

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

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32 **ABSTRACT**

33 Most ride-hailing apps offer different vehicle sizes and quality. This paper investigates the  
34 impacts of such supply-size choices on the operations of a shared autonomous vehicle (SAV)  
35 fleet. A nested service-choice model was implemented across three fleet size scenarios using the  
36 POLARIS agent-based travel demand model in Bloomington City. The study compared fleet  
37 performance under two scenarios: one with diverse service offerings (standard 4-seaters and  
38 larger 6-seaters, in both economy and premium styles) and another with a single economy service.  
39 The demand for 4-seater economy services peaks during commute hours (6-9 AM), while  
40 premium services, especially 6-seater premium SAVs, show negligible demand due to their  
41 higher fares and niche market. Scenario comparisons across three fleet sizes indicate that  
42 offering diverse SAV services leads to greater operational inefficiencies compared to single-  
43 service fleets, including higher wait times, reduced profits, and a 13-percentage-point increase  
44 (from 24.2% to 37.4%) in empty vehicle-miles traveled (eVMT). Luxury and 6-seater SAVs  
45 struggled to achieve profitability due to low demand and higher operational costs. On average,  
46 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.

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

### 3 **BACKGROUND**

4 On-demand ride-hailing services (such as those provided by Uber, DiDi, Ola, and Lyft) are  
5 changing urban travel patterns by quickly connecting drivers with passengers (Wang et al., 2016;  
6 Chen et al., 2020; Ke et al., 2020; Zhou et al., 2022a and 2022b). Shared autonomous vehicle  
7 (SAV) fleets may enable more efficient and cost-effective forms of ride-hailing (Fagnant and  
8 Kockelman 2015; Golbabaei et al., 2021). Such services may reduce reliance on privately and  
9 publicly owned vehicles (Levin, 2017). Unlike traditional ride-hailing, SAV service eliminates the  
10 need for driver wages and tips and can operate 24/7 without breaks (Bosch et al., 2018; Huang and  
11 Kockelman, 2021). However, complex design and high manufacturing costs have delayed SAV  
12 fleet companies from providing citywide services and offering a range of vehicle/service options.  
13 Currently, Waymo is partnering with Uber for all-electric SAV services in San Francisco, Los  
14 Angeles, and Phoenix (with geofenced areas of 55, 79, and 315 sq miles, respectively (Waymo,  
15 2023; 2024a; 2024b and 2024c). Similarly, DiDi is expanding its operations in Shanghai and  
16 Guangzhou and plans to launch its robotaxi service, "Didi Neuron," by 2025 (Ye, 2023).

17 Today's SAV designs are not limited to modified 4-seater vehicles but include 6-seaters without  
18 steering wheels, similar to Amazon-owned Zoox, which is currently testing in many U.S. cities  
19 (Zoox, 2024a and 2024b). SAV services operate in major cities worldwide, including Seoul,  
20 Beijing, and Paris. In China, Baidu, Pony.ai, WeRide, and Didi are leading SAV deployments in  
21 Beijing, Wuhan, and Chongqing (PR Newswire, 2024). Hyundai has deployed RoboRide in  
22 Gangnam and Seoul (AutoVision News, 2023), while Mobileye has initiated operations in Paris  
23 and expanded its testing programs to include Miami and Stuttgart (Mobileye, 2021 and 2022).  
24 SAV fleet operators continue to expand vehicle and service types and seatings that are accessed  
25 through smartphone apps. Although there is a substantial body of literature focusing on standard-  
26 sized AV simulations that analyze the impacts of ride-sharing, pickup and dropoff stop locations  
27 (PUDOs), and optimized SAV repositioning (Farhan and Chen, 2018; Narayanan et al., 2020;  
28 Gurumurthy and Kockelman, 2022; Jing et al., 2020; De Souza et al., 2020; Martinez and Viegas,  
29 2017), less research has focused on the impacts of differentiated SAV services, such as economy  
30 versus premium options and standard (4-seater) versus larger (SUVs + 6 seaters) vehicles on fleet  
31 operations, wait times and profits.

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

1 thorough discussion of the simulation results. Finally, the paper concludes with a summary of the  
2 key findings and their implications.

