SHARED-RIDE OPERATIONS WITH MULTIPLE SERVICE TYPES: PREMIUM VS ECONOMY, STANDARD VS LARGE SAVs

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ABSTRACT

Most ride-hailing apps offer different vehicle sizes and quality. This paper investigates the impacts of such supply-size choices on the operations of a shared autonomous vehicle (SAV) fleet. A nested service-choice model was implemented across three fleet size scenarios using the POLARIS agent-based travel demand model in Bloomington City. The study compared fleet performance under two scenarios: one with diverse service offerings (standard 4-seaters and larger 6-seaters, in both economy and premium styles) and another with a single economy service. The demand for 4-seater economy services peaks during commute hours (6-9 AM), while premium services, especially 6-seater premium SAVs, show negligible demand due to their higher fares and niche market. Scenario comparisons across three fleet sizes indicate that offering diverse SAV services leads to greater operational inefficiencies compared to single-service fleets, including higher wait times, reduced profits, and a 13-percentage-point increase (from 24.2% to 37.4%) in empty vehicle-miles traveled (eVMT). Luxury and 6-seater SAVs struggled to achieve profitability due to low demand and higher operational costs. On average, multi-service fleets experienced a 47% increase in revenue per SAV (rising from \$216 to \$318), but at the cost of an additional \$125 in operational costs per SAV (from \$166 to \$291) and a notable decline in profit, dropping from \$50 per SAV (without services offered) to \$27 per SAV when services offered.

Keywords: Shared autonomous vehicles, demand management, transportation network companies, agent-based modeling

BACKGROUND

On-demand ride-hailing services (such as those provided by Uber, DiDi, Ola, and Lyft) are changing urban travel patterns by quickly connecting drivers with passengers (Wang et al., 2016; Chen et al., 2020; Ke et al., 2020; Zhou et al., 2022a and 2022b). Shared autonomous vehicle (SAV) fleets may enable more efficient and cost-effective forms of ride-hailing (Fagnant and Kockelman 2015; Golbabaei et al., 2021). Such services may reduce reliance on privately and publicly owned vehicles (Levin, 2017). Unlike traditional ride-hailing, SAV service eliminates the need for driver wages and tips and can operate 24/7 without breaks (Bosch et al., 2018; Huang and Kockelman, 2021). However, complex design and high manufacturing costs have delayed SAV fleet companies from providing citywide services and offering a range of vehicle/service options. Currently, Waymo is partnering with Uber for all-electric SAV services in San Francisco, Los Angeles, and Phoenix (with geofenced areas of 55, 79, and 315 sq miles, respectively (Waymo, 2023; 2024a; 2024b and 2024c). Similarly, DiDi is expanding its operations in Shanghai and Guangzhou and plans to launch its robotaxi service, "Didi Neuron," by 2025 (Ye, 2023).

Today's SAV designs are not limited to modified 4-seater vehicles but include 6-seaters without steering wheels, similar to Amazon-owned Zoox, which is currently testing in many U.S. cities (Zoox, 2024a and 2024b). SAV services operate in major cities worldwide, including Seoul, Beijing, and Paris. In China, Baidu, Pony.ai, WeRide, and Didi are leading SAV deployments in Beijing, Wuhan, and Chongqing (PR Newswire, 2024). Hyundai has deployed RoboRide in Gangnam and Seoul (AutoVision News, 2023), while Mobileye has initiated operations in Paris and expanded its testing programs to include Miami and Stuttgart (Mobileye, 2021 and 2022). SAV fleet operators continue to expand vehicle and service types and seatings that are accessed through smartphone apps. Although there is a substantial body of literature focusing on standard-sized AV simulations that analyze the impacts of ride-sharing, pickup and dropoff stop locations (PUDOs), and optimized SAV repositioning (Farhan and Chen, 2018; Narayanan et al., 2020; Gurumurthy and Kockelman, 2022; Jing et al., 2020; De Souza et al., 2020; Martinez and Viegas, 2017), less research has focused on the impacts of differentiated SAV services, such as economy versus premium options and standard (4-seater) versus larger (SUVs + 6 seaters) vehicles on fleet operations, wait times and profits.

Although these TNCs offer a wide range of services, research has been limited on the public's preferences for these services and the impact of their choices on the transportation network. To address this gap, this study analyzed the effects of users' SAV service preferences on transportation systems (e.g., VMT, average trip-length changes within the network) and assessed the economic feasibility of offering various SAV services instead of a single standardized SAV service. These results could assist SAV-owned companies to devise optimal fare strategies and fleet sizes while ensuring that eVMT and operational costs remain within acceptable limits. The next section of this paper provides a comprehensive overview of the agent-based simulation framework used in POLARIS, followed by a comprehensive description of the dataset and the case study region selected for analysis. The following section details the literature review, followed by the implementation of the service choice model across various simulation scenarios, and presents a thorough discussion of the simulation results. Finally, the paper concludes with a summary of the key findings and their implications.

LITERATURE REVIEW

Agent-based modeling (ABM) offers several advantages for simulating ride-hailing networks by representing passengers, drivers, and operators as autonomous agents with individual behaviors. It can capture the decentralized and real-time decision-making, such as dynamic matching and route selection, providing a detailed, micro-level view of the ride-hailing system (Čertický et al., 2014). ABM's flexibility enables it to simulate diverse scenarios, including various dispatching methods, fleet compositions, and demand patterns, allowing for a rigorous evaluation of operational strategies under changing conditions. Past studies have used agent-based simulation approaches to analyze the competitive ride-hailing market. For instance, Mo et al. (2021) used an agent-based simulation model (ABM) to explore the competition between SAVs and public transit (PT) in Singapore. The model assessed the effects of fare and service frequency on market shares. Results indicated that SAVs could capture up to 30% of the PT market share in low-density areas where PT services are less efficient. The simulation also showed that PT services concentrated more on shorter routes and peak hours, increasing efficiency. This study showed the potential for SAVs to complement PT by filling service gaps during off-peak times. Karamanis et al. (2020) also employed ABM and compared the effects of dynamic pricing on monopolistic and competitive SAV fleet scenarios in Greater London. Researchers found that dynamic pricing led to higher revenues than static pricing during non-peak hours in monopoly settings. In contrast, dynamic pricing was more effective during peak hours in competitive scenarios, due to the high waiting times that occurred during these periods. Their results also showed that dynamic pricing led to a higher percentage of shared trips compared to static pricing.

