5021	622
5021	5022	9
5021	5023	20
5021	5024	3
5021	5025	3
5021	5026	105
5021	5027	146

5.1. Probe Data for Transportation System Planning and Operations

Probe data, or data derived from measurements pervasively obtained from instrumented vehicles or travelers, is a wonderful, relatively low-cost source of traffic, trip-making, speed, and other data (Rahman 2019). Eshragh et al. (2017) validated US probe-data accuracy using Bluetooth traffic technology. Overall, probe data sources reflect the operating conditions of different roadway sections while reflecting site to site specifics. They reflect variation in traffic, trip-making, speeds, mode choices, and other behaviors across times of day, roadway links, weather conditions, and traffic settings. The following sections review national and state guidance, key variables, traffic safety impacts, and distinct datasets. Collecting reliable data is key to any transportation system's policy and planning, design and operations, management, and improvement. In an example of speed inference, direct traffic observation, by humans with cameras, stopwatches, radar, and laser guns are often used, reflecting labor-intensive, high-cost, low-accuracy exercises. On-road devices, like pneumatic road tubes and radar recorders, are also used for speed estimation across roadway networks, and most equipment requires frequent maintenance and calibration (WisDOT 2009). Moreover, vehicles cannot be filtered in the data set, vehicle direction may not be evident, on-road devices do not work properly under snow, and they are visible to travelers (as noted above). TxDOT (2015) has found that radar devices tend to underestimate 85th percentile speeds by about 3 mph. Truck, car, bus, and traveler speeds, locations, and behaviors can be tracked much better with on-board/on-person devices, like cell phones and GPS.

Probe vehicle data provide speed information from GPS devices installed on vehicles, cell phones, or vehicle telematics (Remias et al. 2015). Unlike other data sources, probe vehicles cover a wide area with a lower cost and with minimum maintenance and calibration. These data offer statewide and national coverage, at relatively low cost. Figure 35 illustrates the RITIS TMC segment coverage. The National Performance Management Research Data Set (NPMRDS), on the RITIS platform, is available to the Receiving Agency, includes past HERE Technologies, INRIX, and TomTom (2022) datasets. These are among the most common third-party suppliers of probe vehicle-derived speed data in the world. They are provided at 5-minute increments for the National Highway System, coded in a vendor-neutral format according to the Traffic Message Channel (TMC) network of segments. INRIX and RITIS also provide more detailed eXtreme Definition Segments (XDS) for each specific geographic area or route. Both HERE and TomTom also provide speed data for many interconnecting municipal roads (Roelofs & Preisen 2021).

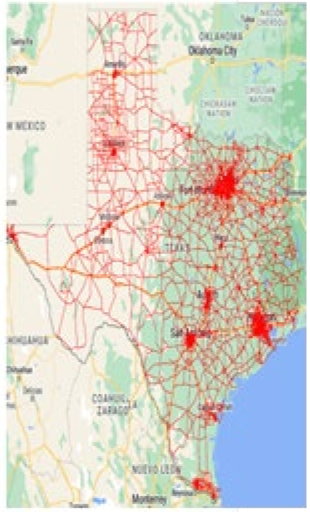


Figure 35. Texas TMC Segments from RITIS' probe data

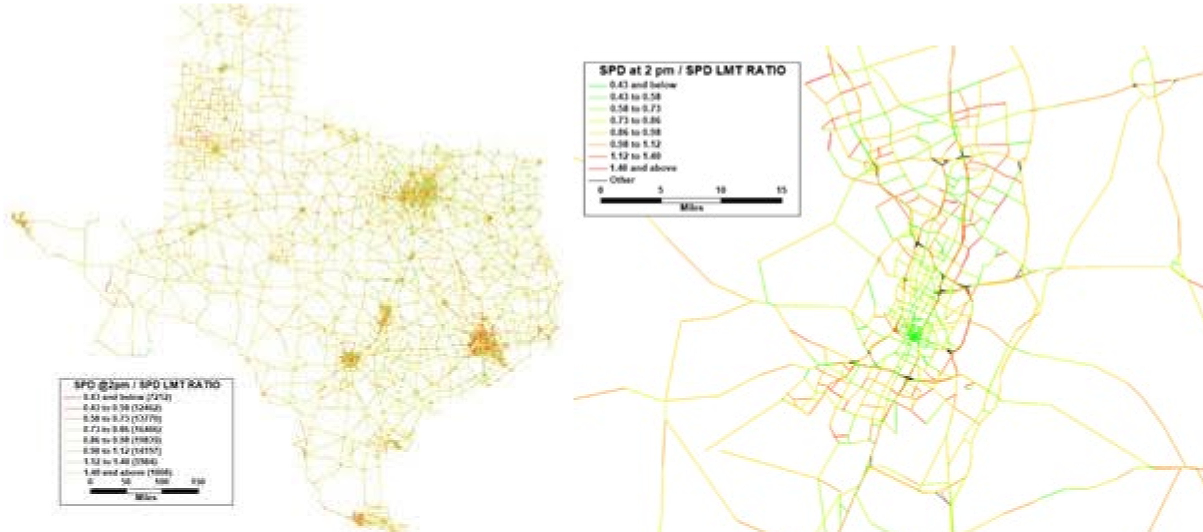
MDOT (2019) uses probe data to calculate reliability and mobility performance measures across Michigan freeways. They previously used HERE data for freeway performance measurement and recently switched to INRIX. In addition to numerous studies that use probe data for corridor-level performance studies (like Espada and Bennett 2015, Hellinga et al. 2008, Mathew et al. 2017, and Vander Laan and Sharifi 2019, Vautin and Walker 2011), a few used probe data for speed-limit setting. Assuming all motorists are visible/instrumented, Kattan et al. (2014) provide an algorithm for variable speed limit setting using probe data (based on changing traffic density). And the Ohio DOT (2014) revised its speed limit tool to use INRIX data for 85th percentile speed calculations, to help flag sites where limits should probably be modified, as illustrated in Figure 36.

INRIX Data

	A	B	C	D	F	G	H	I	J
1	xd_id	measurement_tstam	speed	cvalue		85th Percentile Speed			Instructions
2	1363596473	12/3/2019 9:00	16	70		41			1. Paste INRIX data in cell A1 (Data Columns: ID, Date/Time, Speed, Cvalue)
3	1363596473	12/3/2019 9:01	24	100					Clear Data
4	1363596473	12/3/2019 9:02	22	100		50th Percentile Speed			
5	1363596473	12/3/2019 9:03	22	100		29			
6	1363596473	12/3/2019 9:04	14	100					
7	1363596473	12/3/2019 9:05	14	100		# of Samples >=70	% of Samples		
8	1363596473	12/3/2019 9:06	16	100		59394	92.5%		
9	1363596473	12/3/2019 9:07	17	100					
10	1363596473	12/3/2019 9:08	35	100		10 mph pace			
11	1363596473	12/3/2019 9:09	35	100		22 to 32 mph			
12	1363596473	12/3/2019 9:10	34	100					
13	1363596473	12/3/2019 9:11	14	61					
14	1363596473	12/3/2019 9:12	14	71					
15	1363596473	12/3/2019 9:13	14	72					

Figure 36. Ohio DOT's (2014) Spreadsheet for 85th Percentile Speed Calculation

The Ohio DOT's (2014) Spreadsheet for 85th Percentile Speed Calculation using Remias et al. (2015) used probe data to optimize the speed limit change sites along 265 miles of I-65 in Indiana. INRIX average speed data were posted every minute for segments of length 0.2 to 2 mi. They showed how optimal limit-reduction locations are upstream of congested sites, like work zone locations. They assumed that (static and variable) speed limits were visible to motorists, but overlooked weather and time of day effects. Jha (2017) used INRIX probe data to conclude that the free-flow speed occurs during nighttime hours (9 PM-6 AM) on well-lighted highways, but were unable to use sites with sparse traffic data, including minor arterials. For those roadways, they recommend using midday data (11 AM-3 PM). However, no probe data-based studies have yet considered the impacts of time of day, weather, traffic levels, or crash histories to recommend safe and reliable/robust speed limits on different road types, as this research project can do, for both static and variable speed limit settings, as TxDOT wishes.



a. Texas **b. Austin**

Figures 37. Ratios of INRIX/RITIS Average Speeds to Posted Limits Across Texas and Austin Networks

Figure 37a shows the spatial distribution of what INRIX calls “real-time speed” (averaged over 5 minutes) to speed limit ratio for all RITIS TMC Road segments at 2 pm on Tuesday, November 16, 2021. A total of 90,883 TMC segments were successfully matched to Texas speed limit inventory data, which has 512,779 road segments. Red segments are those who ratio exceeds 1, suggesting that drivers’ speeds regularly exceed the posted speed limit. And Figure 37b shows how 8.4% of Texas’ data segments may have an average (below the 85th percentile) free-flow speed that is 10% higher than the posted speed limit. This means that the 85th percentile speed (at 2 pm on a November Tuesday) may be 20+% higher than the posted speed.

Chapter 6. INRIX and RITIS

The Texas Statewide Analysis Model (SAM) is a large model that covers the entire state of Texas. Due to its large geographic scale, high computation time owing to multiclass traffic assignment with six vehicles classes and four time periods, and an emphasis on infrequent and data-scarce trip types (long-distance and freight), it is costly and difficult to validate and calibrate the model using only traditional data collection methods. To address this issue, we explore the potential of using emerging alternative datasets to validate SAM. Furthermore, we aim to extract the day-to-day demand variation patterns that are currently not modeled in SAM's "typical day" forecasts from these datasets. Analysis so far has focused on RITIS's (Regional Integrated Transportation Information System) Nextgen Trip Analytics V4 dataset. RITIS is a transportation big data aggregation and dissemination platform offering a variety of services, such as real-time monitoring of transportation systems, data archives including probe vehicle trip data, and personal traffic alerts. RITIS's Nextgen Trip Analytics V4 allows for the querying and aggregation of the probe vehicle trip data database provided by INRIX to obtain the Origin-Destination (OD) matrix for a given day and time period. Currently, the Texas dataset is available for the date ranges of March through May and September and November for 2019 and February through April and September through November for 2020 and 2021. The analyses in this memorandum were conducted using the 2021 dataset. The weight class of interest can be specified when submitting a query on Nextgen Trip Analytics V4, allowing for light, medium, and heavy-duty vehicles to be analyzed separately. There are two probe source types: "connected vehicles" (CV) and "location-based services" (LBS). CV trips are recorded through in-vehicle GPS systems. This type of probe data is most common for light and medium-duty vehicles. LBS trips are recorded through cell-phone apps and makes up nearly all of the heavy-duty vehicle trip dataset. Findings for each weight class are presented below.

6.1. Light-duty vehicles (LDVs)

OD trip counts for LDV trips were downloaded from RITIS and processed for 35 weekdays and 15 weekend days in 2021. The total daily trip counts and VMT approximated using shortest-path distances between TAZ centroids are shown in Figure 38. The data of September 18-19, October 16-18, and November 16-18 were identified as outliers and removed from analysis. The cause of these spikes in trip counts are currently being investigated by INRIX. The averages and standard deviations of total trips/day and VMT/day, before and after removing the outliers, are shown in Table 16. The averages and standard deviations of total trips/day and VMT/day by the day-of-the-week and month (with outliers removed) are shown in Table 17 and Table 18, respectively. Trip counts and VMT rise steadily from Monday to Thursday before increasing substantially on Friday. Saturdays also have high trip counts and VMT. Sundays have the lowest trip counts but higher average VMT than Monday, Tuesday, and Wednesday, implying longer trips. Regarding changes from month to month, an increasing trend is observed as the year progresses. Whether this represents a seasonal trend or if it is due to an increase in sample size should be investigated.

