ROBOTAXIS AS TRANSIT: SIMULATION-INFORMED BENEFIT-COST COMPARISONS

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ABSTRACT:
This study investigates the potential to replace buses with shared autonomous vehicles (SAVs) in Austin, Texas, using the POLARIS agent-based activity-based travel demand simulation model. Both transit agency ownership of the fleet and subsidized private services are considered, informing benefit-cost comparisons. The results suggest that it takes a total of 6,000 SAVs to serve the current taxi/ridehailing and bus demand in Austin, Texas when the two are served door-to-door with dynamic ridepooling by separate fleets, but the fleet size requirements could be reduced by 10% or more by integrating the fleets and using bus stops as pickup and drop-off points for bus demand. Travel times of trips previously served by bus see significant reduction when they are served door to door by SAVs. Modest travel time savings are still possible when those trips are served from bus stops. The analysis of transit fleet life cycle costs using the simulation outcomes revealed that agency-owned SAVs are at least 68% more expensive than autonomous battery electric buses (BEBs) serving the current fixed routes but 23% cheaper than human-driven BEBs. The maximum subsidy (to a private SAV operator) to break even with the least expensive agency-owned fleet option (autonomous BEBs) is $3.36 per passenger-trip, a reasonable figure based on expected SAV fares in literature. Overall, the findings highlight opportunities for public-private collaboration to broadly deliver flexible mobility solutions.

Keywords: Shared Autonomous Vehicle, Public Transit, Agent-Based Simulation, Cost Analysis

INTRODUCTION

Over the past decade, ridehailing platforms have revolutionized travel in many cities and regions around the world, offering tremendous flexibility, convenience, and geographical coverage (Tirachini, 2020; Young and Farber, 2019). More recently, shared autonomous vehicles (SAVs) have begun deployment in select cities, including San Francisco, Phoenix, and Austin. The interaction of these two trends is expected to further transform travel in the coming years (Maheshwari and Axhausen, 2021). Yet, public transit agencies have been slow to adapt to these trends, holding onto traditional operational models characterized by fixed routes and high-capacity vehicles. As a result, ridehailing has been shown to have negatively impacted transit ridership is several different contexts (Diao et al., 2021; Erhardt et al., 2022; Kong et al., 2020; Rayle et al., 2016), and automation is expected to exacerbate this trend without any interventions (Khaloei et al., 2021). Traditional transit designs, especially rail rapid transit, can be highly efficient in dense urban settings, where large catchment-area populations generate travel demand that can easily be aggregated throughout the day, supporting an interconnected network of high-frequency routes (Liu et al., 2022; Pan et al., 2017; Polzin et al., 2000). However, their performance often falls short in lower density settings, as the existing travel demand only justifies services that are sparse both spatially and temporally, perpetuating a cycle that contributes to low ridership (Calabrò et al., 2023; Taylor et al., 2009). While transit-oriented development can reshape the urban environment itself and make travel demand easier to aggregate via traditional public transit (Kang and Miwa, 2025), it requires meticulous planning and a high level of coordination among stakeholders, with success dependent on a wide range of factors (Ibraeva et al, 2020). Therefore, transit agencies are often stuck operating underutilized routes at high public costs, primarily to provide minimum-level mobility to disadvantaged populations, rather than as a competitive alternative to private vehicles (Yan et al., 2021). These systems burden users with the need to make significant adjustments to aggregate their demand spatially and/or temporally, such as walking to distant stops, taking indirect routes, and shifting their departure time to match the timetable (Cai and Kwan, 2025).

Several approaches have been proposed to improve public transit with autonomous driving technologies and demand-responsive operations. One frequently proposed idea is to use of SAVs to serve first- and last-mile (FMLM) legs of transit trips (particularly for rail) to improve access/egress travel times and expand catchment areas. Huang et al. (2022) simulated the integration of SAVs with the light-rail system in Austin, coordinating SAV arrivals at stations with the train timetable. Under their dynamic pooling algorithm accounting for train schedules, 28% more travelers were able to arrive on time for their train compared to uncoordinated SAV operations. Mori et al. (2022) considered both stand-alone and FMLM use of SAVs by fusing revealed and stated preference data and embedding mode choice into a static traffic assignment model. Their case study in Nagoya, Japan, indicates a 1.5% net decrease in rail ridership when SAVs are introduced.