Guo et al. (2022) developed a comprehensive optimization framework for SAVs competing with human-driven private vehicles by integrating a binary logit demand model, whose utility depends on travel cost, time, vehicle availability, and parking capacity, with a time–space network-flow formulation that captures both passenger trips and empty-vehicle relocations. Their case study results on Singapore's BlueSG network showed that when demand is low, higher sensitivity boosts profit (by capturing more riders), but when demand is high, it can actually reduce profit by over-investing in service quality. Lowering the per-minute SAV fare attracts enough additional trips to offset the margin loss, while raising fares spurs even more relocations, sustaining high fulfillment rates. They also found that optimal fleet sizing balances utilization and service, resulting in roughly 5-6 requests per vehicle during peak hours, which maintains over 80% fulfillment without excessive idle time. Inturri et al. (2019) used ABM to represent a demand-responsive shared transport (DRST) system, which is situated between traditional public transport and private car usage. The modeling framework, implemented in NetLogo, aims to evaluate and optimize various aspects of DRST, including fleet size, vehicle capacity, and vehicle dispatching. They established two main types of agents: passenger groups and vehicles. However, an important limitation of this study was its omission of a third critical agent, which is driver behavior. In real-world shared mobility systems, three types of agents actively shape system dynamics: passengers, drivers, and fleet operators or owners. The interaction between driver behaviors (positioning, acceptance strategies, and responsiveness) and fleet owner strategies plays a significant role in determining operational efficiency, user experience, and the system-level patterns.

Since service variations do not yet exist and because SAV deployments remain small (and privately managed), this study relies on existing literature about service choice modeling results for conventional/human-driven (HV) ride-hailing businesses. For example, Paronda et al. (2016) compared key performance metrics of Uber and GrabCar to those of conventional taxis in Manila, Philippines. They used travel diaries of regular riders of these three services for 30 days, along with two surveys that collected data about the ease of finding available vehicles for each service. Performance indicators included travel speeds, reliability, passenger expense, and service quality: they estimated Uber's service to be 75% faster and 35% and 28% less expensive than GrabCar and taxis, respectively. Habib (2019) analyzed competition between Uber and other travel modes in the Greater Toronto and Hamilton areas (GTHA) through an integrated mode choice model known as the semi-compensatory independent availability logit (SCIAL) model. They noted that younger persons (both male and female) are more likely to choose Uber. Uber is often used in the late afternoon, evening, and night, complementing transit services that are less available during these times.

A few studies have investigated the spatial and temporal variations in ride-hailing demand and fare. For instance, Huang et al. (2023) analyzed these variations across four platforms in NYC: Uber, Lyft, Juno, and Via. Their findings revealed that competition was most intense during weekday morning rush hours (6 to 8 AM) significantly higher compared to weekends. The study also found that increased competition lowers passenger costs and raises driver income, although excessive competition can reduce the profitability of ride-hailing platforms. However, this research did not differentiate between specific Uber services, such as UberX, UberXL, or premium alternatives. This limitation was addressed by Schwieterman (2019), who explored how service attributes of Lyft Line, UberPool, Lyft, and UberX influence user preferences when choosing between TNCs and public transit. Other studies have focused on the sociodemographic characteristics shaping preferences (Grahn et al., 2020; Gehrke et al., 2020; Young and Farber, 2019). However, these studies did not consider the impact of service choice preferences on the broader transportation network.

Winter et al. (2016) conceptualized an Automated Demand-Responsive Transport System (ADRTS) as a public transportation system using fully automated vehicles to provide shared, on-demand rides without fixed routes or timetables with predefined pickup and drop-off points, ride-sharing within vehicle capacity limits, guaranteeing maximum passenger waiting times. However they used stochastic, event-based simulations to assign vehicles to passenger requests and sought to identify the minimum and optimal fleet sizes needed to satisfy demand while minimizing combined system (operator and user) costs. Unlike ABM, however, this framework does not represent passengers, vehicles, and operators as autonomous decision-making agents with individual behavioral rules. Moreover, they focused exclusively on a shuttle service operating between a train station and a university campus in Wageningen, Netherlands, using real passenger counts for this specific corridor. The operational setup and demand patterns were calibrated to reflect the context of an ongoing pilot of automated electric vehicles, limiting the study to fixed pick-up and drop-off points rather than offering the flexibility of true door-to-door service, a feature that could provide greater user convenience in broader on-demand mobility applications.

This study pivots off Argonne National Laboratory's POLARIS code, which enables micro-simulation of SAV operations with and without DRS (Auld et al., 2016; Gurumurthy et al., 2020). POLARIS is an advanced, open-source, and agent-based modeling framework designed to simulate multi-modal transportation systems at a mesoscopic level, with a separate agent for every member of the regional population. It integrates travel demand, network flow, and traffic assignment models, allowing travel decisions, such as activity planning and route choice, to be modeled simultaneously. The activity models, adapted from Auld and Mohammadian (2009 & 2012), model each traveler's decision-making process across short-term and long-term timeframes, considering activity types, destinations, and preferred modes. The travel demand simulator can perform comprehensive simulations due to its integration of a population synthesizer that can iteratively adjust the agent population averages across various categories to align them with the regional cross-tables. The synthesizer enables the efficient scaling of simulated individual agents, while POLARIS is high-speed C++ code capable of simulating nearly all regions' populations with great efficiency. Using dynamic traffic assignment (Verbas et al., 2018), network traffic is balanced to achieve a dynamic user equilibrium. Unlike aggregate or analytical models, this ABM framework provides flexibility to accommodate heterogeneous agent behaviors, including users with diverse preferences for economy and premium service tiers and vehicles with varying seating capacities. This level of detail enables evaluation of how service differentiation, fare structures, and operational strategies jointly influence both user experience and system performance, insights that would not be accessible through traditional modeling approaches.