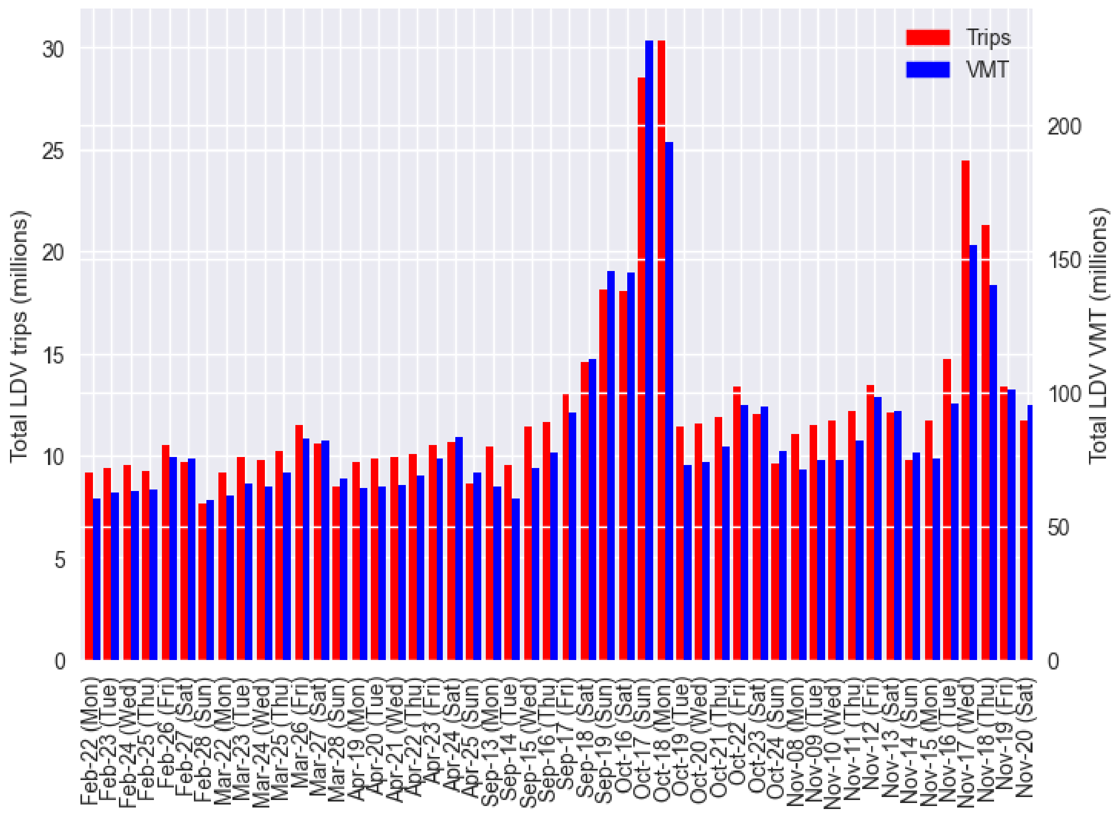


Figure 38. Total LDV Trips and VMT for Each Day in 2021 Downloaded from RITIS

Table 16. Averages and Standard Deviations of Daily LDV Total Trips and VMT in RITIS in 2021 (February through April and September through November)

With Outliers?	Day	#Days in Sample	Average (trips/day)	Std Dev (trips/day)	Average (VMT/day)	Std Dev (VMT/day)
Yes	Weekday	35 days	12.3 M trips/d	4.4 M trips/d	81.7 M mi/d	28.0 M mi/d
	Weekend	15	12.7 M	5.2 M	100.8 M	42.7 M
No	Weekday	31	10.9 M	1.3 M	73.4 M	10.9 M
	Weekend	11	10.1 M	1.4 M	79.7 M	11.0 M

Table 17. Averages and Standard Deviations of Daily LDV Total Trips and VMT in RITIS in 2021 by Day of the Week (February through April and September through November)

Day	#Days in Sample	Average (trips/day)	Std Dev (trips/day)	Average (VMT/day)	Std Dev (VMT/day)
Monday	6 days	10.2 M trips/d	1.0 M trips/d	66.2 M mi/d	5.3 M mi/d
Tuesday	6	10.3 M	0.9 M	66.9 M	5.2 M
Wednesday	6	10.7 M	0.9 M	69.0 M	4.6 M
Thursday	6	10.9 M	1.1 M	73.7 M	6.5 M
Friday	7	12. 3M	1.3 M	88.6 M	10.0 M

Saturday	6	11.2 M	0.9 M	87.3 M	7.5 M
Sunday	5	8.8 M	0.8 M	70.6 M	6.8 M

Table 18. Averages and Standard Deviations of Weekday LDV Total Trips and VMT in RITIS in 2021 by Month

Day	#Days in Sample	Average (trips/day)	Std Dev (trips/day)	Average (VMT/day)	Std Dev (VMT/day)
February	5 days	9.6 M trips/d	0.5 M trips/d	65.2 M mi/d	5.3 M mi/d
March	5	10.1 M	0.8 M	68.8 M	7.4 M
April	5	10.0 M	0.3 M	67.8 M	4.0 M
September	5	11.2 M	1.2 M	73.4 M	11.1 M
October	4	12.1 M	0.8 M	80.5 M	9.0 M
November	7	12.2 M	0.9 M	82.5 M	11.3 M

The average trip counts of the observed OD pairs in the 2021 RITIS LDV dataset were compared against SAM outputs for the 2019 base scenario. Since RITIS contains substantially more intra-zonal trips compared to SAM (26% vs 15% for weekday), all comparisons between RITIS and SAM are limited to inter-zonal trips. Figure 34 shows the distribution of the shortest-path distances (between zone centroids) for RITIS and SAM for inter-zonal trips. For both weekends and weekdays, the RITIS dataset contains more trips that are less than 5 miles compared to SAM. Table 19 shows the comparison of the RITIS average trip table and the SAM trip table for LDVs in terms of trips/day, VMT/day, and average trip distance. The ratio of RITIS to SAM values is the nearly identical for both trip counts and VMT for the average weekday, both being 14.8%. Consequently, the average weekday trip distances are also equal, despite the difference in the distribution of approximate trip distances shown in Figure 39. This suggests that RITIS contains more long-distance trips compared to SAM, in addition to containing more short-distance trips. These patterns are not repeated for the average weekend. The average weekday daily trips and VMT in RITIS are 18.4% and 15.3%, respectively, of those of SAM. The ratio of trip counts of RITIS to that of SAM is high compared to the other ratios, resulting in an average weekend trip distance that is 2 miles shorter for RITIS. This suggest that RITIS may be breaking up long trips on weekends for driver breaks.

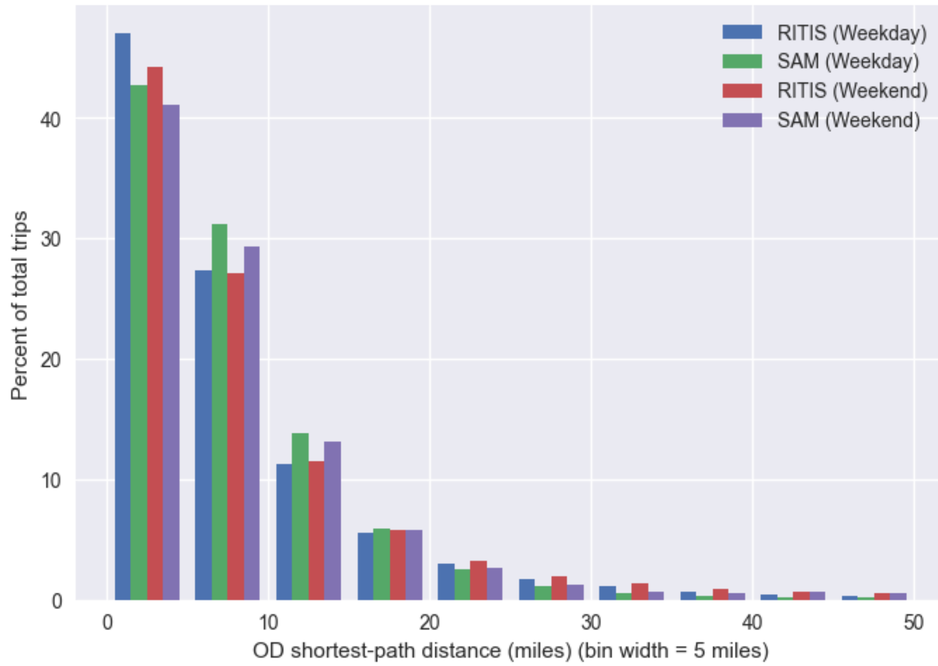


Figure 39. Distribution of shortest-path distances for RITIS and SAM for LDVs (bin width = 5 miles)

Table 19. Trips/day, VMT/day, and Average Trip Distance for Average RITIS LDV Trip Tables and SAM LDV Trip Tables (inter-zonal trips only)

	Trips/day	VMT/day	Average trip distance (miles)
RITIS weekday avg	8.1 M trips/d	73.4 M mi/d	9.1 mi
SAM weekday	54.7 M	496 M	9.1
RITIS weekend avg	7.6 M	79.7 M	10.4
SAM weekend	41.5 M	522 M	12.6

The average weekday LDV trip productions and attractions for inter-zonal trips in RITIS were compared against SAM estimates. Because the correlation between TAZ trip production and attraction were 0.99 and 0.97 in RITIS and SAM, respectively, the productions and attractions were summed. Figure 41 shows the cumulative distribution function of the trip production + attraction across TAZs, ordered with respect to the SAM values. It reveals that trips are more evenly distributed across TAZs in RITIS compared to SAM, with the top 1,000 TAZs in SAM accounting for 64% of origins and destinations in trips, while the same TAZs constituting just 52% in RITIS. Furthermore, Figure 42 shows the production + attraction at each county. The bins of SAM are scaled up by 6.75 to reflect the difference in the total number of trips. The county-level productions + attractions are very similar between RITIS and SAM. However, there are more counties, especially in the southeast, that have higher shares in RITIS compared to SAM. Moreover, weekday HDV flows in RITIS and SAM were mapped at the level of 25 TxDOT districts (Figure 42). The line width between an OD pair is proportional to its share of inter-district trips (i.e., the weights of the lines in each figure sum to 1). Overall, flows between districts are similar between RITIS and SAM, with the highest flows by far between the Dallas and Fort Worth Districts (31% and 42% of inter-district trips in RITIS and SAM, respectively).

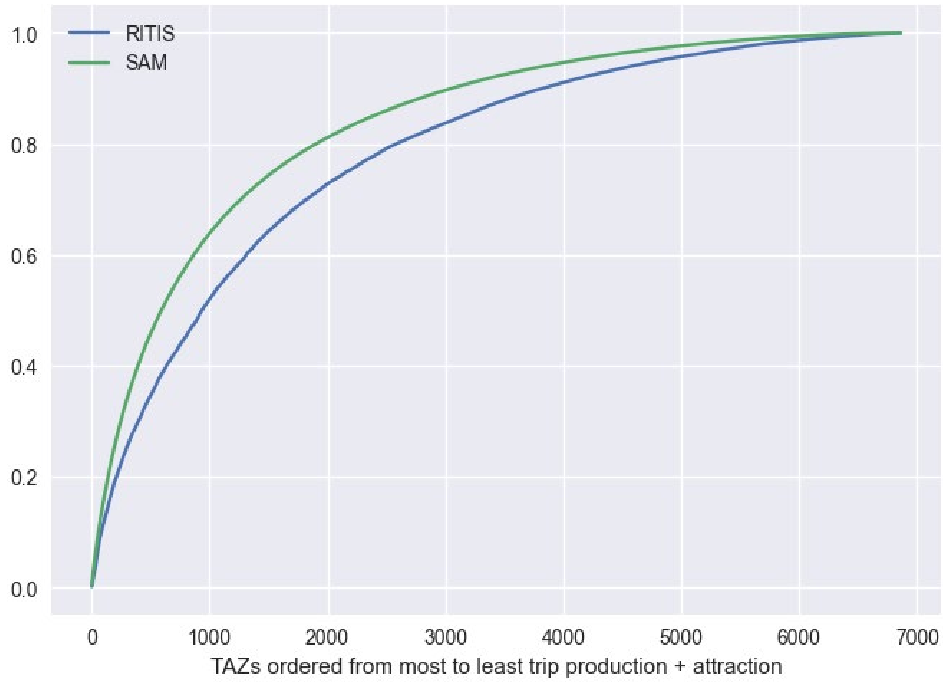


Figure 40. Cumulative Distribution Function of Weekday LDV Trip Production + Attraction at the 6860 TAZs