Other studies have evaluated augmenting or replacing bus lines with demand-responsive SAVs. Shen et al. (2018) focused on bus routes used to access a popular subway station in

Singapore, repurposing the least utilized routes serving 10% of the first-mile demand and serving those trips using SAVs. Huang et al. (2021) microsimulated SAV-based transit operations along a bus corridor, evaluating performance across different vehicle sizes, demand levels, and traffic conditions. They generally found smaller vehicles to be more favorable, offering lower system costs and wait times, with minimal traffic impacts due to shorter dwell times. Fielbaum et al. (2024) proposed an integration design in which on-demand vehicles supplement bus routes, reducing the required bus fleet size and improving service for travelers with long walks to bus stops. The on-demand vehicles operate throughout the day, while bus frequencies are minimized to serve the remaining demand. Users are routed through either mode via a centralized application, in a way that aligns with their interests.

However, a complete replacement of buses with SAVs has surprisingly been little studied, with mixed conclusions. Leich and Bischoff (2019) simulated the replacement of bus lines with SAVs in a suburban area of Berlin, but the results indicated minimal travel time savings and higher operational costs. Conversely, Merlin's (2017) simulation indicates transit demand in Ann Arbor, Michigan, can be served at lower costs using SAVs, especially with ridepooling. Harmony's (2020) analysis of costs and ridership across U.S. transit agencies suggests that Uber and UberPool are more cost effective in 23% and 45% of the cases, respectively. Taking this idea to practice, the town of Innisfil, Canada, has been partnered with Uber since 2017 to deliver a subsidized ridesharing service instead of developing traditional bus routes. The service has been widely popular among residents, forcing the town to increase fares and place monthly ride limitations after budgets were exceeded (Benaroya et al., 2023; Weigl et al., 2022).

As the literature suggests, there is a gap in evaluating a city-wide replacement of buses with SAVs, especially considering integration with an existing ridehailing system. This is relevant to conversations taking place in cities with underperforming and declining bus systems, particularly in North America. Using the POLARIS agent-based transportation simulator, this study evaluates the SAV fleet requirements to serve the current public transit demand across the Austin region, while allowing door-to-door SAV service in various scenarios. CapMetro is the transit agency serving the area, with bus lines almost entirely in the city of Austin but some extending to suburbs in Travis and Williamson counties. Furthermore, it examines the efficiency gain from integrating the service with privately-operated SAVs, rather than the transit agency owning and operating the vehicles, and the subsidies needed to do so. Despite being a radical implementation, the results provide a useful baseline for developing more advanced and optimized autonomous transit systems.

CASE STUDY

This study simulates travel demand, network traffic flow, and transit and SAV operations using the POLARIS agent-based activity-based transportation simulation tool. POLARIS simulates 24-hour activity patterns and travel choices (e.g., destination, mode, and departure time) for a synthesized population and routes them through the network via dynamic traffic assignment (Auld et al., 2016 and 2019, de Souza et al., 2024, Verbas et al., 2018). Additionally, POLARIS's

SAV fleet manager module provides instructions for dispatching and repositioning in response to real-time demand and traffic congestion.

To evaluate the impacts of serving current transit demand in the 6-county region of Austin, Texas, with SAVs, the model was first run with a 25% synthetic population for 50 iterations to generate a converged and representative weekday travel demand profile. The results of this converged run serve as fixed demand inputs across all subsequently simulated scenarios.