Past SAV simulations using POLARIS exist (Dean et al., 2021; Huang and Verbas, 2021; Gurumurthy et al., 2022; Hunter et al., 2024) and a single SAV operator is responsible for the centralized management of ride requests and may reposition SAVs in response to changes in vehicle demand-supply ratios. The SAV operator performs repositioning tasks while maintaining a record of present and potential execution requests. The model addresses the needs of travelers who opt for ride-sharing using the DRS algorithm, which includes a heuristic approach to effectively handle travel delays encountered at various points during the trip, as discussed in the study by Gurumurthy and Kockelman (2022a and 2022b). When an SAV trip request is logged, the operator assigns it to the nearest vehicle to lower the empty vehicle-miles traveled (eVMT) and reduce wait time in a zone-based structure. POLARIS sorts a pool of people who select an SAV as their preferred mode of transportation (after the nested mode choice model is implemented) and presents a list of services nested within a single operator platform (Figure 1). This study extends the existing mode choice model by including a service choice model that assumes a monopoly in the market, where a single operator provides all the SAV services.

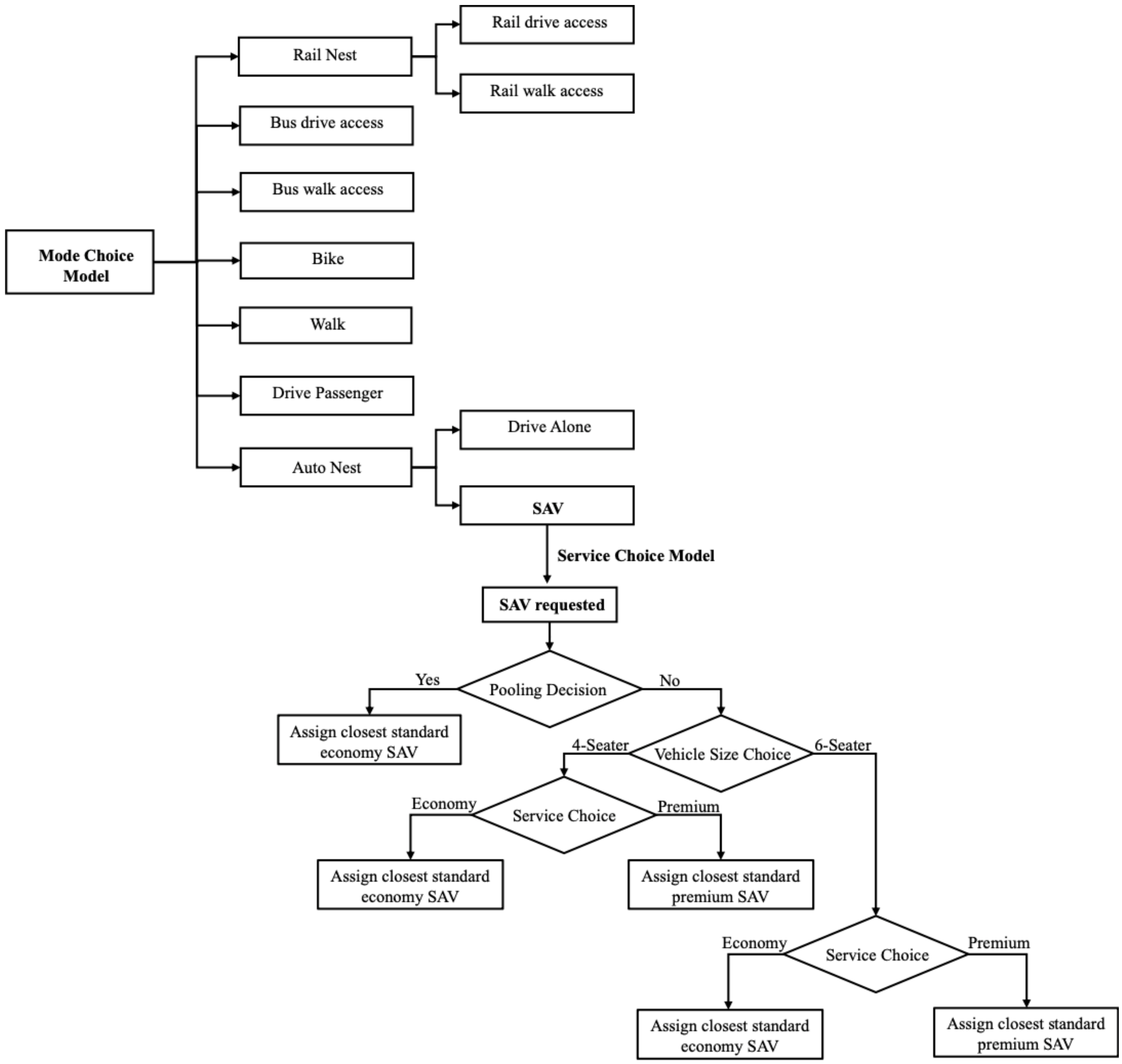


Figure 1 POLARIS Mode Choice Model with Added Service Choice Sub-Model

SERVICE CHOICE MODEL

When an individual opts for a pooled service, a standard-economy SAV (4-seater) is assigned, drawing inspiration from Uber and Lyft operations for pooled rides. For passengers and travel parties who prefer a private ride without sharing with unknown co-passengers, options of 4-seater and 6-seater, economy, and premium vehicles exist. In the ride-matching process, the system enforces an exact match for both service and seating types to ensure compatibility. For example, a request for a "4-seater premium" SAV will only be matched with a vehicle explicitly marked as a 4-seater offering premium service. The SAV fare structure includes a fixed price per trip, a distance-based component, and a trip duration-based component. The mode choice model coefficients (model shown in Figure 1), along with fare and travel-time coefficients influencing the utility of SAV service, are derived from previous SAV and TNC simulation studies conducted in Bloomington by Gurumurthy and Kockelman (2020) and Gurumurthy et al. (2020).. This study uses service-specific population shares of ride-hailing services from NYC's high-volume for-hire vehicle (FHV) trips (TLC 2022 and 2023). It includes information on start and end times, origins and destinations marked by taxi zone ID, the vehicle license number, distance traveled, wait times for riders, whether the service was requested as a shared ride, and if so, whether a match occurred, the total fare, and any additional charges such as tolls, surcharge fees, and airport fees. The service type of each trip was identified by comparing the total fare paid by passengers with the fares calculated using Uber and Lyft fare structures (Lyft, 2024; Majaski, C., 2024) for the given duration and distance. The TLC data's population shares of different user services were later adjusted to align with the Bloomington region. Nesting coefficients were adjusted by running the model iteratively in Bloomington City to obtain the target service shares.

