SUBSIDIZING SHARED AUTONOMOUS VEHICLE OPERATORS TO SERVE BUS RIDERS: RESULTS FROM REGIONAL SIMULATIONS

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ABSTRACT

Objectives: U.S. transit agencies are facing fiscal pressure while needing to plan for disruptions from autonomous vehicles (AVs). This study simulates the replacement of bus routes in Austin, Texas, with 4-seater shared AVs (SAVs) providing subsidized rides alongside their regular ridehailing operations, with the goal of reducing transit agency costs and improving transit user experience.

Methods: The POLARIS agent- and activity-based simulator is used to forecast future travel demand reflecting higher SAV availability. 25 scenarios were simulated to explore the subsidization of SAVs for bus riders on eliminated routes, varying route replacement level, service model (door-to-door vs. stop-to-stop), and fleet size, to compare rider experience and costs with conventional buses.

Findings: Over 95% of bus requests were served (within 15-minute maximum wait time) without expanding the SAV base fleet, even under full replacement of bus services with SAVs. While rejection rates for (former) bus users were higher than those for ride-hailing users due to spatiotemporal demand mismatch during the afternoon peak, this can be mitigated via stop-to-stop operations on high-demand routes. Overall, bus users appear to benefit from substantial travel time improvements under a transition to 4-seater SAV-based service, due to reductions in wait times and walking distances. Cost outcomes are highly sensitive to fares charged by the SAV operator. Under a $1/pickup + $1/mile fare structure, full replacement provides the maximum savings of 25%. Such a shift will cost the agency more than current service if fares are $2/pickup + $2/mile, at which point partial replacement of buses becomes favored instead.

Novelty: This study systematically investigates the replacement of bus routes with subsidized SAV rides, using realistic SAV demand patterns and simulating the interaction between SAV and bus demand across a large metropolitan region.

Practical Applications: The findings give transit agencies insight into key considerations for evaluating SAV partnerships.

INTRODUCTION

U.S. transit agencies are facing an immediate and serious challenge: All are navigating a "fiscal cliff," a large budget shortfall caused by the depletion of federal COVID-relief funds and a lack of sufficient, sustainable funding sources (Siddiq et al., 2023). Ridership reductions and hikes in operating and capital costs have caused costs per passenger mile to more than double nationally since 2015. Agencies must also plan for the future by anticipating changes in travel demand due to demographic shifts and new technologies. Among these technologies, autonomous vehicles (AVs) are expected to profoundly disrupt public transportation, compounding shifts already present from the growth of ridehailing (Maheshwari & Axhausen, 2021). However, transit agencies lack clear strategies for either mitigating potential negative impacts or leveraging new opportunities created by this emerging technology.

Fixed-route transit remains a highly efficient and scalable mode of transport when implemented in supportive contexts, particularly in densely populated urban areas, paired with transit-oriented development (TOD) and dedicated rights of way (Pan et al., 2017; Polzin et al., 2000). By concentrating growth around high-capacity transit corridors, cities can strengthen ridership, improve operational efficiency, and reduce congestion and reliance on private vehicles (Kang & Miwa, 2025). However, in the vast majority of North American cities, fixed-route transit fights a losing battle against dispersed land use patterns and high car ownership rates (Taylor et al., 2009). Large infrastructure projects that transform the urban structure of the region are costly, especially in the U.S., and transit agencies often have little control over, or political support for, such initiatives. Agencies must make do with what limited power they have, offering the best service for their setting and financial constraints. Given these constraints, it may be difficult for existing transit services to compete with the flexibility, convenience, and geographic coverage offered by ridehailing services as costs fall from a transition to shared AVs (SAVs) (Khaloei et al., 2021). However, even if SAVs become widely available at low cost, some segment of the population will continue to require and depend on public transit. Moreover, aggregating travel demand will be essential for controlling the congestion that SAVs (which make motorized travel even easier and requires empty driving) and continued urbanization are likely to produce. Transit agencies' decisions could be important in shaping regional mobility.

The use of SAVs for first- and last-mile (FMLM) connections has been studied as a way to augment transit ridership (Huang et al., 2022; Mori et al., 2022; Wen et al., 2018). The effectiveness of such integrated systems depends on the speed, frequency, coverage, and reliability of the underlying fixed-route network being sufficient to justify the transfer, even with significant fare incentives (Fielbaum et al., 2024; Gurumurthy et al., 2020b; Kumar & Khani, 2022).

In cities without a strong existing transit backbone, a feeder-based approach is less applicable, and alternative strategies are likely more appropriate. Replacing low-demand bus routes, or even entire networks in suburban or rural locations, with SAVs is another strategy being considered to potentially cut costs and provide better service to transit riders (Leich & Bischoff, 2019; Mendes et al., 2017; Merlin, 2017; Shen et al., 2018; Sieber et al., 2020; Winter et al., 2018). Optimization models have been developed to design or modify transit networks considering SAVs (Ng et al., 2024; Pinto et al., 2020).