Several options for replacing buses with SAVs were examined along three key dimensions. First, fleet size is varied to assess differences in vehicle requirements across service configurations, which in turn inform estimates of fixed costs. Second, the service configuration is either door-to-door (D2D) or stop-to-stop (S2S), with the latter using existing bus stops (Figure 1) as pickup and drop-off (PUDO) locations to manage demand and streamline operations. In S2S, only bus demand is aggregated at stops, while taxi demand continues to be served door-to-door. Third, the scenarios differ in fleet integration. In the integrated case, the fleet is jointly operated by a private TNC and the transit agency, enabling the agency to subsidize private operations directly and allowing both taxi and bus demands to be served together. In contrast, separate fleet scenarios maintain independent operations and funding streams between the two entities. All users were assumed to be available for ridepooling.

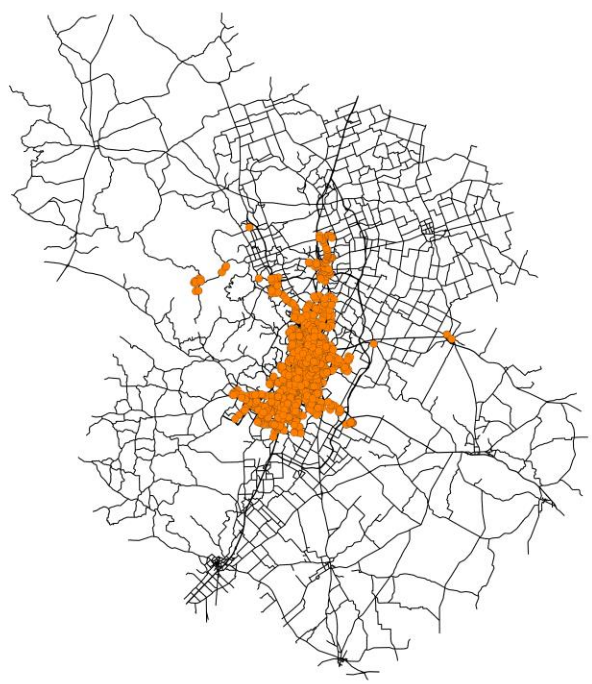

Figure 1. 6-County Austin Network and CapMetro Transit Stops

RESULTS

Under the current day baseline scenario with conventional buses, the forecasted bus demand was 90,664 rides per day when scaled to 100% population (and rounded), which mirrors CapMetro's average weekday boarding estimate (90,591 boardings/weekday on average) as of March 2025 (CapMetro, 2025). The average passenger bus-rider-trip distance was 4.3 miles, and the average vehicle occupancy (AVO) was just 8.0 passenger-miles per revenue-bus-mile, suggesting a severe underutilization of the bus fleet, but typical of the U.S. (FTA, 2024). Additionally, the mode-choice simulation produced 89,284 taxi rides, which were served by SAVs.

Table 1 summarizes SAV fleet performance across scenarios. Since taxi demand is always served door-to-door, the performance does not change between the “D2D Separate” and “S2S Separate” scenarios. Although bus and taxi demand are nearly equal, more bus trips can be served with the same SAV fleet size, while achieving shorter wait times, lower VMT and percentage of empty VMT (%eVMT), and higher AVO, because the demand is more spatially concentrated. In the case of separate fleet operations, VMT of the agency-owned fleet are 27% to 34% less, with 7.1 to 10.4 percentage point lower %eVMT, than that of the private TNC fleet for the same fleet sizes. When the fleets are combined for integrated operation, VMT per SAV and %eVMT only increase slightly compared to the agency-owned fleet serving only the bus demand and remain significantly more efficient than the TNC fleet serving only the taxi demand. This suggests that, from standpoint of the private TNC, capturing the transit demand is operationally beneficial, as long as sufficient subsidies are provided to support the larger fleet. Compared to D2D, serving trips from bus stops cuts VMT by 3% to 5% and lowers %eVMT by 1 percentage point. Operational improvements from S2S seem to be small since the true origins and destinations of transit trips are already close to the bus stops, with access and egress walk times being 6.2 minutes on average.