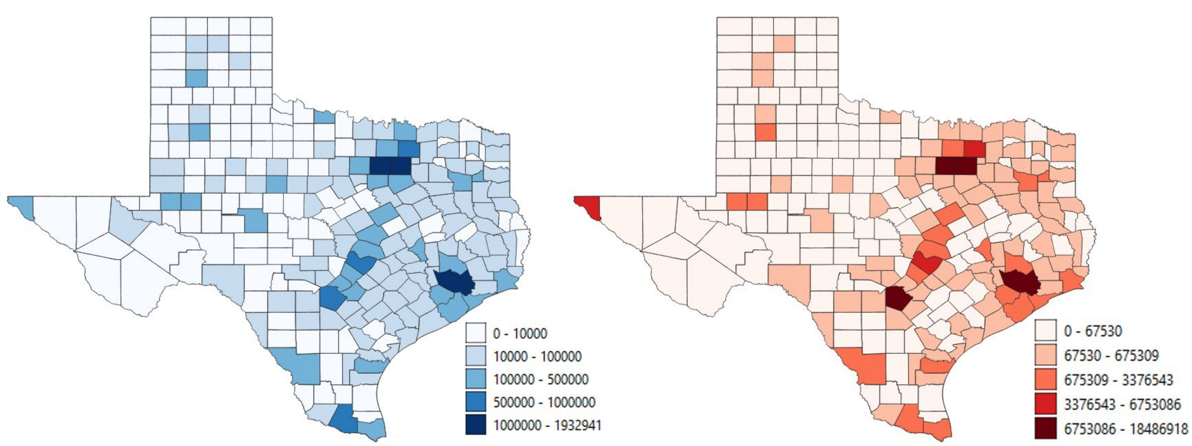


Figure 41. Weekday LDV Trip Production + Attraction at Each County in RITIS (Avg) and SAM

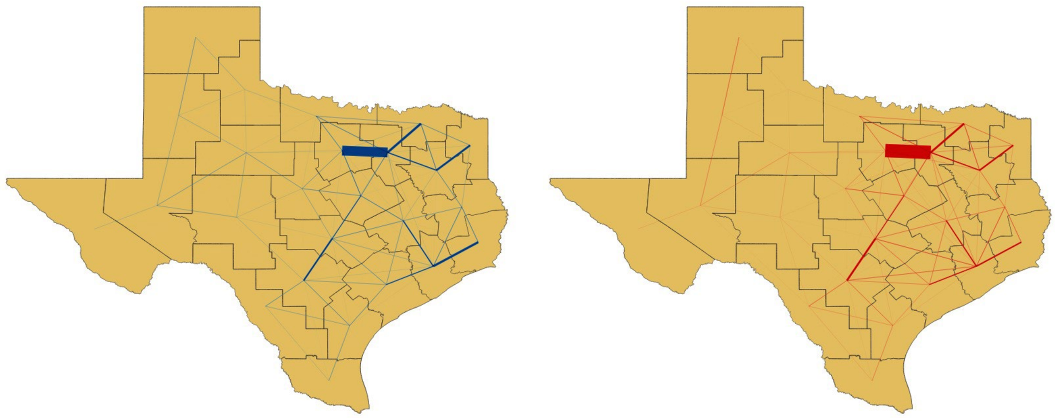


Figure 42. Average RITIS Weekday HDV Flows vs SAM Predicted Flows

Finally, ordinary least squares regression was performed to further evaluate the differences between the RITIS dataset and the SAM counts (at both the TAZ and then the county level of spatial aggregation). OD pairs where the count was 0 in both SAM and RITIS were removed from the analyses. Regression at the level of 6860 SAM zones provided a slope of 4.18 and R-squared of 0.614 (correlation coefficient of 0.784) (Figure 44). The slope is lower than the expected 6.75. The fit is improved at the level of 254 counties with an R-squared of 0.948 (correlation coefficient of 0.974) (Figure 44). The slope of 8.66 is higher than the expected 6.75. However, the slope is highly influenced by the top 8 points with the highest flows. The origin county equals the destination county for these points. After these 8 are removed, the R-squared falls to 0.920 (correlation coefficient of 0.959) and the slope of 5.50 is closer to the expected (Figure 46).

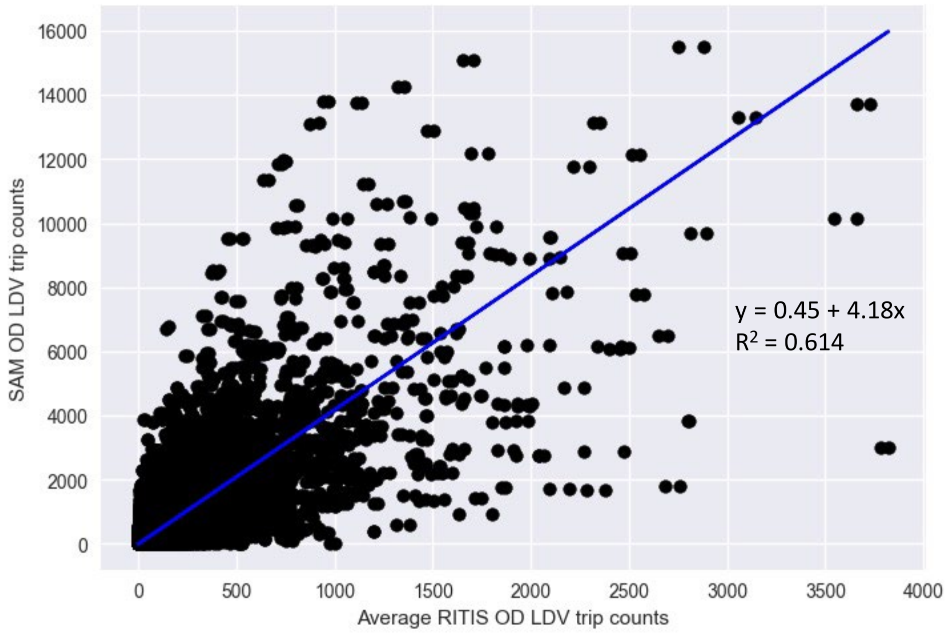


Figure 43. RITIS Average Weekday LDV Counts vs SAM between TAZs (n = 46.5 M)

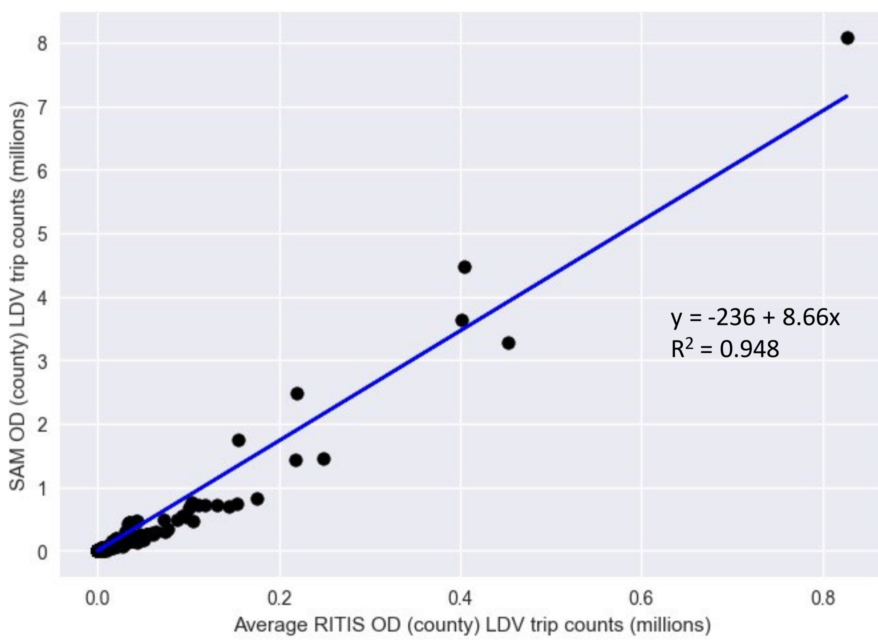


Figure 44. RITIS Average Weekday LDV Counts vs SAM between Counties before Removing 8 High-Count (>1 M LDV Trips/day in SAM) Points (n = 64,509)

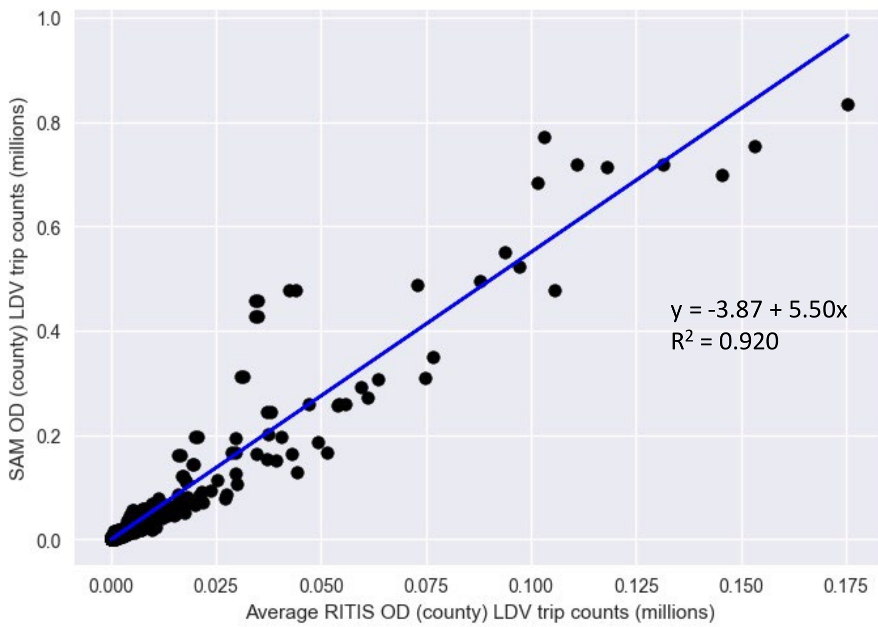


Figure 45. RITIS Average Weekday LDV Counts vs SAM between Counties before Removing 8 High-Count (>1 M LDV Trips/day in SAM) Points (n = 64,501)

6.2. Medium-duty vehicles (MDVs)

OD trip counts for MDV trips were downloaded from RITIS and processed for the same 35 weekdays and 15 weekend days in 2021 as LDVs. The total daily trip counts and VMT approximated using shortest-path distances between TAZ centroids are shown in Figure 47. Interestingly, unusually high counts are observed for the same days as LDVs (September 18-19, October 16-18, and November 16-18), although high counts on weekdays are not as obvious due to the lower trip counts on weekends for MDVs. The averages and standard deviations of total trips/day and VMT/day, before and after removing these outliers, are shown in Table 20. The averages and standard deviations of total trips/day and VMT/day by the day-of-the-week and month (with outliers removed) are shown in Table 21 and Table 22, respectively. Tuesdays have the highest trip counts and VMT on average. Fridays have lower trip counts and VMT compared to other weekdays on average, contrasting LDVs, which have the highest trip counts and VMT on Fridays. Additionally, weekends data average just 32% and 36% of weekday trip counts and VMT, respectively. Regarding changes from month to month, a slight decrease is observed as the year progresses, which is the opposite of what was observed for LDVs. Whether this represents a seasonal trend or if it is due to changes in sampling methods should be investigated.

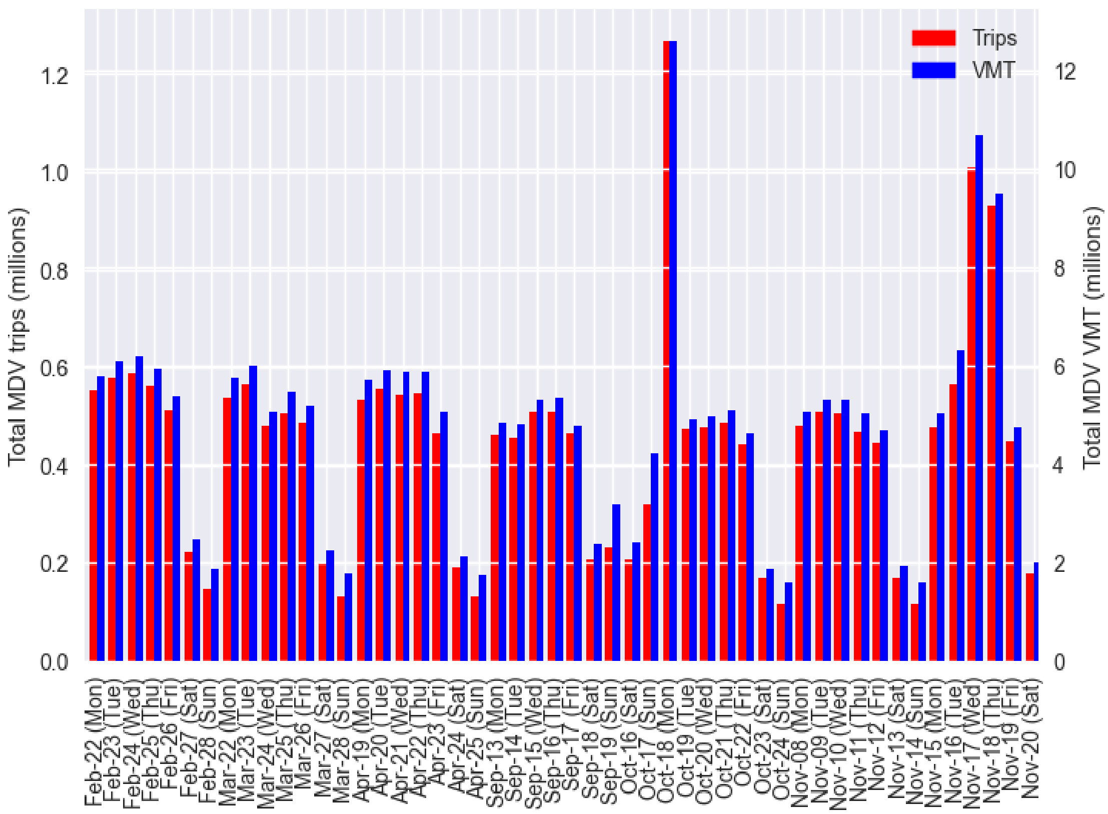


Figure 46. Total MDV Trips and VMT for Each Day in 2021 Downloaded from RITIS

Table 20. Averages and Standard Deviations of Daily MDV Total Trips and VMT in RITIS in 2021 (February through April and September through November)