Past studies on transit route replacements rely on assumptions that are overly optimistic about agencies' control over SAV fleet size and operations decisions, while often also confining SAVs to the routes they replace and/or neglecting demand not generated by transit riders (e.g., ordinary ridehailing customers) that these vehicles would likely also serve. In reality, SAVs will likely continue to be owned by private companies, rather than transit agencies, and operated by those companies directly or in conjunction with ridehailing platforms. It seems most likely that transit agencies will strategically subsidize rides on private SAV fleets rather than owning and operating a dedicated fleet. Owning a dedicated fleet limits transit agencies to whatever scale and scope they can afford, while subsidizing rides allows cities to tap into the full scale and coverage of existing and emerging SAV fleets without acquisition and maintenance costs. In this scenario, decisions like fleet sizing fall outside the transit agency's control. *The question* then becomes: given a certain level of SAV penetration and corresponding fleet size, *can a transit agency subsidize rides in a way that is mutually beneficial for the agency, transit riders, and the SAV fleet owner?* That is, can the agency cut costs while riders enjoy better service and fleet owners increase profits?

To tackle this question, this paper simulates a fleet of 4-seater SAVs that provide subsidized rides to Austin, Texas' existing bus users, while delivering regular ridehailing services to others. The POLARIS transportation system simulation tool (Auld et al., 2016) is used to generate realistic travel demand patterns for all modes (including ridehailing with SAVs), and simulate person- and vehicle-movements over a 24-hour weekday, including fine details of SAV operations with some ridepooling (also known as dynamic ridesharing (DRS)). We investigate service feasibility, quantify impacts on transit rider experience, and compare system costs to those of current, conventional bus service under various SAV fleet sizes, bus route replacement levels, and pickup and dropoff (PUDO) point configurations.

COST OF TRANSIT IN THE U.S. AND AUSTIN, TEXAS

Achieving impactful and cost-effective transit services has long been a challenge for U.S. agencies, a situation further complicated by the COVID-19 pandemic. Figure 1 shows the rise in U.S. and Austin, Texas transit costs between 2015 and 2024, using the National Transit Database (FTA, 2026; APTA, 2026). In 2024, *operating* expenses per passenger-mile in the U.S. were \$2.34 for buses and \$1.69 across all transit modes: more than double their respective 2015 costs. Capital expenses, while varying greatly year to year for individual agencies, average an additional 21% for buses and 45% across all transit modes. This brings the total costs of deploying U.S. transit in 2024 to \$2.87 per passenger-mile by bus and \$2.44 per passenger-mile when averaged across all transit modes, respectively. Recent inflation raises these costs further. In Austin, bus operating costs have jumped 69% between 2021 and 2024, bringing the *operating* cost per passenger mile to \$2.79, triple that of 2015, and *total costs around \$3.58 per passenger-mile* (averaged over various years of capex). Appendix A offers a detailed breakdown of CapMetro's bus expenditures. In contrast, Uber and Lyft rides (in standard vehicles) around Austin average less than \$3 per passenger-mile, and are door-to-door and on demand. (Ridehailing prices can be as high as \$6 per *vehicle*-mile (providing 3 to 5 seats) for short trips, and during peak times of day, when driver supply is low relative to demand – like Saturday nights, when bars close their doors. And as low as \$2 per vehicle-mile for trips of 6+ miles at most times of day, in a standard vehicle.)

The steep increases signal a decline in the cost-effectiveness of U.S. transit spending, due to lower ridership and rising costs. Transit ridership plummeted during the Pandemic and has been slow to recover since then, due to factors like remote work (Edward et al., 2024) and safety concerns while awaiting and riding inside vehicles (Aeschliman and Stathopolous, 2025). Year 2024 U.S. transit passenger-miles were just two-thirds of 2015 levels, both nationally and in Austin. Meanwhile, revenue-vehicle-miles have remained nearly constant over this period.

However, as shown in Figure 1(b), the costs of maintaining past service levels have risen at rates far outpacing inflation.

Figure 1. Transit Costs per (a) Passenger-Mile and (b) Revenue Vehicle-Mile from 2015 to 2024

METHODOLOGY

This study uses the POLARIS activity- and agent-based travel demand simulator (Auld et al., 2016) to simulate regional travel patterns and SAV fleet operations. Broadly, POLARIS constructs a synthetic regional population and simulates each agent's full day of activity and associated travel choices (including mode and destination), and moves the agents through the multimodal network via a dynamic traffic and transit assignment engine (Auld et al., 2019, de Souza et al., 2024, Verbas et al., 2018). POLARIS also simulates the operations of SAV fleets. The SAVs are controlled by a centralized fleet operator, which assigns trips and issues repositioning instructions, with routing that is responsive to network congestion (Gurumurthy et al., 2020a). In this study, the algorithm by Alonso-Mora et al. (2017) is used to optimize ridepooling in real time. The objective is passenger-centric; at each assignment timestep, the algorithm minimizes request rejections and the total wait and detour times for passengers currently being served and in the assignment pool, given the vehicle availability and service quality constraints. Additionally, the repositioning algorithm by de Souza et al. (2020) is used to resolve spatial imbalances in demand and supply. Alongside detailed vehicle movements and fleet statistics, time-dependent zone-level service quality statistics, including travel and wait times, are recorded to inform operations and user mode choices in the next iteration.

CASE STUDY

The Austin 6-county (2-million persons) region was selected as the location of the case study. Figure 2 shows the study area with the road network, bus network, and SAV geofence. The road network was created by first extracting the links included in the Capital Area Metropolitan Planning Organization's (CAMPO's) planning network from the full OpenStreetMap network (Mori et al., 2026), and then restoring full link detail in traffic analysis zones (TAZs) that contain transit stops. This was done to capture local changes in SAV operations resulting from different PUDO point configurations, as explained later. Transit service in Austin is provided by the Capital Metropolitan Transportation Authority (CapMetro). CapMetro's bus network is mostly contained within the city of Austin, with a small number of routes extending beyond it. A geofence for SAVs was constructed to support efficient and profitable service. With TAZs in Travis and Williamson counties as initial candidates, the geofence was iteratively shaped by removing TAZs with trip-end densities less than 20/acre/day, considering only trips occurring fully within the incumbent geofence. After no TAZ could be removed following this criterion, some TAZs were added back to ensure connectivity between the high-trip-density zones, finalizing the geofence.