Previous studies investigating changes in the value of travel time (VOTT) for SAVs compared to TNCs have consistently proposed a reduction in VOTT (Chen and Kockelman, 2016; Perrine et al., 2018; Huang et al., 2020). Perrine et al. (2020) analyzed long-distance U.S. travel, assuming autonomous vehicle (AV) operating costs of \$0.10–\$1.65 per mile and VOTT values of \$3.00–\$9.00 per hour, with a base case of \$0.20 per mile and \$6.00 per hour across all scenarios in the study. Chen and Kockelman (2016) assumed the value of travel time (VOTT) for shared autonomous electric vehicles (SAEVs) to be 35% of standard human-driven private vehicles to reflect the lesser engagement required from passengers, who can instead use travel time for other productive or leisure pursuits. Similarly, Huang et al. (2020) suggested a reduction in VOTT of 30%, from \$15.83 per hour for human-driven vehicles (HVs) to \$11.08 per hour for SAVs, acknowledging the lower perceived travel costs associated with SAVs. In line with these findings, this study assumes a VOTT of \$9.38 per hour for pooled economy SAV services and applies a further 30% reduction for exclusive (non-pooled) services to reflect the increased privacy and time savings associated with avoiding ride-sharing. Building on past research (Chen and Kockelman, 2016; Huang et al., 2020), which proposes a significant influence of service quality travel time costs' perceptions, this study further differentiates between service levels by assuming a 50% reduction in VOTT for premium SAV services compared to economy SAVs, accounting for the enhanced user experience offered by these luxury services.

CASE STUDY REGION

The region under consideration for this study is Bloomington, located in Illinois, USA. The network consists of 185 zones, 2500 nodes, and 7000 links. It is a compact geographical area spanning nearly 74 square-miles and serving as the residence for an estimated population of 120,000 individuals (de Souza et al., 2020; Gurumurthy and Dean 2020; Gurumurthy and Kockelman 2020; Gurumurthy et al., 2020). The study initially synthesized 100% of the population to generate full demand (96,402 ride requests) for 24 hours in the Bloomington region. The demand distribution (see Figure 2) illustrates the number of ride requests across different service and seating types over a 24-hour simulation period. Economy 4-seaters' demand peaks during the morning rush hours (6 AM to 9 AM) at approximately 4,500 requests and maintains relatively high levels through the late morning and early afternoon. The demand gradually declines in the evening, mirroring typical commuter patterns. Economy 6-seaters show moderate demand, peaking around 1,000 requests in the morning and maintaining steady levels throughout the day. In contrast, premium 4-seaters and 6-seaters show consistently low demand, with premium 4-seaters peaking at approximately 200 requests and premium 6-seaters barely exceeding 100 requests throughout the day. Such low demand is due to their higher fares and niche market.

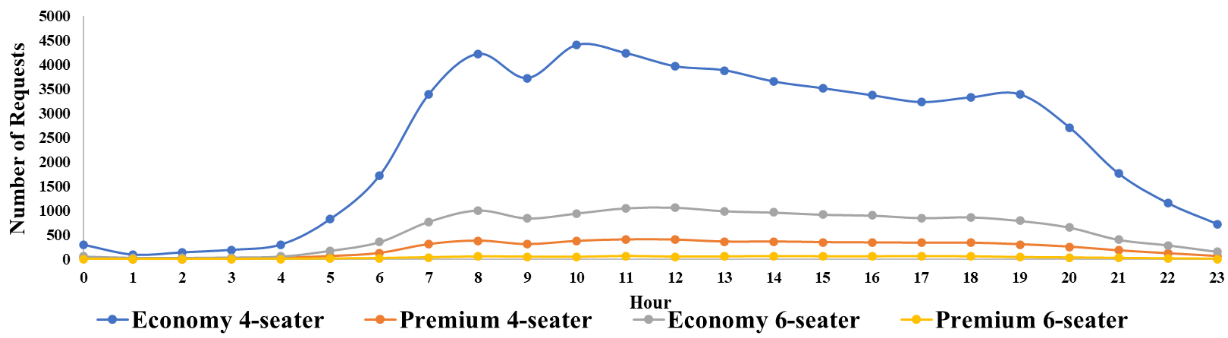


Figure 2 Endogenous Demand Distribution by Service and Seating Type Across the Day