### 3 **LITERATURE REVIEW**

4 Agent-based modeling (ABM) offers several advantages for simulating ride-hailing networks by  
5 representing passengers, drivers, and operators as autonomous agents with individual behaviors.  
6 It can capture the decentralized and real-time decision-making, such as dynamic matching and  
7 route selection, providing a detailed, micro-level view of the ride-hailing system (Čertický et al.,  
8 2014). ABM's flexibility enables it to simulate diverse scenarios, including various dispatching  
9 methods, fleet compositions, and demand patterns, allowing for a rigorous evaluation of  
10 operational strategies under changing conditions. Past studies have used agent-based simulation  
11 approaches to analyze the competitive ride-hailing market. For instance, Mo et al. (2021) used an  
12 agent-based simulation model (ABM) to explore the competition between SAVs and public transit  
13 (PT) in Singapore. The model assessed the effects of fare and service frequency on market shares.  
14 Results indicated that SAVs could capture up to 30% of the PT market share in low-density areas  
15 where PT services are less efficient. The simulation also showed that PT services concentrated  
16 more on shorter routes and peak hours, increasing efficiency. This study showed the potential for  
17 SAVs to complement PT by filling service gaps during off-peak times. Karamanis et al. (2020)  
18 also employed ABM and compared the effects of dynamic pricing on monopolistic and  
19 competitive SAV fleet scenarios in Greater London. Researchers found that dynamic pricing led  
20 to higher revenues than static pricing during non-peak hours in monopoly settings. In contrast,  
21 dynamic pricing was more effective during peak hours in competitive scenarios, due to the high  
22 waiting times that occurred during these periods. Their results also showed that dynamic pricing  
23 led to a higher percentage of shared trips compared to static pricing.

24 Guo et al. (2022) developed a comprehensive optimization framework for SAVs competing with  
25 human-driven private vehicles by integrating a binary logit demand model, whose utility depends  
26 on travel cost, time, vehicle availability, and parking capacity, with a time-space network-flow  
27 formulation that captures both passenger trips and empty-vehicle relocations. Their case study  
28 results on Singapore's BlueSG network showed that when demand is low, higher sensitivity boosts  
29 profit (by capturing more riders), but when demand is high, it can actually reduce profit by over-  
30 investing in service quality. Lowering the per-minute SAV fare attracts enough additional trips to  
31 offset the margin loss, while raising fares spurs even more relocations, sustaining high fulfillment  
32 rates. They also found that optimal fleet sizing balances utilization and service, resulting in roughly  
33 5-6 requests per vehicle during peak hours, which maintains over 80% fulfillment without  
34 excessive idle time. Inturri et al. (2019) used ABM to represent a demand-responsive shared  
35 transport (DRST) system, which is situated between traditional public transport and private car  
36 usage. The modeling framework, implemented in NetLogo, aims to evaluate and optimize various  
37 aspects of DRST, including fleet size, vehicle capacity, and vehicle dispatching. They established  
38 two main types of agents: passenger groups and vehicles. However, an important limitation of this  
39 study was its omission of a third critical agent, which is driver behavior. In real-world shared  
40 mobility systems, three types of agents actively shape system dynamics: passengers, drivers, and  
41 fleet operators or owners. The interaction between driver behaviors (positioning, acceptance  
42 strategies, and responsiveness) and fleet owner strategies plays a significant role in determining  
43 operational efficiency, user experience, and the system-level patterns.

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

15 A few studies have investigated the spatial and temporal variations in ride-hailing demand and  
16 fare. For instance, Huang et al. (2023) analyzed these variations across four platforms in NYC:  
17 Uber, Lyft, Juno, and Via. Their findings revealed that competition was most intense during  
18 weekday morning rush hours (6 to 8 AM) significantly higher compared to weekends. The study  
19 also found that increased competition lowers passenger costs and raises driver income, although  
20 excessive competition can reduce the profitability of ride-hailing platforms. However, this research  
21 did not differentiate between specific Uber services, such as UberX, UberXL, or premium  
22 alternatives. This limitation was addressed by Schwieterman (2019), who explored how service  
23 attributes of Lyft Line, UberPool, Lyft, and UberX influence user preferences when choosing  
24 between TNCs and public transit. Other studies have focused on the sociodemographic  
25 characteristics shaping preferences (Grahn et al., 2020; Gehrke et al., 2020; Young and Farber,  
26 2019). However, these studies did not consider the impact of service choice preferences on the  
27 broader transportation network.