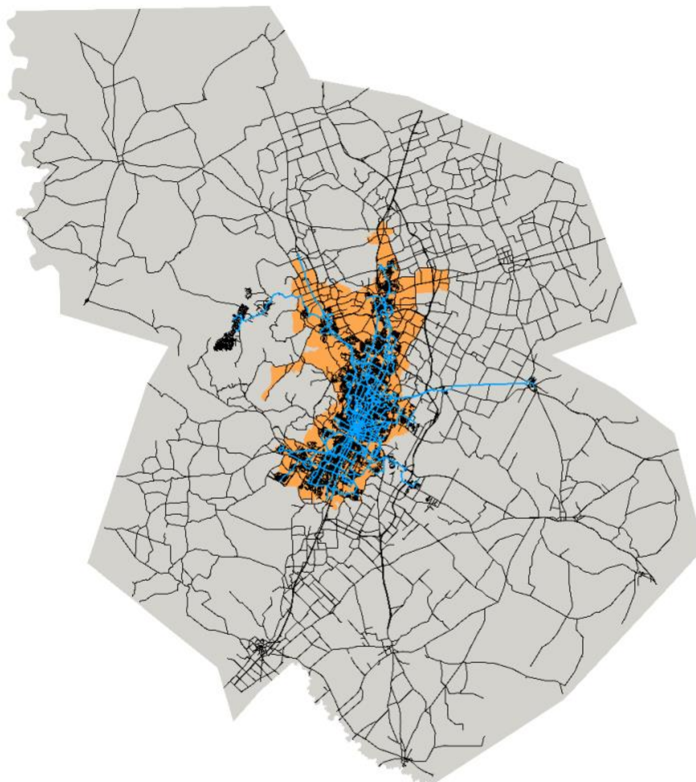

Figure 2. 6-County Austin Network (black) with CapMetro Bus Network (blue) and SAV Geofence (orange)

The POLARIS model of Austin was run with a 25% synthetic population to generate a converged and representative present-day weekday travel demand profile. When scaled to 100% population, 90,960 bus boardings were recorded, which mirrors CapMetro's March 2025 average weekday boardings. The average passenger bus-rider-trip distance was 3.0 miles, and the average vehicle occupancy (AVO) was just 5.6 passenger-miles per revenue-bus-mile. Walk and wait times accounted for more than half of the 42-minute average total travel time for bus riders. The distribution of passengers across routes were highly skewed, with the top 8 and 16 routes (out of 69) serving 50% and 75% of bus rides, respectively.

After validating the present-day model, the model was then adjusted to generate a future demand reflecting a higher level of SAV penetration compared to today. To do so, the alternative specific constant for SAVs in the mode choice model was iteratively adjusted to achieve a SAV mode share of 3% while letting the model sufficiently converge. The Alonso-Mora et al. (2017) ridepooling algorithm was used with a 15-minute maximum wait time and a max detour time of 50% of the solo-ride travel time for each request. All riders were assumed to be willing to share their rides with a stranger at a fare of $1 per pickup plus $1 per mile, calculated using the direct route distance. The base fleet size of 7,000 SAVs was found to be the minimum fleet size that achieves the 3% mode share (190,000 rides) while rejecting less than 5% of ride requests every hour. These SAV riders are referred to as 'TNC users' from this point on (where TNC stands for Transportation Network Company, a term codified for ride-hailing businesses in California law). As a result of increased SAV adoption, bus boardings fell 37%, to 57,184 boardings per day. The results of this POLARIS run were used as fixed demand inputs for all subsequently simulated scenarios, with a fraction or all of the bus demand added to the base 3% SAV mode share, depending on the route replacement level being tested.

The scenarios for serving bus users with SAVs were varied in three ways. First, different levels of route replacement by SAVs were tested: eliminating the bottom 53 routes serving just 25% of rides, the bottom 61 routes serving 50% of rides, or all 69 bus routes (leaving bus users fully dependent on the SAV fleet). Second, the bus users were served either door-to-door (D2D) or stop-to-stop (S2S), with the latter using existing bus stops as PUDO locations to streamline operations. In S2S, bus users on replaced routes were served at their nearest bus stop using the 4-seater SAVs, while existing TNC users continued being served door-to-door (D2D). The D2D scenarios primarily serve as a benchmark for the S2S scenarios, since D2D bus users are served identically to TNC users. Third, the SAV fleet size was varied to evaluate if additional vehicles are needed to serve the added demand.

RESULTS

A summary of the simulation results with the base fleet size of 7,000 SAVs is presented in Table 1. Over 95% of requests by bus users can be served without expanding the fleet, even for a full replacement of bus routes, which represents a 20.6% increase in SAV demand. However, the percentage of rejections for bus user requests is substantially higher than that for TNC users, and it is not lower for smaller increase in SAV demand. The increase in demand is satisfied through more frequent ridepooling, as shown by higher average vehicle occupancies (AVOs). Yet, AVO is generally low across the board, since the passenger-oriented algorithm rarely assigns pooling outside peak hours with vehicle scarcity. Serving bus users from existing bus stops (S2S) decreases the rejection rates but only on high-demand routes, as indicated by the difference in rejection rates between D2D and S2S scenarios. Wait times and in-vehicle travel times (IVTTs) increase with additional demand, while percentage of empty vehicle-miles traveled (%eVMT) remains steady across scenarios.