Table 1. SAV Fleet Performance Results across 16 Scenarios

Scenario	Demand Served	Fleet Size	Passenger Trips per SAV per day	VMT per SAV per day	VHT per SAV per day	% eVMT	Revenue Distance AVO	Median Wait Time (min)
D2D & S2S Separate	Taxi	2000 SAVs	35.9 trips	352.6 mi/d/SAV	12.8 hr/d/SAV	41.7%	1.31 pax	14.0 min
		2500	33.9	314.1	11.5	40.4	1.26	8.6
		3000	29.7	264.2	9.5	40.3	1.19	5.7
D2D Separate	Bus	2000	41.3	258.5	11.4	32.5	1.48	5.5
		2500	35.8	220.8	9.8	32.3	1.42	4.7
		3000	30.2	186.8	8.2	33.2	1.31	3.9
S2S Separate	Bus	2000	42.3	250.6	11.0	31.3	1.49	5.2
		2500	36.2	208.9	9.3	31.1	1.40	4.1
		3000	30.1	178.5	8.0	32.1	1.30	3.6
D2D integrated	Bus and Taxi	4000	40.5	298.6	11.9	34.0	1.40	7.0
		4500	37.8	275.9	11.2	33.8	1.37	6.0
		5000	35.4	255.5	10.5	33.6	1.35	5.5
		5500	32.6	231.8	9.3	33.8	1.30	4.7
		6000	29.9	214.1	8.5	33.9	1.27	4.4
S2S Integrated	Bus and taxi	4000	40.7	294.5	11.9	33.8	1.40	6.8
		4500	37.9	272.5	11.0	33.9	1.38	6.0
		5000	35.7	250.0	10.2	33.2	1.35	5.2
		5500	32.6	228.5	9.1	33.7	1.29	4.4
		6000	29.9	210.7	8.5	33.8	1.26	4.3

Figure 1 shows the maximum number of trips, including both bus and taxi demand, that can be served by the total number of SAVs in operation across all fleets. The largest number of requests can be satisfied when the fleets are integrated, and bus demand is served from bus stops. Fleet integration is more influential than the choice between S2S and D2D operations, as the "D2D Integrated" scenario performs nearly as well as the superior "S2S Integrated" configuration. The results suggest that fleet integration can reduce fleet size requirements by 10% or more.

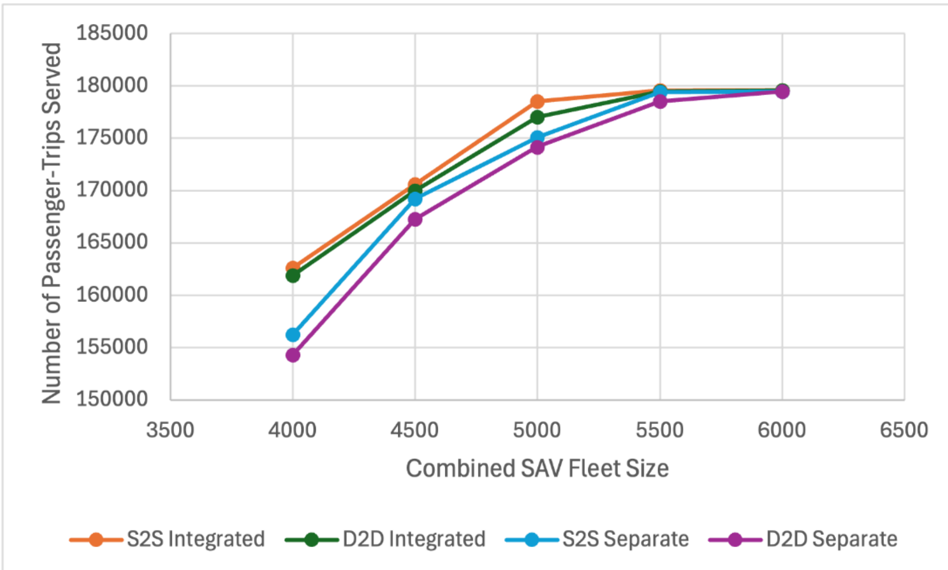

Figure 1. Maximum Number of Passenger-Trips Served by Fleet Size and Operation Scenario