With Outliers?	Day	#Days in Sample	Average (trips/day)	Std Dev (trips/day)	Average (VMT/day)	Std Dev (VMT/day)
Yes	Weekday	35 days	555,001 trips/d	168,029 trips/d	5.84 M mi/d	1.67 M mi/d
	Weekend	15	182,863	52,041	2.23 M	0.66 M
No	Weekday	31	504,829	41,231	5.33 M	0.46 M
	Weekend	11	161,255	34,305	1.93 M	0.26 M

Table 21. Averages and Standard Deviations of Daily MDV Total Trips and VMT in RITIS in 2021 by Day of the Week (February through April and September through November)

Day	#Days in Sample	Average (trips/day)	Std Dev (trips/day)	Average (VMT/day)	Std Dev (VMT/day)
Monday	6 days	507,862 trips/d	34,490 trips/d	5.36 M mi/d	0.40 M mi/d
Tuesday	6	523,610	47,301	5.50 M	0.52 M
Wednesday	6	517,746	38,210	5.46 M	0.44 M
Thursday	6	513,733	32,193	5.46 M	0.35 M
Friday	7	467,429	23,055	4.93 M	0.27 M
Saturday	6	188,875	19,199	2.11 M	0.20 M

Sunday	5	128,110	11,519	1.71 M	0.11 M

Table 22. Averages and Standard Deviations of Weekday MDV Total Trips and VMT in RITIS in 2021 by Month

Day	#Days in Sample	Average (trips/day)	Std Dev (trips/day)	Average (VMT/day)	Std Dev (VMT/day)
February	5 days	558,700 trips/d	26,465 trips/d	5.88 M mi/d	0.28 M mi/d
March	5	516,120	32,203	5.50 M	0.35 M
April	5	529,498	32,498	5.69 M	0.32 M
September	5	480,608	24,722	5.02 M	0.25 M
October	4	470,643	15,676	4.89 M	0.17 M
November	7	477,501	22,889	5.02 M	0.22 M

The average trip counts of the observed OD pairs in the 2021 RITIS MDV dataset were compared against SAM outputs for the 2019 base scenario. Since RITIS contains more intra-zonal trips compared to SAM (28% vs 22% for weekday) as it was for LDVs, all comparisons between RITIS and SAM are again limited to inter-zonal trips. Table 23 shows the comparison of the RITIS average trip table and the SAM trip table for LDVs in terms of trips/day, VMT/day, and average trip distance. For weekdays, the average MDV trip total daily trip count of RITIS is 125% of that of SAM, while the VMTs are nearly equal. For weekends, the average MDV trip total daily trip count and VMT of RITIS are 39% and 36% of those of SAM, respectively, as there is virtually no change in SAM from weekday to weekend. These discrepancies suggest that the MDV class in RITIS does not refer to the same group of vehicles as SAM. As further comparison is not meaningful, this concludes the analysis of the MDV data from RITIS.

Table 23. Trips/day, VMT/day, and Average Trip Distance for Average RITIS MDV Trip Tables and SAM MDV Trip Tables (inter-zonal trips only)

	Trips/day	VMT/day	Average trip distance (miles)
RITIS weekday avg	364,225 trips/d	5.33 M mi/d	14.6 mi
SAM weekday	290,549	5.35 M	18.4
RITIS weekend avg	114,486	1.93 M	16.9
SAM weekend	290,573	5.35 M	18.4

6.3. Heavy-duty vehicles (HDVs)

OD trip counts for LDV trips were downloaded from RITIS and processed for the same 35 weekdays and 15 weekend days in 2021 as LDVs and MDVs. The total daily trip counts and VMT approximated using shortest-path distances between TAZ centroids are shown in Figure 48. Unusually high counts are observed for the same days as LDVs and MDVs (September 18-19, October 16-18, and November 16-18). The averages and standard deviations of total trips/day and VMT/day, before and after removing the outliers, are shown in Table 24. The averages and standard deviations of total trips/day and VMT/day by the day-of-the-week and month (with outliers removed) are shown in Table 25 and Table 26, respectively. In general, there are more trips at the beginning of the workweek (starting with Monday), but higher VMT mid-week. Fridays have lower trip counts and VMT compared to other weekdays on average. Additionally, weekends data average just 51% and 64% of weekday trip counts and VMT, respectively. Like MDVs but unlike LDVs, a decreasing trend is observed as the year progresses, with the weekday average of November being ~20,000 trips or 24% less than that of February.

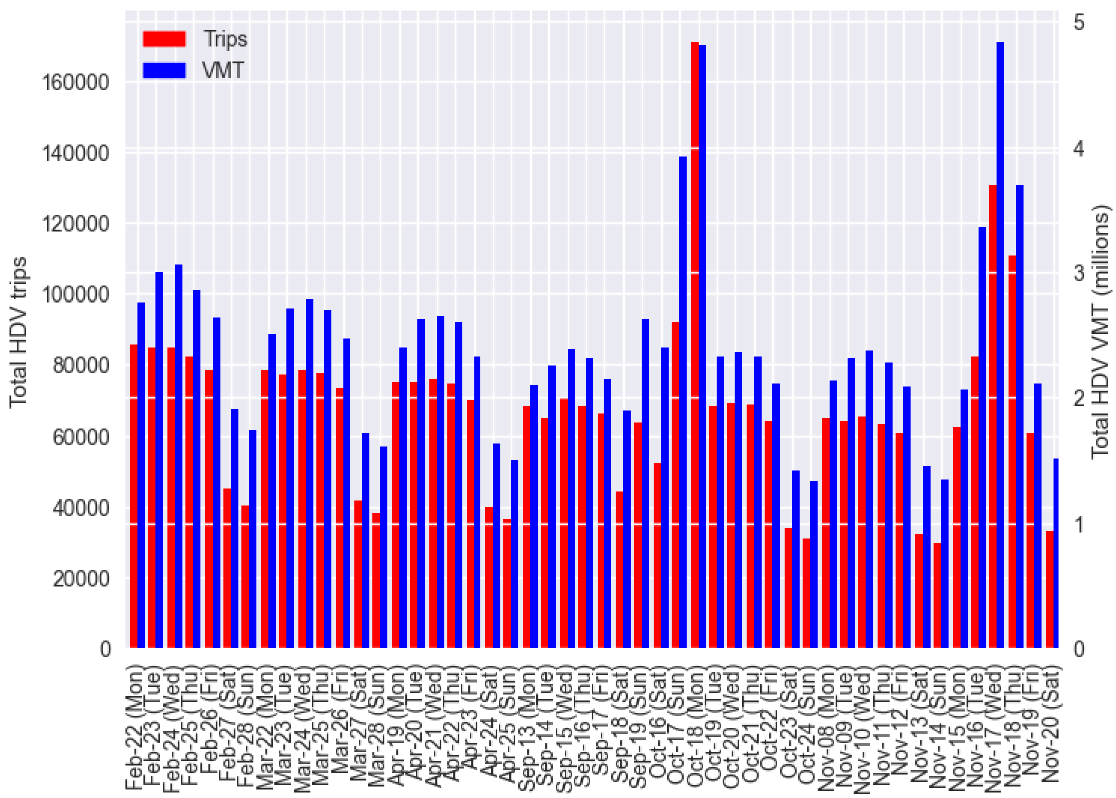


Figure 47. Total HDV Trips and VMT for Each Day in 2021 Downloaded from RITIS

Table 24. Averages and Standard Deviations of Daily HDV Total Trips and VMT in RITIS in 2021 (February through April and September through November)

With Outliers?	Day	#Days in Sample	Average (trips/day)	Std Dev (trips/day)	Average (VMT/day)	Std Dev (VMT/day)
Yes	Weekday	35 days	77,605 trips/d	21,013 trips/d	2.64 M mi/d	0.65 M mi/d
	Weekend	15	43,548	15,583	1.87 M	0.66 M
No	Weekday	31	71,653	7,282	2.45 M	0.27 M
	Weekend	11	36,442	4,646	1.56 M	0.17 M

Table 25. Averages and Standard Deviations of Daily HDV Total Trips and VMT in RITIS in 2021 by Day of the Week (February through April and September through November)

Day	#Days in Sample	Average (trips/day)	Std Dev (trips/day)	Average (VMT/day)	Std Dev (VMT/day)
Monday	6 days	72,483 trips/d	8,076 trips/d	2.33 M mi/d	0.25 M mi/d
Tuesday	6	72,371	7,361	2.54 M	0.26 M
Wednesday	6	74,070	6,611	2.60 M	0.26 M
Thursday	6	72,415	6,349	2.51 M	0.22 M
Friday	7	67,601	6,125	2.27 M	0.20 M
Saturday	6	37,598	4,697	1.60 M	0.17 M
Sunday	5	35,054	4,182	1.51 M	0.16 M

Table 26. Averages and Standard Deviations of Weekday HDV Total Trips and VMT in RITIS in 2021 by Month

Day	#Days in Sample	Average (trips/day)	Std Dev (trips/day)	Average (VMT/day)	Std Dev (VMT/day)
February	5 days	83,216 trips/d	2,726 trips/d	2.86 M mi/d	0.15 M mi/d
March	5	76,994	1,897	2.63 M	0.12 M
April	5	74,101	2,201	2.52 M	0.13 M
September	5	67,593	1,931	2.24 M	0.11 M
October	4	67,614	1,982	2.28 M	0.10 M
November	7	63,038	1,770	2.20 M	0.12 M

The average trip counts of the observed OD pairs in the 2021 RITIS HDV dataset were compared against SAM outputs for the 2019 base scenario. SAM has two trip tables for HDVs: freight and non-freight. Non-freight HDVs serve the local area whereas freight accounts for more long-distance trips. These two trip tables were combined into one HDV trip table for SAM. Since RITIS contains substantially more intra-zonal trips compared to SAM (20% vs 9.5% for weekday), as it was for LDVs and MDVs, all comparisons between RITIS and SAM are again limited to inter-zonal trips. Figure 49shows the distribution of the shortest-path distances (between zone centroids) for RITIS and SAM for inter-zonal trips. Interestingly, the distance distributions of RITIS do not compare the same way to those of SAM between weekends and weekdays. For the average weekday, the RITIS contains more trips shorter than 20 miles compared to SAM, accounting for 50% of trips in RITIS but only 40% in SAM. For the average weekday, however, the RITIS contains a similar share of trips shorter than 20 miles as SAM but more trips over 80 miles. Table 27 shows the comparison of the RITIS average trip table and the SAM trip table for LDVs in terms of trips/day, VMT/day, and average trip distance. The average weekday daily trips and VMT in RITIS are 16.6% and 14.5% of those in SAM, respectively. The average trip distance in RITIS is 6.3 miles shorter than that of SAM. This suggests that RITIS is breaking up trip for driver breaks. On the other hand, the average weekend daily trips and VMT in RITIS are 9.7% and 13.0% of those in SAM, respectively, as the decrease in HDV trips from weekdays to weekends is 47.3% in RITIS but only 10.0% in SAM. Furthermore, the average weekend distance is 9.4 miles longer than the average weekday distance in RITIS but 10.2 miles shorter in SAM. These inconsistencies between weekdays and weekends cannot be explained by sampling or trip definition differences between RITIS and SAM and suggests that SAM's weekend model should be reviewed for how it models HDVs and freight.