On the supply side, the fleet consists of 82% 4-seater economy SAVs, 10% 4-seater premium, 7% 6-seater economy, and the rest 6-seater premium. Within each 4- and 6-seater SAV service, 90% of SAVs were allocated for economy rides. The maximum time for an SAV to arrive for pickup (before the rider is "lost") was 10 minutes. When matching the trip request from the demand side to the supply side by the operator, the vehicle was not assigned if a service type requested was not available within a 10-minute range. Figure 3 shows the distribution of supplied SAVs by service and seating type over a 24-hour simulation period. Economy 4-seaters' supply peaks during morning hours (6 AM to 9 AM) with over 1,000 SAVs, reflecting high demand during peak commuting times. Their supply gradually falls after 9 AM, stabilizes in the afternoon, and declines in the late evening. Economy 6-seaters show a steadier supply pattern.

Premium 4-seaters and 6-seaters, however, have consistently lower supply levels throughout the day. The spatial demand analysis across Bloomington shows (see Figure 4) significant variations in trip requests across different parts of the city, closely tied to its land use, population density, and key activity hubs. There is a consistently high density of trip requests in the downtown area of Bloomington, including those near Market Street, Locust Street, and the White Place Historic District. Meanwhile, low-demand areas are concentrated in the peripheral zones of the city, such as regions near Iron Coyote Challenge Park, Eagle View Park, and neighborhoods beyond Fox Creek. There was negligible demand observed for 6-seater premium requests across the city, likely due to their high fares.

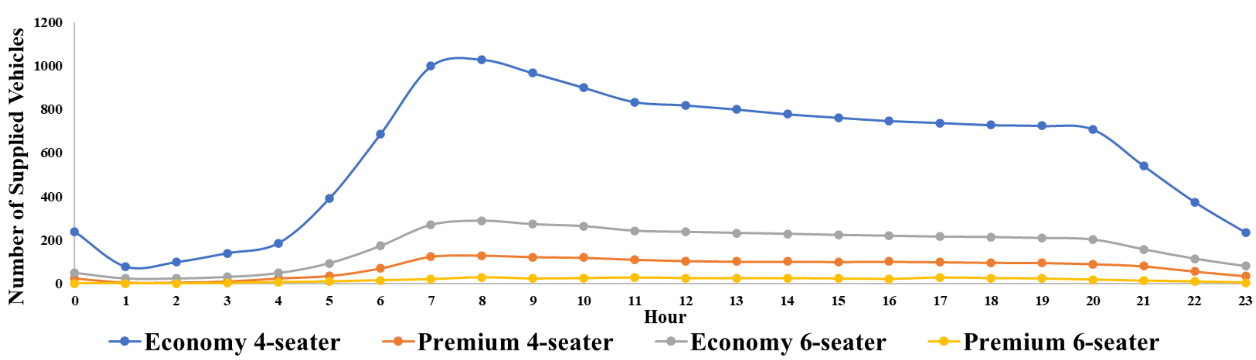
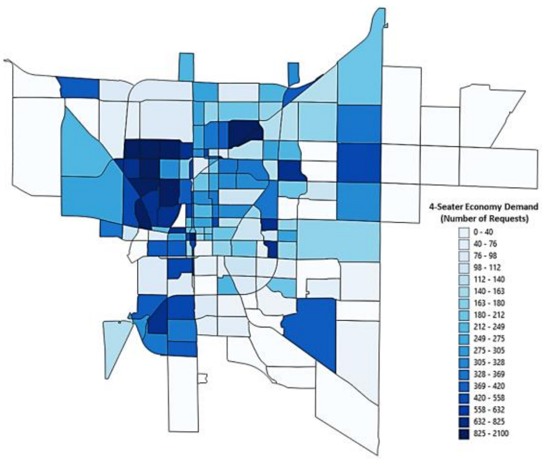
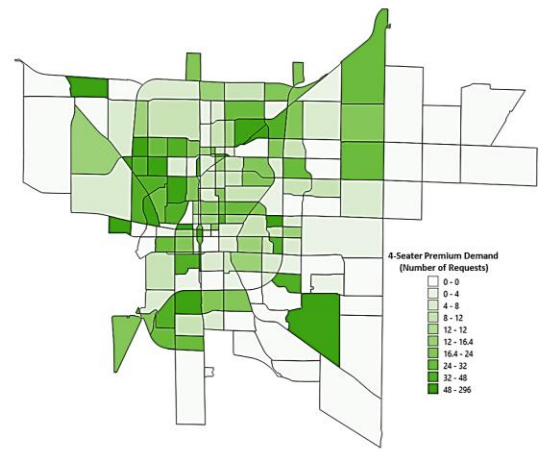


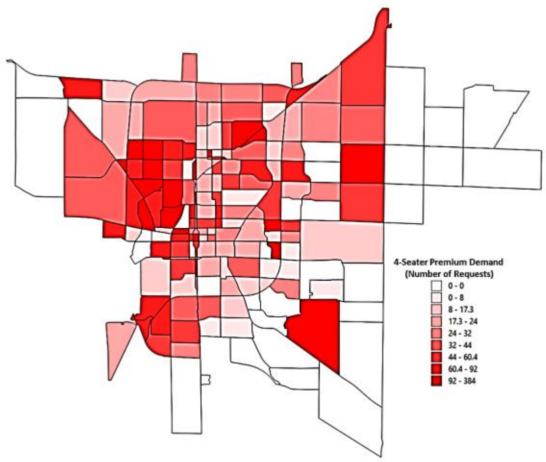
Figure 3 Hourly Supply of SAVs by Service and Seating Type