Table 2 shows the change in average travel times of trips originally served by bus across scenarios. D2D operations significantly reduce average total travel times, by up to 16 minutes. Much of the travel time reductions come from the elimination of walk times, which are 12.5 minutes on average per trip across access and egress legs. At sufficient fleet sizes, the wait times are less than the average bus wait time. Reductions in in-vehicle travel times (IVTTs) are minor in comparison, suggesting that the pooling leads to many detours or people only take the bus when the route to their destination is relatively direct. For S2S, it was assumed that travelers request an SAV once arriving at the stop. Therefore, the average walk time was the same as the baseline scenario with conventional buses. Travel time savings in the S2S scenarios were less than that of D2D or longer than the baseline when fleet sizes were inadequate. However, average travel time savings of up to 4.5 minutes was observed for larger fleet sizes, thanks to reductions in IVTT and wait times. This indicates the potential to serve current bus demand in Austin with SAVs while maintaining comparable service levels, if costs are lower than those of large conventional buses.

Table 2. Average Travel Times of Trips Originally Taken by Bus Under Each Scenario

	SAV Fleet Size*	Average IVTT (min)	Average Wait Time (min)	Average Walk Time (min)	Average Total Travel Time (min)
Baseline	0 (471 buses)	18.1 min	8.5 min	12.5 min	39.2 min
D2D Separate	2000	18.8	11.8	0.0	30.6
	2500	18.6	9.1	0.0	27.7
	3000	16.8	6.2	0.0	23.1
S2S Separate	2000	18.2	10.6	12.5	41.2
	2500	17.3	6.9	12.5	36.7
	3000	16.4	5.7	12.5	34.6
D2D Integrated	4000	19.5	13.9	0.0	33.4
	4500	19.3	12.5	0.0	31.8
	5000	19.9	11.0	0.0	30.9
	5500	18.3	7.0	0.0	25.3
	6000	17.8	6.6	0.0	24.3
S2S Integrated	4000	19.7	13.9	12.5	46.1
	4500	18.9	12.3	12.5	43.7
	5000	19.7	9.6	12.5	41.7
	5500	17.8	6.6	12.5	36.8
	6000	17.4	6.1	12.5	35.9

*Available to serve the bus demand

To assess possible options for transit fleet replacement, 12-year lifecycle cost estimates were calculated based on simulation results and cost parameters from Quarles et al. (2020). The breakdown of the costs is presented in Table 3. The first three options maintain the current fixed bus routes and consider the replacement of 471 buses owned by CapMetro with diesel buses, battery electric buses (BEBs), and autonomous BEBs (CapMetro, 2025). For SAVs, two vehicle prices were considered, and SAVs were assumed to be electric. The lower estimate assumes \$30,000 for an average sedan and \$40,000 for automation, while the current price of a Waymo vehicle is used as a high estimate (\$75,000 for Jaguar I-Pace and \$100,000 for automation) (Campbell, 2025). Energy consumption of SAVs were assumed to 0.25 kWh/mi, while the maintenance cost was set at \$0.116/mi. SAV fleet sizes were set at 3,000 and 2,500 for D2D and S2S, respectively, based on the number of trips that can be served. SAVs are assumed to have a 6-year lifespan (half that of buses) following the more intensive use indicated by their VMT. Other cost assumptions can be found in Table 1 of Quarles et al. (2020).

Unlike in Quarles et al. (2020), no cost savings were found for human-driven BEBs. Due to the lower VMT obtained from simulation results, the lower per mile costs of BEBs did not offset the higher fixed costs. However, automation delivers drastic cost savings, as driver costs make up 79% of the costs of human-driven bus fleets. Agency-operated SAV fleets are more expensive than autonomous BEBs, due to the larger fleet size requirements and more frequent replacement. The lowest estimated lifecycle cost for SAVs is 68% higher than that of autonomous BEBs. However, all cost estimates of agency-owned SAV fleets are less expensive than that of the human-driven options, suggesting that SAV-based transit could be offered within the current budget if the service improvements justify it. If the agency is interested in serving the bus demand with SAVs, it should likely subsidize a private TNC, rather than owning the fleet themselves. Doing so within the budget of autonomous BEBs, which is the most economical option, and accounting for lost fare revenue, the subsidy would need to be $3.36 per passenger trip or less. For these trips to be equally profitable for the TNC as any other trip served by their fleet, the average fare of these trips would need to be $4.61 or less, assuming the share paid by passengers is the current rate of $1.25 per ride. With the average transit trip being only 4.2 miles, this is a reasonable figure within the range of anticipated fares (Fagnant and Kockelman, 2018), signaling sufficient opportunity for the transit agency to partner with a private TNC.