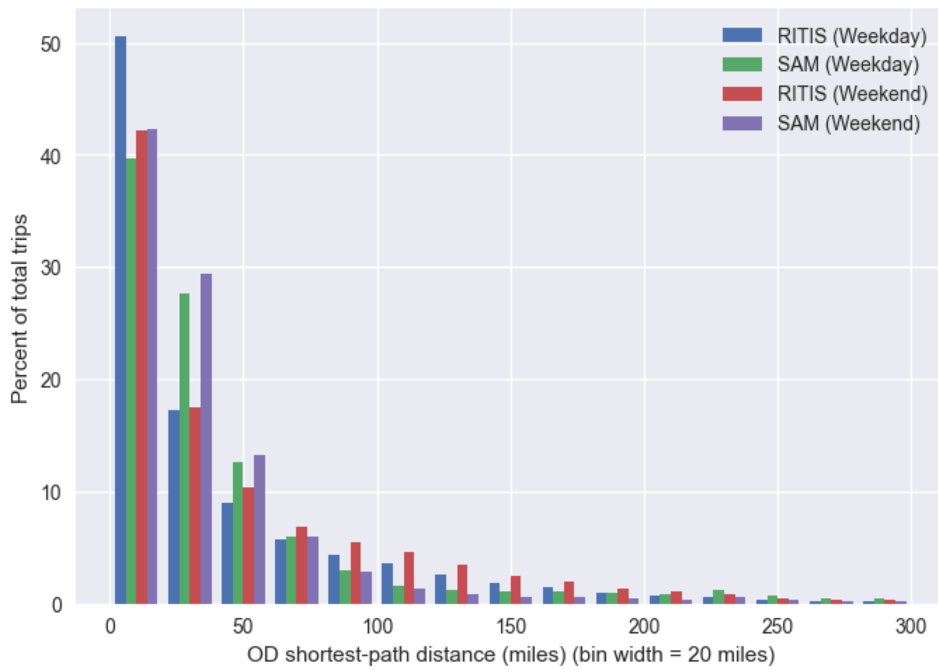


Figure 48. Distribution of shortest-path distances for RITIS and SAM for HDVs (bin width = 20 miles)

Table 27. Trips/day, VMT/day, and Average Trip Distance for Average RITIS HDV Trip Tables and SAM HDV Trip Tables (inter-zonal trips only)

	Trips/day	VMT/day	Average trip distance (miles)
RITIS weekday avg	57,254 trips/d	2.45 M mi/d	42.7 mi
SAM weekday	344,350	16.9 M	49.0
RITIS weekend avg	29,930	1.56 M	52.1
SAM weekend	309,994	12.0 M	38.8

The average weekday HDV trip productions and attractions for inter-zonal trips in RITIS were compared against SAM estimates. Because the correlation between TAZ trip production and attraction were 0.99 and 0.96 in RITIS and SAM, respectively, the productions and attractions were summed. Figure 50 shows the cumulative distribution function of the trip production + attraction across TAZs, ordered with respect to the SAM values. It reveals that trips are more evenly distributed across TAZs in RITIS compared to SAM, with the top 1,000 TAZs in SAM accounting for 68% of origins and destinations in trips, while the same TAZs constituting just 48% in RITIS. This was also observed for LDVs. However, there seems less of an agreement in the ranking of the TAZs by production + attraction, as portrayed by the roughness of the curve for RITIS. Furthermore, Figure 51 shows the production + attraction at each county. The bins of

SAM are scaled up by 6.01 to reflect the difference in the total number of trips. Although Figure 43 shows that RITIS has trips spread more evenly spatially distributed, Figure 50 reveals that there are some areas missing trips in RITIS, namely western Texas. Moreover, weekday HDV flows in RITIS and SAM were mapped at the level of 25 TxDOT districts (Figure 43). The line width between an OD pair is proportional to its share of inter-district trips (i.e., the weights of the lines in each figure sum to 1). RITIS and SAM are similar in terms of high freight flows from Laredo to the Dallas and Fort Worth districts, through San Antonio, Austin, and Waco districts. However, SAM has more flows to and from the Houston district compared to RITIS.

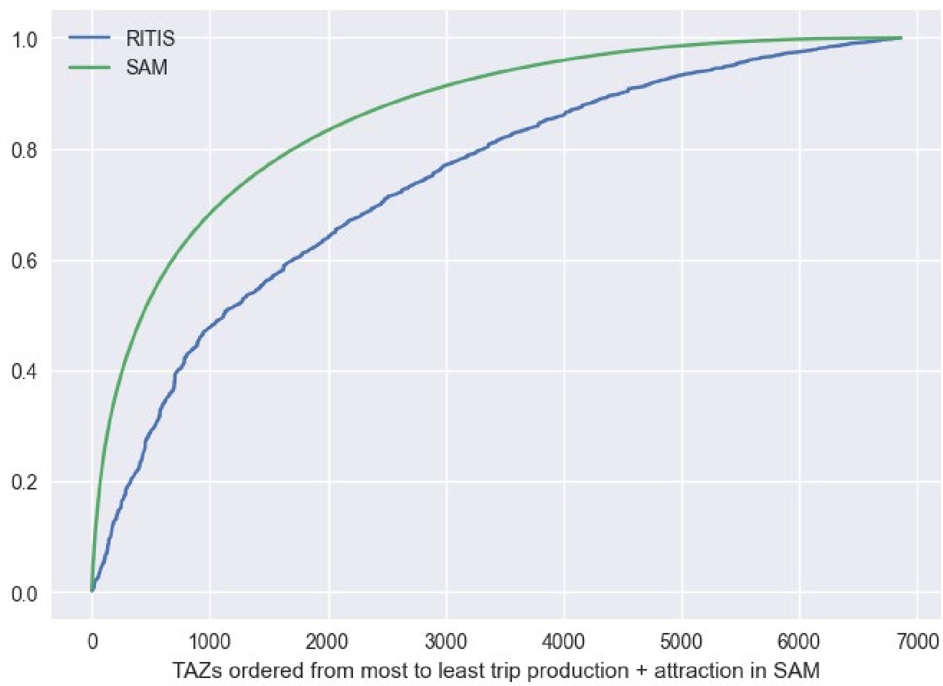


Figure 49. Cumulative Distribution Function of Weekday HDV Trip Production + Attraction at the 6860 TAZs

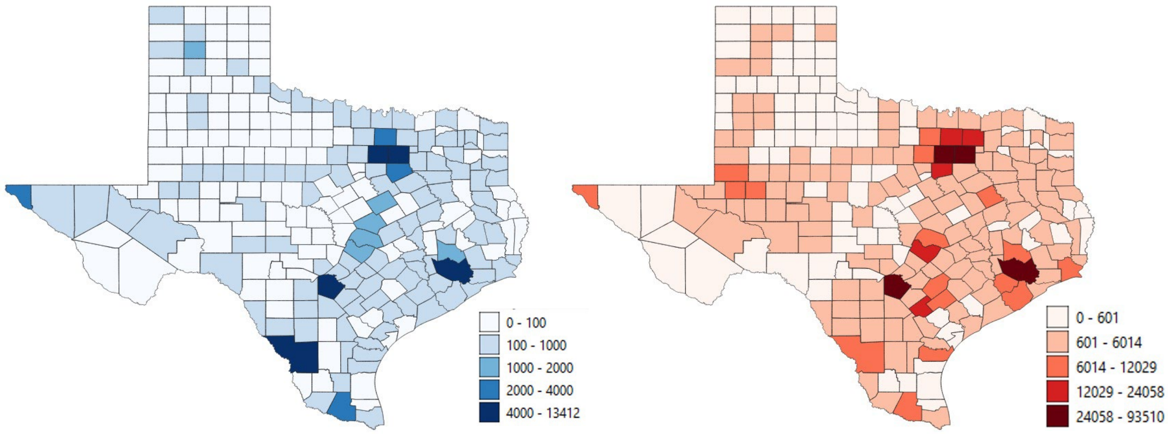


Figure 50. Weekday HDV Trip Production + Attraction at Each County in RITIS (Avg) and SAM

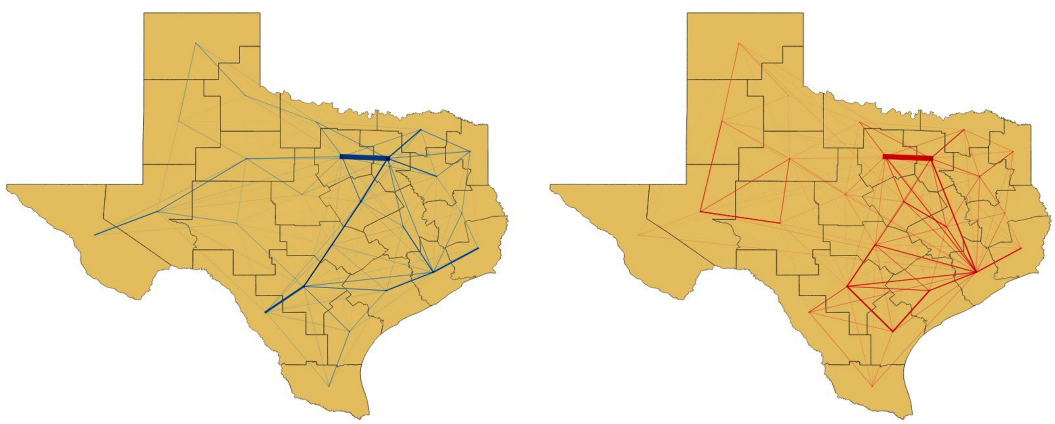


Figure 51. Average RITIS Weekday HDV Flows vs SAM Predicted Flows

Finally, ordinary least squares regression was performed to further evaluate the differences between the RITIS dataset and the SAM counts (at both the TAZ and then the county level of spatial aggregation) OD pairs where the count was 0 in both SAM and RITIS were removed from the analyses. Although the fit at the level of 6680 SAM zones was extremely poor with no discernable relationship (Figure 52), regression at the level of 254 counties provided a much-improved fit with R-squared = 0.639 (correlation coefficient of 0.80), suggesting reasonable fit (Figure 53). However, the 14 outlier points at high flows (with origin zone equaling destination zone mostly) are controlling the slope (which is less than half what it should be) and the fit statistic. When those 14 are removed, the R2 falls to 0.302 (correlation coefficient of 0.55), and the slope of 4.59 is closer to the expected (Figure 54).

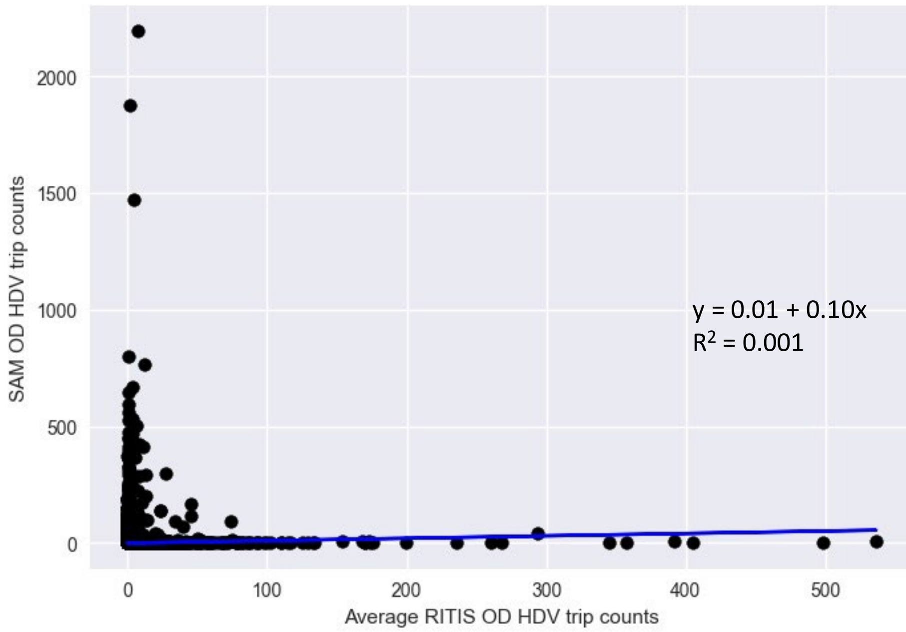


Figure 52. RITIS Average Weekday HDV Counts vs SAM between TAZs (n = 38.5 M)