Table 1. Summary of Simulation Results with 7,000 SAVs

Bus Replacement Level	% SAV Demand Increase	Service Type for Bus Users	% Requests Rejected (Bus Users)	% Requests Rejected (TNC Users)	Avg Wait Time (min)	Avg IVTT (min)	Avg Veh Occupan. (AVO)	% Empty VMT (eVMT)
0%	0%	-	-	0.1%	4.4 min	13.2 min	1.04 pax.	31.1%
25%	6.1%	D2D	4.5%	0.2%	4.6	13.6	1.05	31.4%
		S2S	4.2%	0.2%	4.6	13.7	1.05	31.5%
50%	11.1%	D2D	4.1%	0.4%	4.9	14.2	1.06	31.3%
		S2S	2.6%	0.4%	4.8	14.2	1.06	31.2%
100%	20.6%	D2D	5.0%	1.3%	5.1	14.9	1.09	30.9%
		S2S	2.9%	1.1%	5.1	14.6	1.09	30.9%

Notes: D2D = Door to door service for bus users, S2S = using existing bus stops as PUDO locations for bus users, Requests rejected = requests unable to be unserved within 15 minutes, AVO is computed based on revenue-miles only (so vehicle is carrying at least one passenger [pax]).

Figure 3 shows the change in select metrics when the fleet size is increased beyond 7,000 SAVs. While increasing the fleet size tends to decrease rejections for TNC user requests, it does not appear to have the same effect for requests by bus users. The advantage of S2S for serving bus users remains clear across fleet sizes. Expectedly, wait times decrease when the fleet size is increased. IVTT also decreases with fleet size for 50% replacement or above, but it does not decrease to the baseline level.

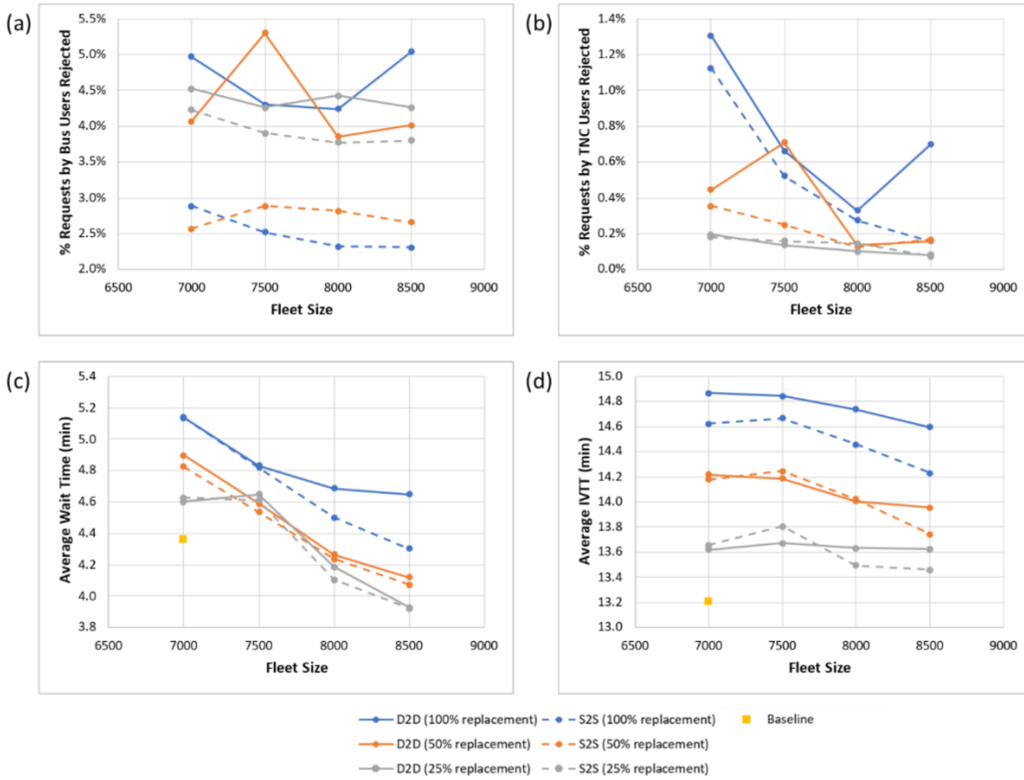

Figure 3. Impacts of Fleet Size on (a) % Requests by Bus Users Rejected, (b) % Requests by TNC Users Rejected, (c) Average Wait Time, and (d) Average In-Vehicle Travel Time (IVTT)

The spatial and temporal patterns of request rejections were analyzed to obtain insight into why a small percentage of bus user requests cannot be served, regardless of the quantity of demand added or SAV fleet size. Figure 4 shows the number of rejections by hour of day. Most of the rejections occur in the afternoon peak between 2 and 5 PM. Despite less than a 5% 24-hour rejection rate, hourly rejection rate could reach 26.6% for bus users during this time period. Therefore, we focus on this period for our spatial analysis.