Table 3. 12-Year Lifecycle Costs for Transit Agency Fleets

	Purchase Price (USD)	Average Annual VMT (Per Vehicle)	Annual Fuel Expense	Annual Maintenance Cost	Annual driver cost	12-Year Vehicle Lifecycle Cost	12-Year Fleet Lifecycle Cost
Human-driven diesel bus	$350,000	38,153 mi	$19,076	$24,075	$271,000	$4.120 M	$1.940 B
Human-driven BEB	$650,000	38,153	$5,769	$12,667	$271,000	$4.123 M	$1.942 B
Autonomous BEB	$750,000	38,153	$5,769	$12,667	$0	$971 K	$457 M
SAV–D2D Separate (low)	$70,000	68,187	$1,193	$11,319	$0	$290 K	$870 M
SAV–S2S Separate (low)	$70,000	76,241	$1,334	$12,656	$0	$308 K	$770 M
SAV–D2D Separate (high)	$175,000	68,187	$1,193	$11,319	$0	$500 K	$1.500 B
SAV–S2S Separate (high)	$175,000	76,241	$1,334	$12,656	$0	$518 K	$1.295 B

CONCLUSIONS

This study simulated the replacement of buses with SAVs in the Austin 6-county region, exploring several operation scenarios. Using the POLARIS agent-based activity-based travel demand simulation model, the present-day travel demand was first generated, including 90,000 bus trip and 90,000 taxi/ridehailing trips, which served as the demand inputs for all other scenarios studied. 17 total scenarios were simulated, with various fleet sizes, PUDO points for bus demand (D2D or S2S), and fleet operation models (integrated or separate). When serving taxi/ridehailing and bus demand door-to-door with separate SAV fleets, bus demand was served more efficiently, with shorter wait times, lower VMT and %eVMT, and higher AVO, due to the spatial concentration of origins and destinations. Capturing this demand seems operationally beneficial for a private TNC, making it likely that they would agree to expand their fleet and serve subsidized trips. By integrating the fleets and using bus stops as PUDO points for bus demand, fleet size requirements were able to be reduced by 10% or more. Transit riders see significant travel time reductions if they are served door-to-door but only minor reductions if they are served from bus stops and can only request a ride once arriving at the stop. Cost-benefit comparisons of various transit fleet replacement options were conducted based on simulation results. Autonomous BEB serving fixed routes was the most cost-effective option with a 12-year lifecycle cost of $457 million. A flexible SAV fleet owned and operated by the transit agency would be at least 68% more expensive than autonomous BEBs but at least 23% cheaper than a human-driven BEBs. However, subsidizing a private SAV operator would be more cost effective than autonomous BEBs (and brings travel time benefits to both bus and taxi/ridehailing customers) if the subsidy could be kept under $3.36 per passenger trip, which is a reasonable figure based on expected SAV fares in literature. The findings highlight opportunities for public-private collaboration to broadly deliver flexible mobility solutions, and the results of this study can be used as a baseline for developing more advanced autonomous transit designs.

A major limitation of this study is the use fixed demand, when such service changes would lead to mode shifts in reality. Specifically, substantial increases in ridership could be expected if bus trips were suddenly served door-to-door. However, the D2D scenarios were meant to serve as a benchmark for the S2S scenarios, for which the fixed demand assumption is more valid. Future studies could focus on demand changes induced by the shift from fixed line to flexible transit operations.

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