(a) 4-Seater Economy



(b) 4-Seater Premium



(c) 6-Seater Economy

Figure 4 Spatial Distribution of 4 and 6-Seater SAV Demand Across Economy and Premium Services in Bloomington City

The VOTT and fares for SAVs were tailored to reflect a range of service levels and pricing structures similar to those of Uber and Lyft in U.S. cities (Lyft, 2024; Majaski, C., 2024). Economy 4-seater (standard) SAV fares were assumed with a base fare of $2 plus $1.00 per mile and $0.25 per minute. A typical (4-seater standard) SAV's ownership cost was assumed to be $40 per day, plus another $1.00 per mile (Loeb and Kockelman, 2018; Bösch et al., 2018; Arbib and Seba, 2017). For economy XL SAVs, a higher cost structure was applied, with $60 per day and $1.50 per mile, with fares priced 50% higher than those for economy SAVs (Lyft, 2024). Premium (luxury) SAVs, intended for a more upscale service level, were assumed to incur twice the operating costs and fares of economy SAVs. Ride-sharing fares were reduced by 40% to encourage pooling (Gurumurthy et al., 2019), but DRS is allowed/assumed only in the 4-seater economy service type. The 100% endogenous demand was then reduced to 25% of the total to compare SAV operations across different fleet sizes, with and without service offerings. A fixed party size distribution adopted by Huang et al. (2024) was applied to this fixed demand. It assumes that 65% of trips involve solo riders, 25% involve two-person parties, and 10% include three or more parties. Three different fleet sizes of SAVs were tested with the DRS (pooling) option.

RESULTS

The demand distribution shown in Figure 2 was analyzed across three fleet sizes (Scenario 1, 2 and 3), each with four service options (see Table 1). The simulation results show that average wait times, VMT per SAV, and eVMT increased as total fleet size was reduced (fewer SAVs tried to meet the same demand). In Scenario 1, premium SAVs' wait time is 32%, higher than standard economy service (rose from 4.7 to 6.2 minutes). In contrast, 6-seater SAVs showed approximately the same average wait time as 4-seater economy SAVs at 4.8 minutes. The average vehicle occupancy (per revenue-mile and revenue-minute) values were consistent across scenarios and service types. The AVO per revenue mile ranged between 1.55 and 1.77 occupants per mile across all scenarios. Similarly, the AVO per revenue minute showed stable values across scenarios, ranging between 1.54 and 1.68 occupants per minute. For instance, economy SAVs showed an AVO of 1.66 occupants per minute in Scenario 1, compared to 1.54 for luxury services. The average party size across all scenarios was 1.61 occupants, resulting from applied party size distribution (Huang et al., 2024) on fixed demand. The eVMT for 4-seater economy SAVs in Scenario 1 was found to be 37%, which remains stable in Scenario 2 even as the fleet size is reduced from 500 to 375 SAVs. However, when the fleet size was further reduced to 120 SAVs, eVMT rose to 40%, an 8% rise (from Scenario 2) due to fewer SAVs available to meet the same demand.

Revenue per SAV values indicate a better financial viability of economy services than luxury options. In Scenario 1, 4-seater economy SAVs generated \$257 per SAV, more than triple the revenue of luxury SAVs (approximately \$188 per SAV). Similarly, 6-seater economy SAVs earned \$277 per SAV, outperforming luxury services. In Scenario 3 (250 people per SAV), the revenue for 4-seater economy SAVs increased to \$445 per SAV, while luxury services showed slight improvement but still lagged at \$256 per SAV due to lower demand. Profit per SAV values further showed the economic advantage of economy SAVs over luxury services. In Scenario 1, 4-seater economy SAVs achieved a profit of \$59 per SAV, whereas luxury services operate at a loss of - \$209 per SAV. For 6-seater economy SAVs, the profit is modest at \$69 per SAV. In Scenario 2, as fleet sizes shrink, profitability for 4-seater economy SAVs remains at \$115 per SAV, while luxury services improve marginally but remain uncompetitive, with a profit of only - \$260 per SAV in the smallest fleet.

Table 2 presents fleet performance metrics when riders were presented with just single standard service, with the choice of dynamic ride-pooling across three fleet sizes: 500 SAVs (Scenario 1), 375 SAVs (Scenario 2), and 250 SAVs (Scenario 3). The results indicate that median peak-hour wait times increase as fleet size reduces, rising from 4.2 minutes in Scenario 1 to 4.5 minutes in Scenario 2 and further to 5.3 minutes in Scenario 3, reflecting the reduced availability of SAVs to meet demand. Average VMT per SAV rises significantly as fleet size reduces, growing from 164 miles in Scenario 1 to 212 miles in Scenario 2 and 279 miles in Scenario 3. The percentage of eVMT rises slightly across scenarios, from 25.6% in Scenario 1 to 27.5% in Scenario 2 and 28.9% in Scenario 3. Despite this, AVO per revenue mile and revenue minute, remains consistent across scenarios. AVO per revenue-mile ranges between 1.89 and 2.19 occupants per mile, while AVO per revenue-minute varies slightly from 1.91 to 2.23 occupants per minute. Profitability improves significantly as fleet size decreases. Revenue per SAV increases from \$322 in Scenario 1 to \$445 in Scenario 2 and \$649 in Scenario 3. Correspondingly, profit per SAV rises from \$156 to \$229 and ultimately to \$344 in the third fleet scenario, driven by improved vehicle usage, though at the cost of higher eVMT and longer wait times.