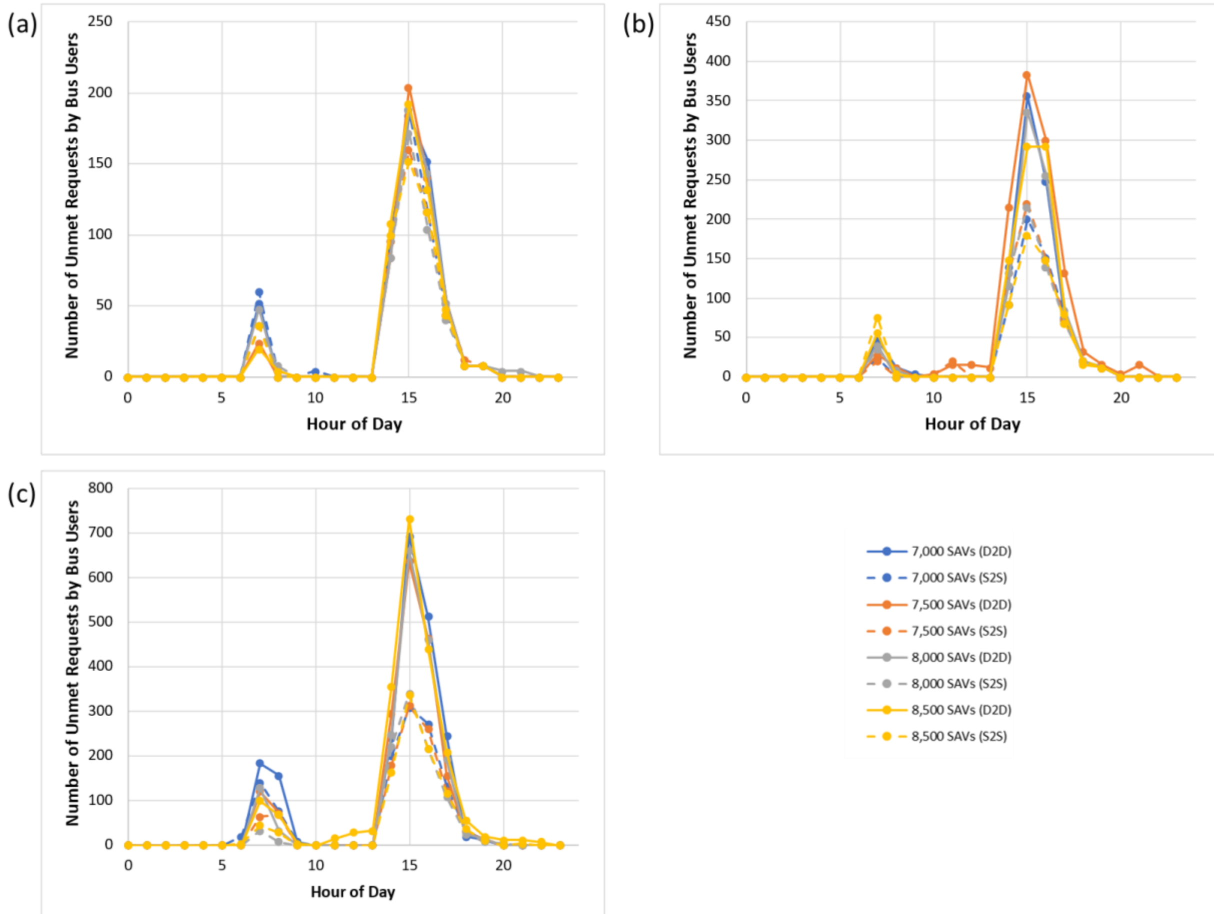

Figure 4. Number of Unmet Requests by Bus Users for (a) 25%, (b) 50%, and (c) 100% Bus Replacement by Hour of Day

Figure 5 shows the spatial distributions of the origins and destinations of TNC and bus trips between 2 and 5 PM within the SAV geofence. It can be observed that the spatial patterns for the two types of trips vary substantially. Bus trips are more concentrated in the core of the geofence for both its origins and destinations, whereas the distribution TNC trips are more diffused, especially for the destinations. The locations of the rejections of bus user requests are highly concentrated in the two high-density origin areas. It should also be noted that 47% of bus trips take place during this time period compared to 39% for TNC-user trips. Therefore, the rejection patterns of bus-user requests can be explained by the intense concentration of demand during peak periods in core locations. This concentration cannot be well addressed by increasing fleet size, since the vehicle flows needed to serve it do not arise from the patterns of TNC-user trips. This suggests that the spatiotemporal synergy between TNC- and bus-user requests is an important factor to evaluate, and that conclusions on the feasibility of operations cannot be drawn from the quantity of added demand alone.