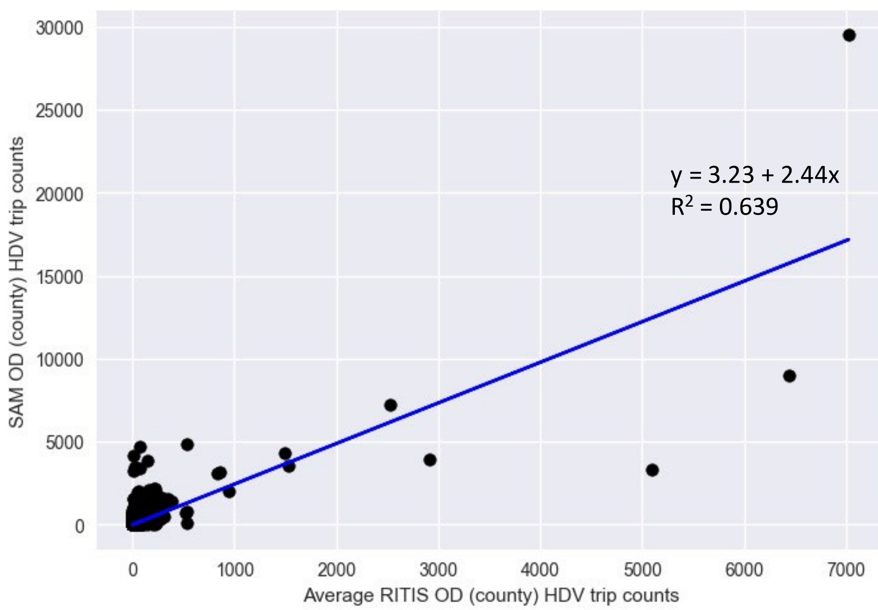


Figure 53. RITIS Average Weekday HDV Counts vs SAM between Counties before Removing 14 High-Count (>500 HDV Trips/day in RITIS) Points (n = 63,440)

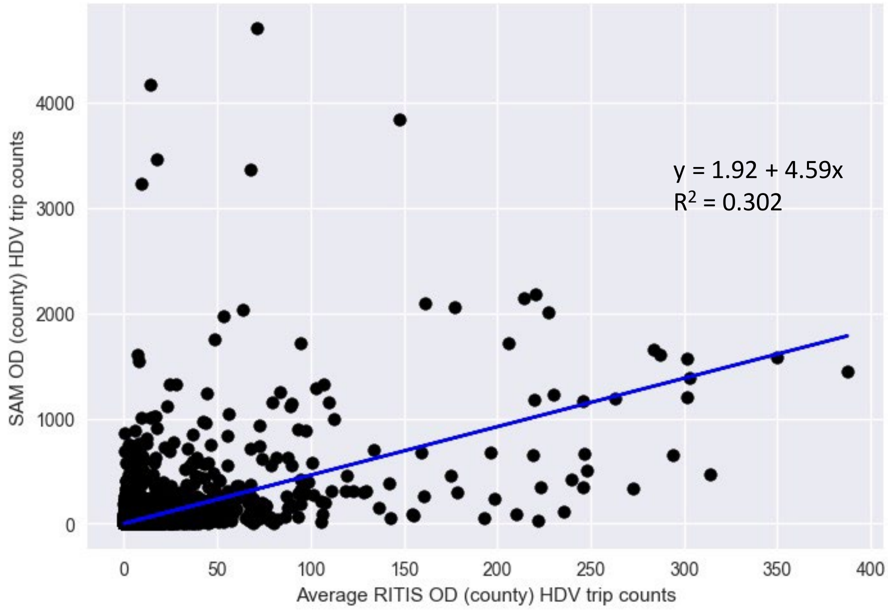


Figure 54. Weekday HDV Counts vs SAM between Counties before Removing 14 High-Count (>500 HDV Trips/day in RITIS) Points (n = 63,426)

6.4. Permanent Traffic Recorders (PTRs)

From 2013 through 2022, TxDOT maintained 398 PTR stations, which records traffic counts using loop detectors. The locations of these PTR stations are shown in Figure 56 (left). The number of stations in the dataset varies by year and fluctuates throughout each year as shown in Figure 57. This makes it difficult to directly observe variations in total traffic volumes across the state. Of the 398 stations in the data set, 178 that have data for more than 90% of days from 2019 through 2022 were identified (Figure 56 right). There does not seem to be an obvious spatial bias for the location of the qualifying stations. Missing values and values over 5 standard deviations away from the mean in 2019, 2021, and 2022 were imputed as the average for the day of the week for the same month over the 3 years. Counts from February 13-17, 2021, and February 3, 2022, were kept because the cause can be identified as winter storms. For 2020, missing values were imputed using the same method but averaged using data from just 2020. The resulting total daily traffic counts over the four years are plotted in Figure 57. The start of 2020, 2021, and 2022 are offset by 1, 3, and 4 days respectively to align the days of the week. The demand patterns align well over the four years, setting aside extraordinary events such as the COVID-19 pandemic and the winter storms in 2021 and 2022. The peaks and valleys of the oscillations are Fridays and Sundays, respectively, with their ratio ranging between 4:3 and 3:2. January clearly has the least traffic volume, but the differences between the other months are not as visible. Holiday rush days, such as the day before Fourth of July or Thanksgiving, seem to have similar traffic volumes as typical Fridays at the PTR stations, as congestion feedback is causing the caps to stay fairly flat.

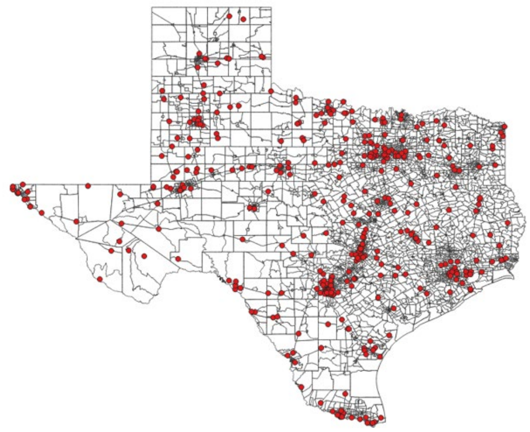


Figure 55. All 398 PTR Station Locations and 178 Stations Used in Figure 52

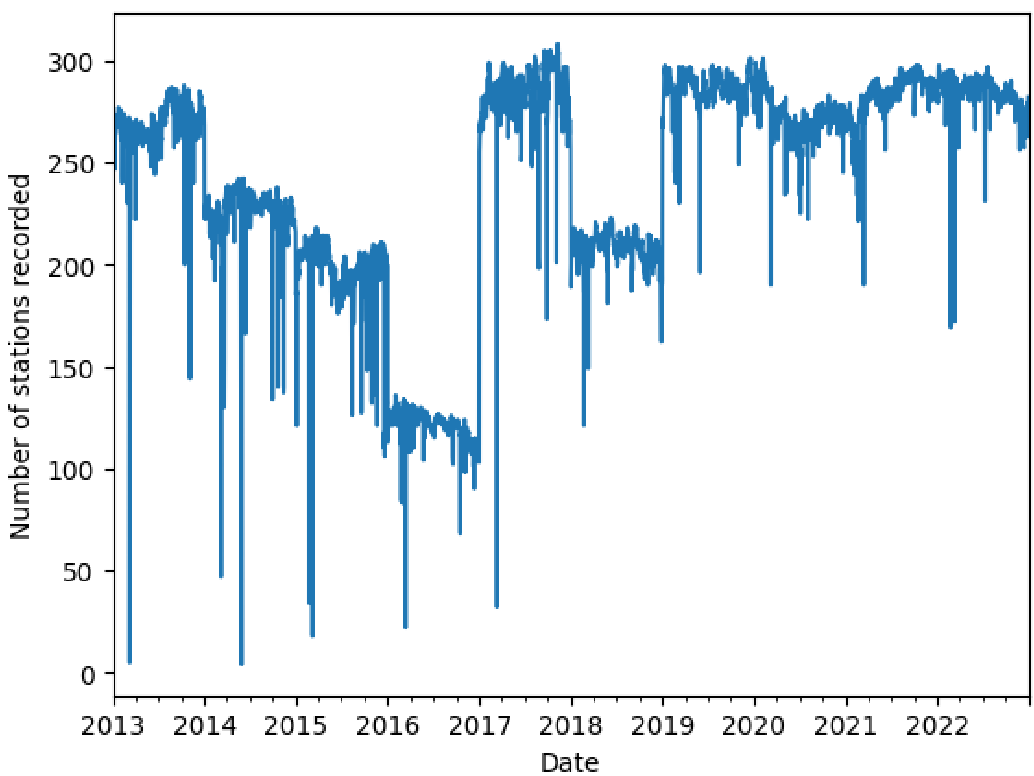


Figure 56. Number of Distinct PTR Stations in the Dataset for Each Day

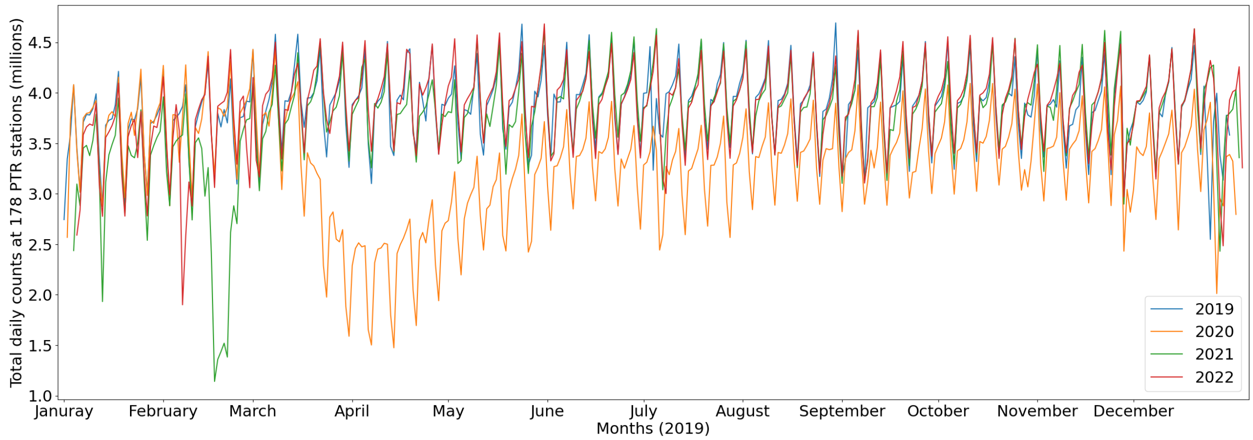


Figure 57. Total Daily Traffic Counts Across 178 PTR Stations from 2019 through 2022

Regression was used to study the demand variations through the year for all PTR stations. The daily total traffic counts at each station were standardized to z-scores using the mean and standard deviation at the station over the 10 years. The explanatory variables include days of the week, month, year, and holiday. In addition, variables for certain holidays and surrounding days that are widely reported to have large changes in traffic patterns were added. These holidays are Memorial Day, Fourth of July, Labor Day, Thanksgiving, and Christmas. The regression result is shown in Table 28. The R-squared was 0.362 (n = 885.274). On average, traffic volumes fluctuate by 1.63 standard deviations over the course of a week, with Sundays being the least busy and Fridays being the busiest. The difference between Mondays and Tuesdays was statistically insignificant. January is the least busy month, while June and July are the busiest. The largest increase (0.344 standard deviations) occurs from February to March. The largest decrease (0.438 standard deviations) occurs from December to January. Traffic volumes have been steadily increasing since 2013, with the 2022 counts being 0.89 standard deviations above 2013 counts on average. Even the pandemic-affected counts of 2020 were higher than that of 2014. Traffic volumes fully recovered and surpassed 2019 levels in 2022. Looking at specific holidays, increased traffic was widely reported on certain days surrounding these holidays, such as Fridays before Memorial Day and Labor Day weekends, on Tuesday and Wednesday before Thanksgiving and on the Sunday after Thanksgiving Day, and on the day before Christmas Eve, were confirmed, except for the day after Christmas. Furthermore, compared to other holidays, these five holidays saw greater reduction in traffic volumes. The total decrease was greater than 1 standard deviation for Fourth of July, Thanksgiving Day, Friday after Thanksgiving Day, and Christmas Day. The total increase was greater than 1 standard deviation for the Wednesday before Thanksgiving Day.