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

42 This study pivots off Argonne National Laboratory's POLARIS code, which enables micro-  
43 simulation of SAV operations with and without DRS (Auld et al., 2016; Gurumurthy et al., 2020).  
44 POLARIS is an advanced, open-source, and agent-based modeling framework designed to

1 simulate multi-modal transportation systems at a mesoscopic level, with a separate agent for every  
2 member of the regional population. It integrates travel demand, network flow, and traffic  
3 assignment models, allowing travel decisions, such as activity planning and route choice, to be  
4 modeled simultaneously. The activity models, adapted from Auld and Mohammadian (2009 &  
5 2012), model each traveler's decision-making process across short-term and long-term timeframes,  
6 considering activity types, destinations, and preferred modes. The travel demand simulator can  
7 perform comprehensive simulations due to its integration of a population synthesizer that can  
8 iteratively adjust the agent population averages across various categories to align them with the  
9 regional cross-tables. The synthesizer enables the efficient scaling of simulated individual agents,  
10 while POLARIS is high-speed C++ code capable of simulating nearly all regions' populations with  
11 great efficiency. Using dynamic traffic assignment (Verbas et al., 2018), network traffic is  
12 balanced to achieve a dynamic user equilibrium. Unlike aggregate or analytical models, this ABM  
13 framework provides flexibility to accommodate heterogeneous agent behaviors, including users  
14 with diverse preferences for economy and premium service tiers and vehicles with varying seating  
15 capacities. This level of detail enables evaluation of how service differentiation, fare structures,  
16 and operational strategies jointly influence both user experience and system performance, insights  
17 that would not be accessible through traditional modeling approaches.