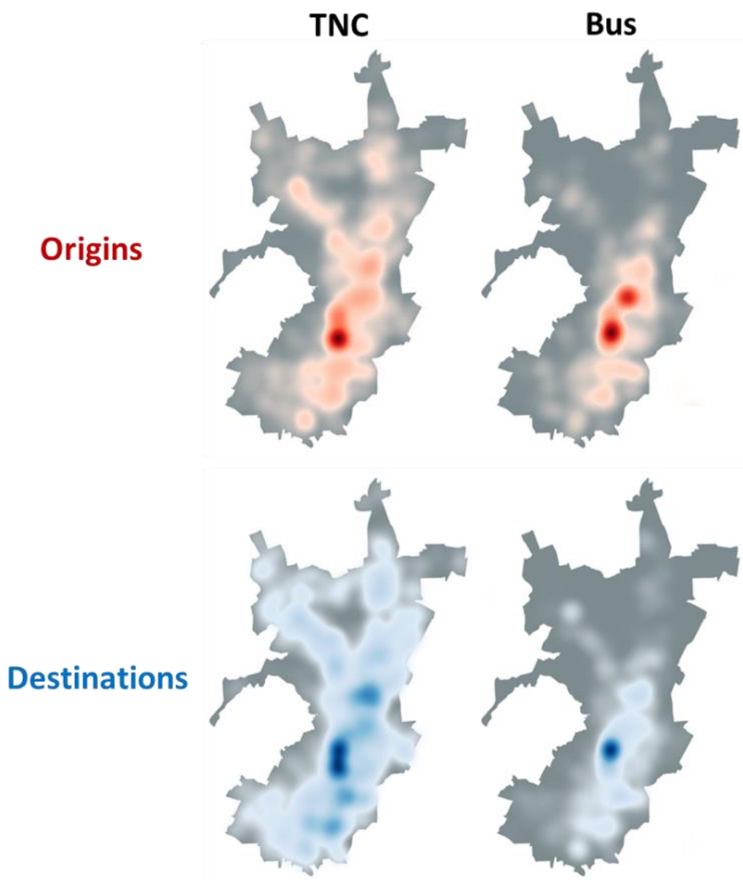

Figure 5. Heatmap of Origins and Destinations of TNC and Bus trips Between 2 and 5 PM in the SAV Geofence

Figure 6 shows the change in travel times of trips made by TNC users and bus users broken down into components. Serving bus users with SAVs has little impact on the travel times of TNC users, with the average total travel time increasing by less than 1.5 minutes. Most of the increase is in the wait time, which can be mitigated by expanding the fleet, as shown in Figure 3(c). The average travel experiences of bus users improve substantially for both D2D and S2S operations across all replacement levels. While IVTT remains nearly the same as taking the fixed-route bus under the baseline scenario, bus riders enjoy shorter wait and walk times when served by SAVs. The walk time decreases for S2S, since users now walk to the nearest stop rather than the one serving their route, which is on average 72% farther than the nearest stop.

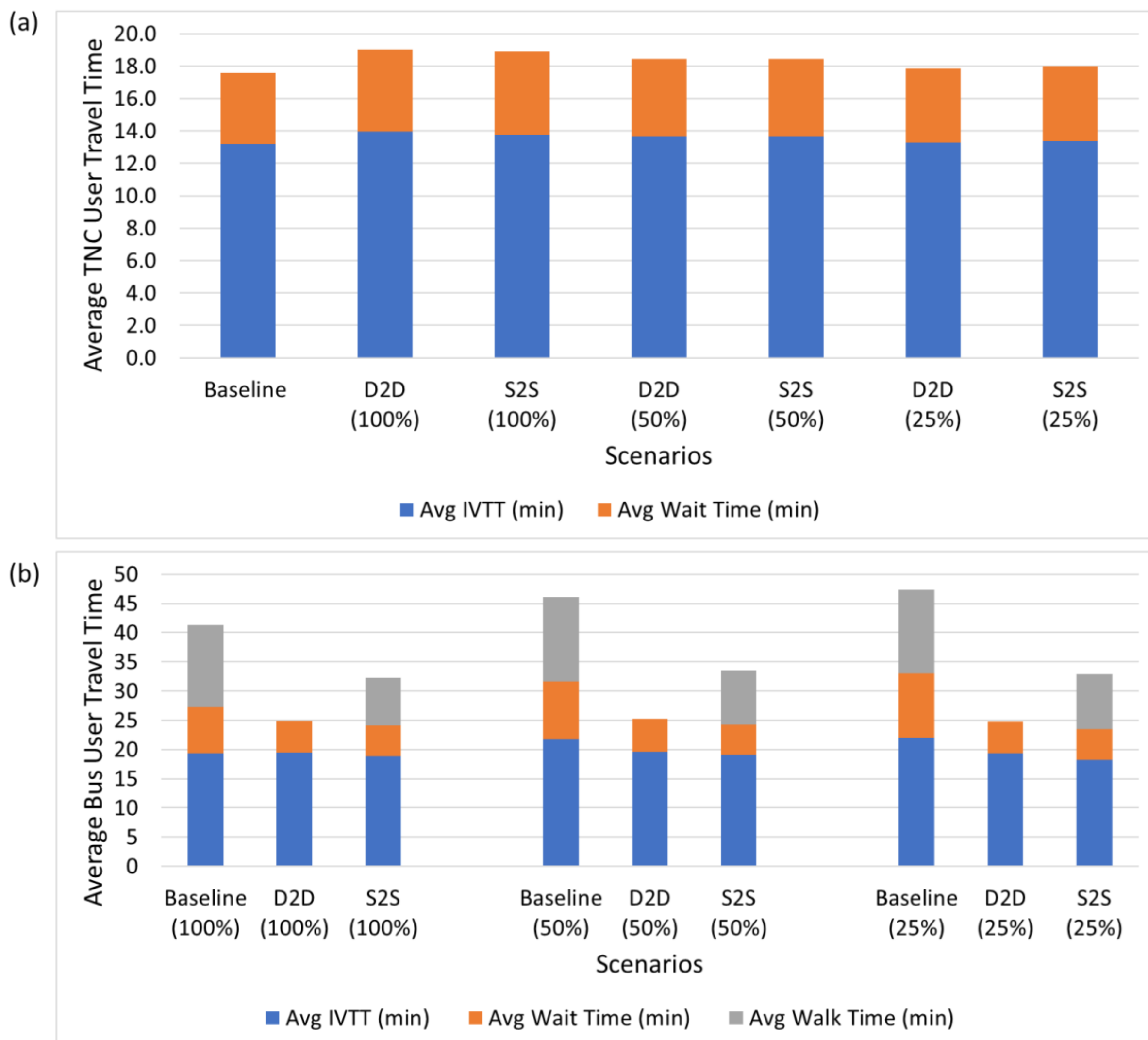

Figure 6. Average Travel Times of (a) TNC Users and (b) Bus Users by Components Across Scenarios with 7,000 SAVs