Table 28. PTR Daily Traffic Count Z-Score Regression Result

Variable	Estimate (t)
Constant	-0.945 (-233)
Monday/Tuesday (base day)	0

Wednesday	0.088 (31.5)
Thursday	0.281 (101)
Friday	0.852 (302)
Saturday	-0.202 (-72.5)
Sunday	-0.778 (-277)
January (base month)	0
February	0.149 (35.3)
March	0.493 (119)
April	0.314 (75.7)
May	0.450 (107)
June	0.570 (137)
July	0.5294 (126)
August	0.465 (112)
September	0.402 (95.3)
October	0.498 (121)
November	0.484 (110)
December	0.438 (102)
Year 2013 (base year)	0
Year 2014	0.142 (37.5)
Year 2015	0.339 (86.3)
Year 2016	0.506 (111)
Year 2017	0.612 (172)
Year 2018	0.737 (191)
Year 2019	0.850 (239)
Year 2020	0.210 (58.5)
Year 2021	0.801 (224)
Year 2022	0.891 (250)
Federal holiday	-0.307 (-46.3)
Friday before Memorial Day	0.445 (26.5)
Memorial Day	-0.301 (-16.6)
July 3	0.307 (16.7)
Fourth of July	-0.736 (-41.1)
Friday before Labor Day	0.518 (31.4)
Labor Day	-0.099 (-5.58)
Tuesday before Thanksgiving	0.669 (40.2)
Wed before Thanksgiving	1.275 (75.8)
Thanksgiving Day	-1.121 (-62.2)
Friday after Thanksgiving	-1.199 (-70.9)
Saturday after Thanksgiving	-0.102 (-6.00)
Sunday after Thanksgiving	0.890 (52.9)
December 23	0.364 (21.6)

Christmas Eve	-0.720 (-40.7)
Christmas	-1.691 (-95.0)
December 26	-0.216 (-11.9)

**Federal holidays include New Year's Day, Martin Luther King, Jr. Day, Presidents' Day, Memorial Day, Independence Day, Labor Day, Veterans Day, Thanksgiving, and Christmas.*

Overall, the RITIS Nextgen Trip Analytics V4 and PTR datasets show some potential in capturing variations in demand. However, special care and more analysis must be taken in order to use them to validate SAM or introduce demand variations in SAM equations. Specifically, analysis of trip tables in RITIS showed unexplained spikes in demand, possible differences in the definition of a trip and vehicle types, and spatial biases. PTR data, while demonstrating consistent demand variation patterns, have some inherent issues. Because the PTR stations are located only along major roadways, it has a tendency to underestimate demand variations in both directions, as it does not capture differences in route choice at various levels of demand.

Conclusions

This TxDOT research project and report focus on the integration of AVs, SAVs, and ATrucks into the transportation network, necessitating substantial modifications to the mode choice component of the model. This involves script adjustments in skim creation, mode choice, traffic assignment, and report generation, as discussed in detail. An anticipated 15% rise in trip production rates in 2040 accommodates the expected growth in travel demand driven by AVs, especially for those without cars, those with mobility limitations, and elderly persons. For short-distance trips, mode splits are fixed by the modeler's own design (since SAM allows mode shifts only in the LD trips), The VOTT for AVs and SAVs was assumed to be 20% less than traditional human-driven vehicles (HVs), with operating costs of \$0.60 and \$1.00 per mile, respectively. The operating costs for ATrucks were assumed to be 1.5 times those of HTrucks to account for automation equipment cost and additional training expenses for humans supervising the truck) with a 25% reduction in VOTT for all AV scenarios (except for scenario 3 which assumes 50% reduction in VOTT). For trips that are less 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.

Results show that, for trips that are longer than 50 miles, AVs + SAVs (personal) captured a 14% of market share, accompanied by a 17 percentage-point decline in human-driven "drive alone" mode. This shift can be attributed to a 25% reduction in Vehicle VOTT, allowing individuals to use their time more effectively. Personal AV driving with two or more occupants had share of 7% and 11%, respectively. SAV driving captured mode share of 3% and 4% when used with three or more occupants, while human-driven shared rides saw fall of 5% and 10% points with same party size. 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 exceeding 50 miles but less than 400 miles.

Average trip length rose across all vehicle categories, with light, medium, and heavy-duty trucks experienced rise of 35%, 32%, and 28%, in their mean trip distance travelled. This trend indicates an inclination for covering greater distances, likely due to the removal of 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% comes from more driving, longer trips, less flying, and a shift to ATrucks. Due to much higher VMT loads on the Texas network (as encoded in SAM, which is about 80% of centerline miles in the State of Texas), travel speeds are estimated to fall by about 35% on average (for the coded network). The VHT jumped by about 304%, largely thanks to passenger travel favoring the AM and PM peaks and mid-day, where travel speeds fell by 68%, 67%, and 40%. Speeds during night-time remained steady. Scenario analyses reveal that predicted mode shares of AVs, SAVs, and ATrucks are sensitive to cost variations.

The integration of ATrucks into the transportation system shifts the distribution of consumer manufacturing goods, with ATrucks emerging as the dominant choice, occupying approximately 43% of tons moved, while tonnage moved with HTruck fell by 39 percentage point across all commodities. This shift was found particularly in trips involving metallic and nonmetallic materials, consumer manufacturing, paper, petroleum, and food, which witness a decline of over 40 percentage-point in trips made by Htrucks, consequently leading to a rise in the share of trips made by ATrucks. The study presents six distinct scenarios, each examining the effects of different factors on transportation choices and network characteristics. In the first scenario, SAVs are made 40% less expensive, ATrucks costing 20% more than HTrucks, and personal AVs remaining cost-neutral. These changes triggered a shift towards ground travel, particularly in the drive-alone mode. Business long-distance person trips ranging from 50 to 400 miles saw a 10% rise, while non-business trips within the same distance range have experienced a 15% rise. Conversely, air travel has saw a decline of 20% in business trips and 15% in non-business person trips within this distance bracket. On the other hand, inter-city rail' market share fell by 15% and 13% for business and non-business long-distance trips, respectively.

The second scenario, the operational costs of personal AVs was increased by 33%, while SAV costs were kept unchanged. The findings show 41 percentage point decline in "drive-alone" trips exceeding 400 miles. The third scenario deals effects of further 50% reduction in VOTT for AV passengers. These changes led to over 23% rise in VMT across expressways, arterials, interstates, and other freeways. This shift in travel behavior is mirrored in reduced airport boarding (by 5%) specifically at Dallas/Fort Worth International Airport, George Bush International Airport, and San Antonio Airport. The fourth scenario introduces parameters that promotes AVs over HVs. The findings show that in large urban areas, where despite the availability of AVs, a considerable portion of LD trips (38%) still involve traditional HVs. However, the removal of HVs caused a 10% rise in "drive-alone" AV trips. Additionally, SAVs trips saw a rise of 10% for two occupants and a 21% rise for three or more occupants. The fifth scenario explores the impact of high costs associated with personal ownership of AVs, leading individuals to favor SAVs and shifting back to HVs. As a result, a preference for SAVs led to an 11% mode share for "drive alone" SAVs in case of business trips. Final scenario considers empty SAVs driving within the transportation network, included by a 20% fall in average passenger occupancy. The findings show rise in average VMT across all road types. Local streets saw the spike of 53% in VMT during morning peak hours and 37% rise during evening peak hours, closely followed by collector and local street roads.

This research project provides a thorough evaluation of different datasets that the TxDOT has access to. The main focus is on determining the most appropriate source for verifying the results of the Statewide Analysis Model (SAM) travel demand model. The study assesses the effectiveness of INRIX's Traffic Message Channel (TMC) segments, which cover a large part of the on-system network. This evaluation takes into account the extensive duties of TxDOT in managing and fixing more than 80,000 centerline-miles of highways, which facilitate over 70% of the State's yearly vehicle-miles traveled. TxDOT, which serves a population of 29 million and many visitors, can gain advantages from the research team's comprehensive datasets that are specifically focused on Texas. These datasets have been collected over many years of expertise in transportation design, planning, and operations.

The study also shows the use of INRIX data to analyze speed distributions, revealing significant variations in real-time speeds across the major metropolitan regions of Texas. In addition, it provides a visual comparison between INRIX segments and the routes managed by TxDOT, as well as public roadways in the Austin area, showing broad coverage in the region. The base 2019 SAM results were compared against several alternative data sources. Results show that the RITIS data reveals some patterns for HDV travel over the course of a week, however, there are some unexplained variations in the total number of trips and VMT in the data, such as a decreasing trend over the available months and some sudden spikes (over 2x the normal levels).

Additionally, the average weekday HDV trip distance in RITIS is 10 miles shorter than that in the SAM forecast, suggesting that RITIS is breaking up trips for driver breaks. There are also spatial sampling biases in RITIS with trips distributed more unevenly compared to SAM. Chiefly, it is missing flows to and from west Texas and the Houston area. Furthermore, ordinary least squares regression was used to compare the OD trip counts between RITIS and SAM. Regression at the TAZ level provided an extremely poor fit, and while aggregating to the county level improved the fit, the slope was heavily controlled by a few outliers with very high flows. In addition, regression was performed on permanent traffic recorder (PTR) data from 2023 through 2022 to reveal demand variations. The daily total traffic counts at each station were standardized to z-scores. Results reveal that on average, traffic volumes fluctuate by 1.63 std dev over the course of a week, with Sundays being the least busy and Fridays being the busiest. Results also show that January is the quietest month, while June and July are the busiest. Furthermore, demand variations around a few select holidays were studied in detail in the regression, revealing that Wednesday before Thanksgiving and Christmas see the largest increase and decrease, respectively, from a regular comparable day in the same month.

The study also includes an algorithm developed to detect intermediary "trips" that function as quick breaks within longer travel chains using the National Household Travel Survey (NHTS) and its TRIP data file (trippub.csv). The TRIP data file treats each trip segment as a separate journey, even includes brief breaks made on the way to a main destination. The algorithm uses travel coordinates, dwell times at destinations, and trip purposes to differentiate between intentional and accidental stops. Upon implementing the method on the NHTS 2016/17 sample, the number of LD trips undergoes a little reduction of 3.4%. The algorithm initially relies on the coordinates and goals of journeys, and then takes into account the successive segments of the trips to detect changes in direction. It also identifies return trips and distinguishes between shifts in transportation mode and actual destinations.

A limitation of this study is in the scope of the modifications made for the new scenario. The updates in the SAM-V4 "AV/ATruck Scenario" to reflect integration of AVs, SAVs and ATrucks were restricted to the mode choice step. While these updates can allow for forecast of shifts in trip distribution (when feedback loops are included), mode splits and assignment due to these new modes, they cannot predict the change number of trips (or trips produced). For a more realistic model, the enhancement of the trip generation step is required and will the next step in the future work planned. Huang et al. (2020) assumed a 15% rise in the trip generation rates, for their Texas megaregion travel demand model, following the study conducted by Harper et al. (2016) to account for new trip-making that will be enabled by AVs. The Harper et al. (2020) study estimated a 14% rise in VMT as AVs offer a convenient transportation option for individuals who are unable to drive due various reasons (such as age, lack of license, or medical condition). Another limitation of this study as mentioned in the earlier section is the exclusion of full feedback loops from traffic assignment to trip distribution in the models. Feedback loops were excluded due to the long run-times and this omission limits the ability to produce realistic travel times, which may impact the accuracy of the results. Incorporating these feedback loops is recommended for future work, as it would enhance the model's ability to capture the dynamic interactions between traffic assignment and trip distribution.

Another limitation stems from SAM itself. Since short-distance trips constitute a significant portion of overall travel, their allocation based on fixed splits introduces a lack of realism. 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 hampers the ability to fully assess the impacts of AVs. Further research should explore alternative methods to incorporate more dynamic splits for short-distance trip allocation within SAM. Another significant drawback of SAM is the absence of bus as a mode in the long-distance mode choice model. This was because of the challenges in obtaining data, particularly because most inter-city bus operations in Texas are managed by private companies. The absence of a bus as a mode is a significant limitation as it neglects an important transportation option for long-distance trips. Future efforts should aim to address this limitation by obtaining relevant bus data or exploring alternative methodologies to incorporate bus travel in SAM. Lastly, another potential SAM issue of concern is SAM's auto occupancy factor assumption used after the mode choice step, where person-trips are converted to vehicle trips. Specifically for trips over 400 miles within income group 3, which is unusually high at 7.57. This could likely be an error due to inadvertent consideration of bus modes (which is not of the modes available in SAM's long-distance trips option) from NHTS during rate estimation.

Limitations of the SAM-V4 Model

Several TxDOT SAM-V4 model limitations are as follows:

- **Fixed Splits for Short-Distance Trips (<50 miles):** The use of fixed splits for short-distance trips, particularly those under 50 miles, is one the limitations of the model.

Given that the majority of trips fall within this category, the model's depiction of travel patterns and comparative scenarios may not accurately represent real-world conditions.

- **Exclusion of Bus Mode in Long-Distance (LD) Model:** The absence of the bus mode in the Long-Distance (LD) model is another limitation, especially considering the significance of buses for long-distance trips in Texas. This exclusion hinders the model's ability to capture a comprehensive view of transportation modes.