Table 1 Fleet Performance Metrics for the Bloomington City with Service Choices, DRS

	Scenario 1				Scenario 2				Scenario 3			
	4-seater (standard size)		6-seater (XL)		Standard		XL		Standard		XL	
	Economy	Lux	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux
SAV fleet size (25% population)	500 SAVs				375 SAVs				250 SAVs			
Population per SAV	79 Persons /SAV				105 Persons/SAV				158 Persons/SAV			
25% Fixed Demand (# Requests)	19,412 ride requests per day				19,540 rides				19,530 rides			
SAVs per service type (%)	408 SAVs	50	36	6	310	14	37	14	210	21	16	3
# Served rides	16,253 rides	491	686	0	12,381	577	459	0	8,985	464	325	0
Average wait time (min)	4.7 min	6.2	4.8	-	5.14	6.9	4.67	-	6.4	9.09	7.17	-
Average travel distance/SAV rider (miles)	4.4 miles	5.3	4.2	-	4.6	5.5	4.5	-	4.8	6.5	4.8	-
Average VMT/SAV (miles/day)	282 mi/day	112	135	-	282	131	132	-	299	218	169	-
% empty VMT	37% empty	28%	41%	-	37%	34%	41%	-	40%	34%	42%	-
SAV trips/SAV/d	39.8 trips	9.8	19.1	-	40.4	15.3	17.0	-	42.8	22.1	20.3	-
Average party size (SAV/d)	1.61 persons	1.55	1.6	-	1.61	1.58	1.63	-	1.60	1.59	1.62	-
Idle time/day (hour /SAV)	18 hours	18.9	17.8	-	15.5	20.3	19.9	-	14.5	17.1	18.4	-
AVO (per revenue-mile)	1.67 occupants per revenue-mile	1.55	1.6	-	1.77	1.58	1.63	-	1.69	1.59	1.62	-
AVO (per revenue-min)	1.66 occupants per revenue-min	1.54	1.59	-	1.75	1.58	1.63	-	1.68	1.61	1.61	-
Cost per SAV ($/SAV/day)	$198/SAV/day	397	348	120	311	335	259	259	330	516	313	120
Revenue per SAV ($/SAV/d)	$257/SAV/day	188	277	-	407	153	189	-	445	256	241	-
Profit per SAV ($/SAV/day)	$59/SAV/day	-209	-71	-	97	-182	-69	-	115	-260	-73	-

Figure 5 illustrates the economic performance of SAV fleets across three fleet sizes (500, 375, and 250 SAVs) under two operational scenarios: fleets with service choices (offering both economy, premium, and XL SAV services) and fleets without service choices (offering a single economy service). The metrics compared include cost and profit per SAV. Fleets with service choices experience higher costs, rising from $226 per SAV in Scenario 1 to $341 per SAV in Scenario 3. Despite this, profit per SAV remains low, increasing modestly from $22 in Scenario 1 to $70 in Scenario 3. In contrast, fleets without service choices showed superior financial performance. Costs per SAV remain relatively lower than those with service choices, rising from $166 in Scenario 1 to $305 in Scenario 3. Profit per SAV rises substantially from $156 in Scenario 1 to $344 in Scenario 3, indicating the financial advantage of single-service fleets and improved operational efficiency as fleet sizes shrink.

The operational inefficiencies of multi-service fleets are further evident in the eVMT values (see Figure 6). Fleets with service choices experience higher VMT per SAV as fleet sizes reduce, rising from 159 miles in Scenario 1 to 273 miles per SAV in Scenario 3. Similarly, eVMT per SAV increases significantly, from 55 miles in Scenario 1 to 109 miles in Scenario 3. In contrast, fleets without service choices show better operational efficiency. VMT per SAV increases more steadily, rising from 164 miles in Scenario 1 to 279 miles in Scenario 3, but remains relatively controlled compared to fleets with service choices. Similarly, eVMT per SAV is substantially lower than the scenario with service choices, increasing from 36 miles in Scenario 1 to 72 miles in Scenario 3.

Table 2 Fleet Performance Metrics for the Bloomington City without Service Choices-DRS

	Scenario 1	Scenario 2	Scenario 3
SAV type	Economy 4-Seater		
SAV fleet size (25% population)	500 SAVs	375 SAVs	250 SAVs
Population per SAV	80 People/SAV	80 People/SAV	120 People/SAV
25% Fixed Demand (Requests)	12,965 requests	12,972	12,998
# Served Requests	12,963 rides	12,956	11,241
Median peak-hour wait time (min)	4.2 min	4.5	5.3
Avg traveled distance per person per day (mi)	4.8 miles	5	5.7
Avg VMT per SAV (mi) per day	164 miles	212	279
% eVMT	25.6% empty	27.5%	28.9%
SAV trips/vehicle/day	26.04 trips	34.79	45.4
Idle time per day (hour /SAV/day)	16.8 hours	15.8	15.1
Avg party size	1.6 persons	1.6	1.5
AVO (per revenue-mile)	1.89 occupants/ revenue-mile	1.97	2.19
AVO (per revenue-min)	1.91 occupants/ revenue-min	1.99	2.23
Cost per SAV ($/SAV/day)	$166.3/SAV/day	$216.1	$304.6
Revenue per SAV ($/SAV/day)	$322.0/SAV/day	$444.6	$648.9
Profit per SAV ($/SAV/day)	$155.8/SAV/day	$228.5	$344.3