Table 2 compares the costs between conventional buses and subsidizing SAV operators under the more realistic and operationally beneficial S2S operations. The cost for conventional buses were calculated based on simulated VMT and cost parameters from Table 1 of Quarles et al. (2020). Only costs directly influenced by the vehicle choice and VMT are assumed to vary: rolling stock, fuel, maintenance, and purchased transportation (drivers). These categories made up 56% of the actual total bus-related expenditures by CapMetro from 2015 to 2024 (Table A1). Bus users are assumed to always pay the standard bus fare, with the transit agency subsidizing the remainder to cover the SAV operator's standard fare. The fare paid by bus riders is the same across scenarios, so this amount is not subtracted from the cost shown in the table. SAV fares were calculated based on the direct route (non-shared) distance for each request. Savings from eliminating bus routes were assumed to be proportional to the reduction in revenue VMT.

The best bus route replacement strategy is highly dependent on the SAV fare. If SAV fares are $1/pickup + $1/mile, serving all bus riders with SAVs emerge as the best option, providing a net 24.8% saving, assuming the indirect bus-related costs (44% of bus expenditure) remain constant. However, if SAV fares are $2/pickup + $2/mile, 25% replacement becomes the best option, providing 7.3% savings, while a full replacement becomes more expensive than current costs. Although only bus users were eligible to be served via subsidized SAVs in the simulations, real-world implementations of subsidized ridehailing programs are prone to budget overruns due to the popularity of the service (Benaroya et al., 2023; Weigl et al., 2022). The best options for either fare assumptions provide room for CapMetro to accommodate additional rides under the current budget for conventional buses. However, higher replacement levels are not robust to fare changes, based on the large changes in the cost within the plausible fare range.

Table 2. Cost of Serving Bus Users with S2S SAVs under Various Bus Route Replacement Scenarios

Bus Replacement Level	% Reduction in Bus Revenue VMT	$1/pickup + $1/mile SAV Fare	$2/pickup + $2/mile SAV Fare
		Cost per Day to Transit Agency	Cost per Day to Transit Agency
0%	0%	$443,021	$443,021
25%	43.6%	$317,481	$385,231
50%	62.0%	$295,784	$423,201
100%	100%	$246,807	$455,060

CONCLUSIONS

This study simulated the replacement of bus routes in Austin, Texas, with SAVs providing subsidized rides alongside their regular ridehailing operations. Using the POLARIS agent- and activity-based simulator, future travel demand reflecting higher SAV availability was forecasted to serve as the demand input for the scenarios studied. 25 total scenarios were simulated, varying bus route replacement levels, D2D versus S2S service for bus users, and fleet size.

Under a 3% SAV mode-split future, simulation results indicate that over 95% of bus user requests can be served without expanding the n=7000 SAV fleet, even under 100% replacement of Austin's 69 bus routes. However, bus user rejection rates remain persistently higher than those of base-case TNC users, regardless of route-replacement level and fleet expansion. This gap can be attributed to a spatiotemporal mismatch, since bus demand concentrates sharply in core areas during the afternoon peak, while TNC demand is relatively diffuse (over time and space). The SAV routes and positions, driven by the dominant TNC patterns, do not naturally align with Austin's bus routes and bus riders' origins and destinations during this afternoon peak period, leading to high rejection rates at that time. S2S operations for bus riders uses existing bus stops as pickup points, and mitigates the high-rejection-rate problem on high-demand routes. These findings suggest that transit agencies and SAV operators should evaluate the space-time synergies between transit and ridehailing demand when assessing service feasibility.

Despite the localized service shortfalls, bus riders overall experienced substantial travel time savings thanks to accessing SAV-based services (when compared to the fixed-route-bus base case) due to reductions in wait times and walking distances, although their IVTT remained similar. Impacts of adding bus riders' demand on existing TNC users were minor and can be mitigated through SAV fleet expansion. Cost outcomes were highly sensitive to the SAV fares, and assumptions of fixed costs for CapMetro (pessimistically assumed to be 44% of current costs, or roughly $1.50 per bus-passenger-mile, even when offloading all bus rides to the SAV operator). At \$1/pickup + \$1/passenger-mile SAV service costs, replacing Austin's entire bus network was most cost-effective, yielding savings of 25% relative to conventional bus costs. Conversely, at \$2/pickup + \$2/mile, only replacing the lowest-demand routes emerged as the best option, providing 7% in savings for CapMetro. These findings give transit agencies insight into the key considerations for evaluating potential partnerships with SAV operators.

Future work can implement decision-making at the individual-route level, allowing more flexible determination of which routes to replace, along with modifications such as shortening routes or reducing hours of service. Researchers can consider automating the fixed-route buses themselves as another alternative (as in Quarles et al. [2020]) and explore how the results generalize across cities with different demand geographies and transit networks.