- **Lack of documentation:** The SAM's documentation requires additional refinement, specifically improving the instructions for customizing result queries for an updated network. Presently, the existing report files exclusively provide information on VMT changes categorized by road type. However, these files do not encompass details regarding changes in VMT and Vehicle Hours Traveled (VHT) associated with newly introduced transportation modes.

- **Extended Runtime Challenges:** The prolonged runtime of the model presents challenges for calibration and scenario testing. The omission of outer feedback loops (due to very long runtime), particularly in traffic assignment to trip distribution, results in a runtime exceeding 20 hours. Incorporating feedback loops is crucial for achieving more realistic results. However, long runtimes and occasional random model failures makes it difficult to execute this enhancement smoothly.

- **Resource Intensive Assignment Model:** The model demands substantial data resources, approximately 100 GB without incorporating outer feedback loops. During runtime, this requirement is potentially up to 200 GB per model. Thus, executing this model requires a powerful computer with abundant storage space. Compounding the challenge, TransCAD limits the concurrent execution to a maximum of two models at any given time.

Addressing these limitations would enhance the overall robustness and applicability of the SAM-V4 model.

Value of Research (VOR): LD-AV Implementation

The use of autonomous vehicles (AVs, SAVs and ATrucks) across Texas' transportation network will have wide-ranging impacts, totaling billions of dollars a year. This implementation project updated TxDOT's Statewide Analysis Model (SAM) code to enable these new mode options, simulated the results in a far-future year (2040) and summarized those results for transportation planners, policymakers, businesses, network designers, and the public at large.

Such advance work is crucial for decision-makers to anticipate AVs', SAVs', and ATrucks' impacts for more informed investments, policies, and practices, by allowing for more proactive planning and responsive actions to address expected increases in highway demand, pavement wear, emissions, and congestion, alongside expected reductions in travel costs and crashes.

Travel Time Benefits

Without AVs, US passenger-vehicles' VOTT are roughly \$20 per vehicle-hour (Schrank, 2021). Since AV occupants can all pursue productive activities, rather than one person always driving, Zhong et al. (2020) anticipates about 25% to 30% lower VOTTs and therefore 25 to 30% lower travel time cost burdens. (Rashidi et al. 2020, Kolarova et al. 2019) In this project's base-case simulations, VOTTs for AV and SAV users were assumed to fall 20% (in each of 4 household income classes). SAVs and AVs are also expected to notably increase access for the elderly and impaired, while lowering ownership levels of private vehicles (thanks to SAV fleets, where trips are purchased one at a time).

ATrucks do not require an operator to rest every 11 hours of "driving", so a commercial vehicle fleet's daily operating hours, distances, and deliveries or pickups may double, while bringing costs and fees down (per ton-mile moved, for example). Texas' transportation planners, investors, and policymakers need to anticipate what these massive transportation changes can and will do to traffic, the economy, and the environment. This project work allows TxDOT and its consultants to start addressing these billion-dollar questions. For example, with 25M vehicle-hours of Texas network use a day, on average, is worth roughly \$500M in travel time costs. So, a 20% perceived savings is worth about \$100M per day, or \$36 billion a year. Texas also has about \$30 billion in (economic-only) crash costs per year (USDOT, 2020), and AVs are expected to lower crash frequencies by about 85% (Li and Kockelman 2018). Thus, AVs' safety benefits may be over \$20 billion a year (Clements and Kockelman 2017). Of course, lowered costs generally mean added demand, and possible gridlock (Huang et al. 2020). Helping smooth such transition is key for all communities across Texas.

Benefit-Cost Ratio

If this project influences just one-hundredth of just one percent of the future improvement in time-cost and safety savings readily attributed to AVs, this one-year project's economic benefit would be \$5.6 million from just one year of impacts. If one discounts that annual benefit over just 10 years of future benefits, using a conservatively high discount rate of 10%, the net present value is nearly \$35 million in benefits. These emerge from this \$159,916 TxDOT implementation project alone, suggesting (very conservatively) a benefit-cost ratio or "value of research" (VOR) of 215. To summarize:

Project cost: \$159,917
Benefits estimated conservatively: \$35M
Initial benefit-cost ratio: <u>215:1</u>
In summary, the rough quantitative analysis conservatively suggests more than a 200-fold benefit that exists in addition to TxDOT's ongoing efforts in preparing for a future where AVs are readily available in the marketplace.

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Appendix

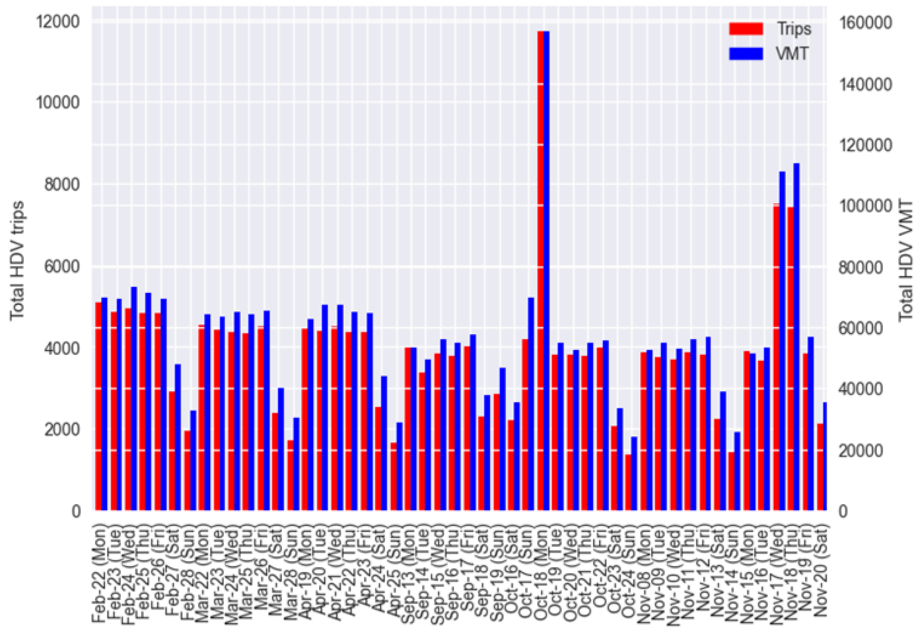

Figure A1. Total HDV Trips and VMT for Each Day in 2021 Downloaded from RITIS (6-8 am)

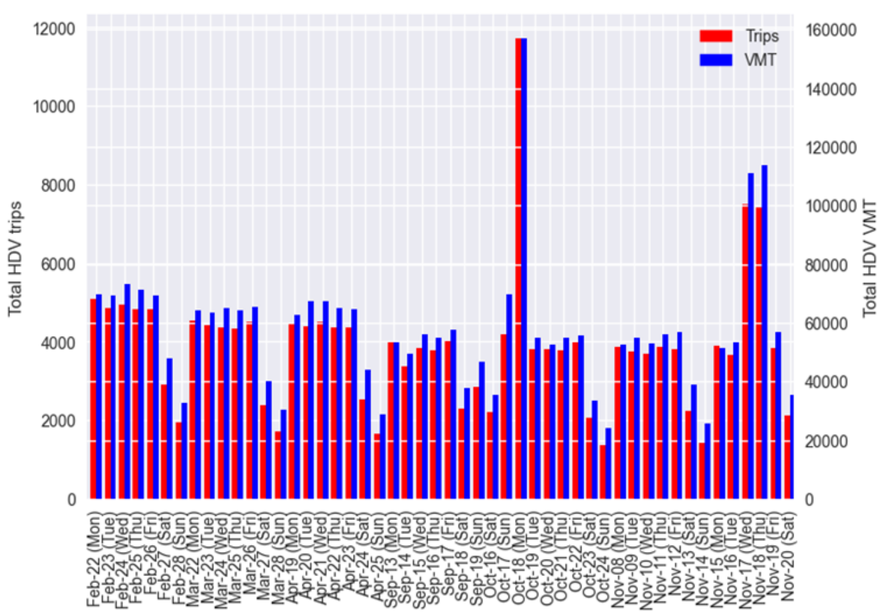

Figure A2. Total HDV Trips and VMT for Each Day in 2021 Downloaded from RITIS (8 am - 2 pm)

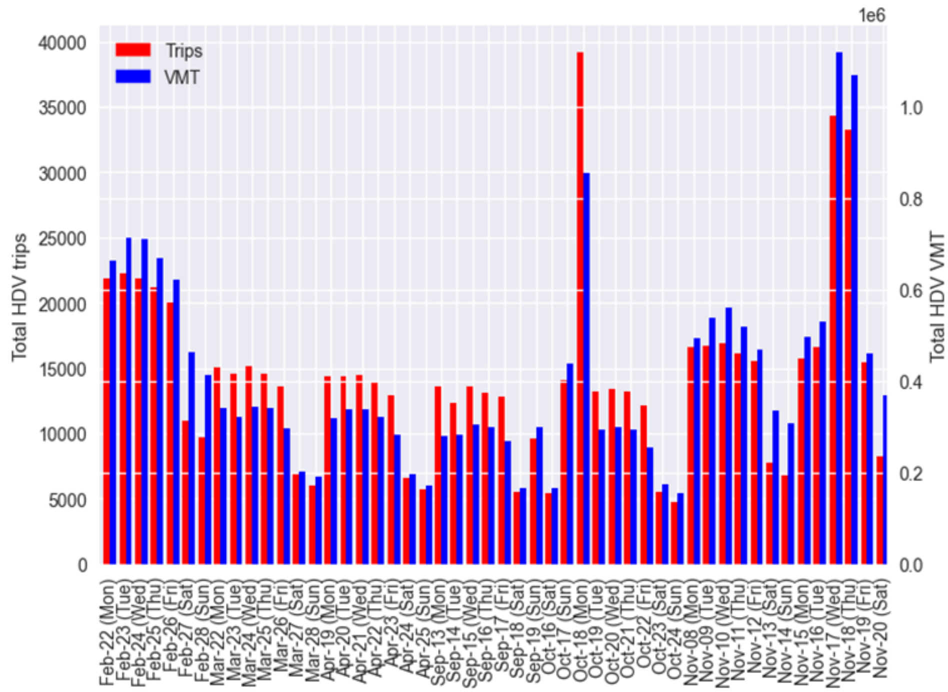

Figure A3. Total HDV Trips and VMT for Each Day in 2021 Downloaded from RITIS (2-6 pm)

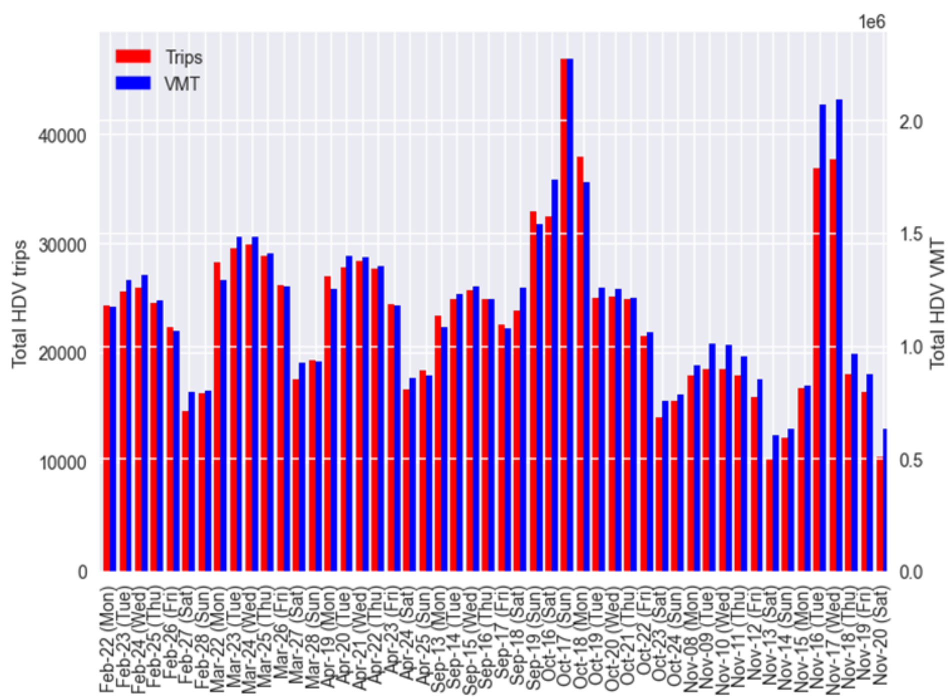

Figure A4. Total HDV Trips and VMT for Each Day in 2021 Downloaded from RITIS (6 pm - 6 am)