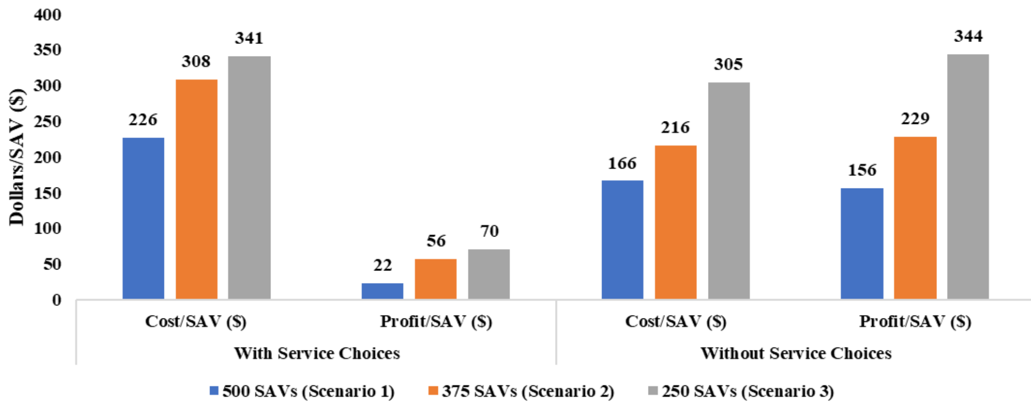


Figure 5 Comparison of Costs and Profits per SAV Across Fleet Sizes and Service Choices

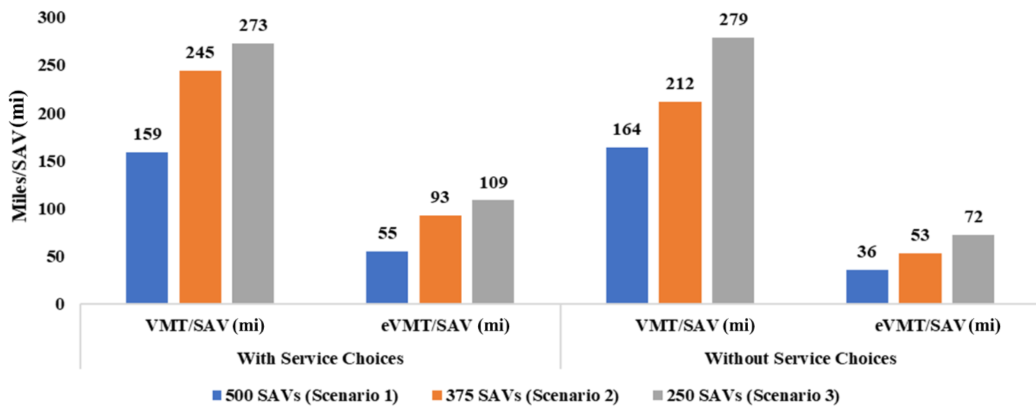


Figure 6 Comparison of VMT and eVMT per SAV Across Fleet Sizes and Service Choices

CONCLUSIONS

This research investigated the relative effects of providing various service options within a single SAV fleet. It applied a nested service-choice model to evaluate operational efficiency across three fleet sizes, assuming a centralized single-operator managing ride requests and vehicle repositioning. A comparison was conducted between two scenarios, one involving service offerings and the other without, using POLARIS, an agent-based simulator in Bloomington City. The temporal demand distribution showed that 4-seaters' demand peaks during the morning rush hours (6 AM to 9 AM) and maintained relatively high levels through the late morning and early afternoon. This demand gradually declined in the evening, mirroring typical commuter patterns. Economy 6-seaters showed moderate demand, peaking in the morning and maintaining steady levels throughout the day. In contrast, premium 4-seaters and 6-seaters showed consistently low demand, with premium 6-seaters showing negligible activity throughout the day due to their higher fares and limited market.

The fleet performance findings showed that offering multiple service types allows operators to cater to a broader customer base but also introduces operational challenges such as higher wait times, reduced profits, and increased eVMT. Across fleet sizes and types, multi-service fleets experienced a 47% increase in revenue per SAV, rising from $216 per SAV (with no services offered) to $318 per SAV (with services offered). However, this came at the cost of a 76% rise in operational cost per SAV, from $166 to $291 per SAV, while profit declined significantly from

$50 per SAV (with no services offered) to $27 per SAV (with services offered). Fleets with diverse service offerings showed an average increase of just 4% in VMT per SAV, rising from 206 miles per SAV (without service) to 213 miles per SAV (with service). However, empty VMT increased significantly, from 50 miles per SAV to 80 miles per SAV, representing a 60% increase when services are offered. 6-seater premium SAV services were significantly underutilized due to a lack of demand. Both economy XL and premium services incurred losses across all fleet sizes, primarily due to their higher operational costs and limited demand. In contrast, 4-seater economy SAVs consistently outperformed in financial metrics due to higher trip volumes and lower operational costs, benefiting from streamlined fleet management and reduced repositioning trips.

However, a key limitation of this study is its strict enforcement of exact matching between service types and seating capacities, which contributes to the inefficiencies associated with diverse fleets. Relaxing this constraint, allowing vehicles to serve across service types based on real-time demand, can significantly reduce eVMT and improve overall fleet usage. For instance, an XL SAV could serve a smaller group assigned to a 4-seater, or a premium SAV could fulfill an economy request during peak demand. Incorporating options that allow users to select vehicles with lower expected wait times or choose reduced fares in exchange for longer waits could enhance user experience. Expanding the financial modeling framework to include dynamic pricing strategies, subsidies, or incentives aligned with service and operational goals would provide deeper insights into the economic viability and policy implications of different SAV service configurations. Moreover, introducing competition and interactions with other transport modes would better position SAVs within the broader mobility network.

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AUTHOR CONTRIBUTIONS

The authors confirm the contribution to the paper as follows: Conceptualization, data curation, formal analysis, investigation and methodology: Priyanka, P.; Gurumurthy, K.M; and Kockelman, K.; Resources and Software: Gurumurthy, K.M, Jayashankar, N; and Priyanka, P.; Project administration and Supervision: Kockelman, K. and Gurumurthy, K.M; Visualization and Writing – original draft: Priyanka, P., Kockelman, K.; Writing – review & editing: Kockelman, K. and Gurumurthy, K.M; The authors confirm their respective contributions to this manuscript as outlined above. We acknowledge and thank Aditi Bhasker for her review and valuable feedback.

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