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APPENDIX A. CAPMETRO EXPENDITURES

Table A1 shows the breakdown of CapMetro's operating and capital costs for its bus service. CapMetro relies on private contractors to manage its drivers and operate its buses, making purchased transportation the largest component of its operating expenditures. CapMetro utilized two different contractors during this span. While nearly all categories of operating expenditures have steadily increased over the years, 2022, 2023, and 2024 saw significant hikes in spending for salaries and wages (for direct employees of CapMetro), services, and materials and supplies. The three items are primarily associated with general administration and vehicle operations, general administration, and vehicle maintenance, respectively. The increase in maintenance expenditures can likely be attributed to a failed shift to an all-electric bus fleet (Bernier, 2024). Capital expenditures vary greatly from year to year, depending on rolling stock and facility investments. Across the ten years, capital expenditures average to an additional 28% on top of operating costs. Total operating and capital expenditures across all CapMetro services, including demand-responsive transit, hybrid rail, and future light rail service, are shown at the bottom of Table A1.

Table A1. CapMetro Bus Operating and Capital Expenses

	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Expense, Operating Total	**$134.4 M**	**$145.9 M**	**$145.9 M**	**$154.7 M**	**$165.6 M**	**$159.5 M**	**$161.1 M**	**$197.6 M**	**$236.7 M**	**$271.9 M**
Operating Expense by Object Class:										
Salaries and Wages	$11.5 M	$12.4 M	$13.1 M	$14.4 M	$15.5 M	$16.4 M	$16.9 M	$25.3 M	$30.6 M	$36.5 M
Fringe Benefits	$7.5 M	$7.5 M	$9.4 M	$9.4 M	$10.2 M	$10.5 M	$10.9 M	$14.7 M	$16.2 M	$17.8 M
Services	$10.7 M	$12.5 M	$11.6 M	$12.6 M	$13.1 M	$14.3 M	$17.3 M	$26.0 M	$33.2 M	$31.7 M
Materials and Supplies	$14.1 M	$13.2 M	$11.2 M	$10.1 M	$10.4 M	$10.5 M	$8.9 M	$13.6 M	$27.1 M	$29.4 M
Utilities	$1.8 M	$1.8 M	$2.1 M	$2.2 M	$2.1 M	$2.2 M	$2.3 M	$2.4 M	$2.8 M	$3.5 M
Casualty and Liability	$0.8M	$0.2 M	$0.3 M	$0.3 M	$0.4 M	$0.2 M	$0.2 M	$0.3 M	$0.2 M	$0.7 M
Purchased Transportation	$86.1 M	$95.7 M	$96.1 M	$103.9 M	$111.9 M	$103.6 M	$103.3 M	$113.5 M	$123.8 M	$148.9 M
Other	$2.0 M	$2.6 M	$2.1 M	$1.8 M	$1.9 M	$1.8 M	$1.4 M	$1.9 M	$2.7 M	$2.8 M
Operating Expense by Function Class:										
Vehicle Operations	$20.2 M	$17.2 M	$16.3 M	$16.5 M	$18.5 M	$18.7 M	$16.4 M	$22.8 M	$30.4 M	$36.6 M
Vehicle Maintenance	$0.6 M	$0.2 M	$2.2 M	$1.7 M	$2.1 M	$2.5 M	$1.6 M	$10.8 M	$25.5 M	$29.2 M
Non-Vehicle Maintenance	$2.1 M	$1.7 M	$2.0 M	$2.1 M	$2.9 M	$2.6 M	$3.1 M	$3.5 M	$6.4 M	$4.9 M
General Administration	$25.4 M	$31.1 M	$29.3 M	$30.5 M	$30.2 M	$32.1 M	$36.8 M	$47.1 M	$50.6 M	$52.3 M
Purchased Transportation	$86.1 M	$95.7 M	$96.1 M	$103.9 M	$111.9 M	$103.6 M	$103.3 M	$113.5 M	$123.8 M	$148.9 M
Expense, Capital Total	**$9.3 M**	**$25.0 M**	**$50.9 M**	**$18.9 M**	**$30.7 M**	**$50.9 M**	**$18.2 M**	**$33.3 M**	**$166.4 M**	**$100.9 M**
Rolling Stock	$0.0 M	$22.4 M	$45.7 M	$8.6 M	$11.9 M	$24.8 M	$0.0 M	$0.8 M	$34.0 M	$42.9 M
Facilities, Guideway, Stations, Admin. Bldgs.	$0.8 M	$0.4 M	$1.0 M	$2.9 M	$3.7 M	$11.8 M	$5.6 M	$4.3 M	$99.0 M	$22.7 M
Other	$8.4 M	$2.3 M	$4.1 M	$7.3 M	$15.1 M	$14.4 M	$12.6 M	$28.2 M	$33.4 M	$35.3 M
Expense, Operating Total (All Modes)	**$193.8 M**	**$215.9 M**	**$217.0 M**	**$227.6 M**	**$235.1 M**	**$230.4 M**	**$237.6 M**	**$284.6 M**	**$346.3 M**	**$391.4 M**
Expense, Capital Total (All Modes)	**$21.2 M**	**$45.1 M**	**$97.1 M**	**$77.0 M**	**$100.2 M**	**$91.7 M**	**$45.2 M**	**$66.1 M**	**$218.2 M**	**$142.7 M**

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