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

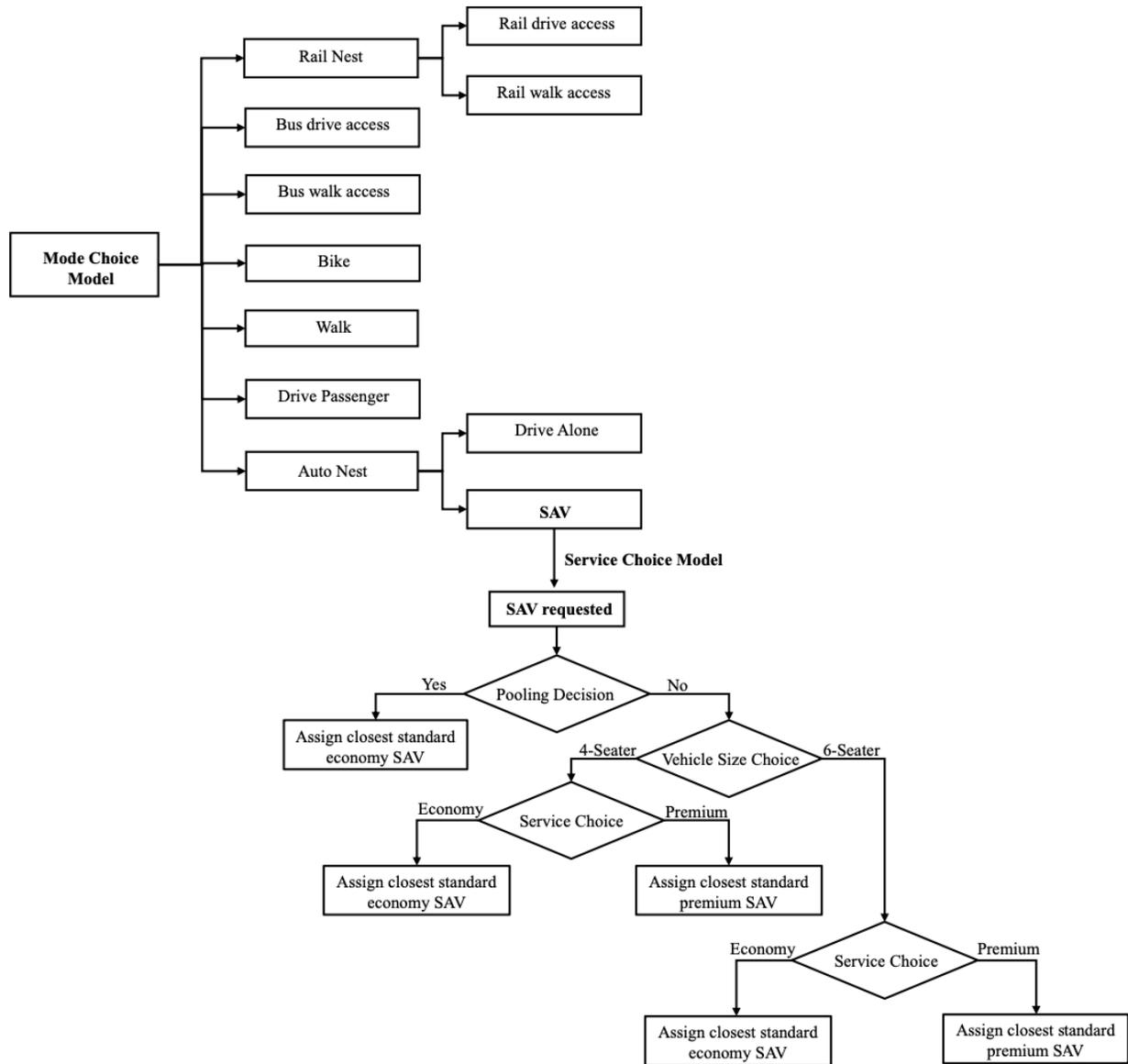


Figure 1 POLARIS Mode Choice Model with Added Service Choice Sub-Model

### 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

1 uses service-specific population shares of ride-hailing services from NYC’s high-volume for-hire  
2 vehicle (FHV) trips (TLC 2022 and 2023). It includes information on start and end times, origins  
3 and destinations marked by taxi zone ID, the vehicle license number, distance traveled, wait times  
4 for riders, whether the service was requested as a shared ride, and if so, whether a match occurred,  
5 the total fare, and any additional charges such as tolls, surcharge fees, and airport fees. The service  
6 type of each trip was identified by comparing the total fare paid by passengers with the fares  
7 calculated using Uber and Lyft fare structures (Lyft, 2024; Majaski, C., 2024) for the given  
8 duration and distance. The TLC data's population shares of different user services were later  
9 adjusted to align with the Bloomington region. Nesting coefficients were adjusted by running the  
10 model iteratively in Bloomington City to obtain the target service shares.

11 Previous studies investigating changes in the value of travel time (VOTT) for SAVs compared to  
12 TNCs have consistently proposed a reduction in VOTT (Chen and Kockelman, 2016; Perrine et  
13 al., 2018; Huang et al., 2020). Perrine et al. (2020) analyzed long-distance U.S. travel, assuming  
14 autonomous vehicle (AV) operating costs of \$0.10–\$1.65 per mile and VOTT values of \$3.00–  
15 \$9.00 per hour, with a base case of \$0.20 per mile and \$6.00 per hour across all scenarios in the  
16 study. Chen and Kockelman (2016) assumed the value of travel time (VOTT) for shared  
17 autonomous electric vehicles (SAEVs) to be 35% of standard human-driven private vehicles to  
18 reflect the lesser engagement required from passengers, who can instead use travel time for other  
19 productive or leisure pursuits. Similarly, Huang et al. (2020) suggested a reduction in VOTT of  
20 30%, from \$15.83 per hour for human-driven vehicles (HVs) to \$11.08 per hour for SAVs,  
21 acknowledging the lower perceived travel costs associated with SAVs. In line with these findings,  
22 this study assumes a VOTT of \$9.38 per hour for pooled economy SAV services and applies a  
23 further 30% reduction for exclusive (non-pooled) services to reflect the increased privacy and time  
24 savings associated with avoiding ride-sharing. Building on past research (Chen and Kockelman,  
25 2016; Huang et al., 2020), which proposes a significant influence of service quality travel time  
26 costs’ perceptions, this study further differentiates between service levels by assuming a 50%  
27 reduction in VOTT for premium SAV services compared to economy SAVs, accounting for the  
28 enhanced user experience offered by these luxury services.

## 29 **CASE STUDY REGION**

30 The region under consideration for this study is Bloomington, located in Illinois, USA. The  
31 network consists of 185 zones, 2500 nodes, and 7000 links. It is a compact geographical area  
32 spanning nearly 74 square-miles and serving as the residence for an estimated population of  
33 120,000 individuals (de Souza et al., 2020; Gurumurthy and Dean 2020; Gurumurthy and  
34 Kockelman 2020; Gurumurthy et al., 2020). The study initially synthesized 100% of the population  
35 to generate full demand (96,402 ride requests) for 24 hours in the Bloomington region. The demand  
36 distribution (see Figure 2) illustrates the number of ride requests across different service and  
37 seating types over a 24-hour simulation period. Economy 4-seaters’ demand peaks during the  
38 morning rush hours (6 AM to 9 AM) at approximately 4,500 requests and maintains relatively high  
39 levels through the late morning and early afternoon. The demand gradually declines in the evening,  
40 mirroring typical commuter patterns. Economy 6-seaters show moderate demand, peaking around  
41 1,000 requests in the morning and maintaining steady levels throughout the day. In contrast,  
42 premium 4-seaters and 6-seaters show consistently low demand, with premium 4-seaters peaking  
43 at approximately 200 requests and premium 6-seaters barely exceeding 100 requests throughout  
44 the day. Such low demand is due to their higher fares and niche market.

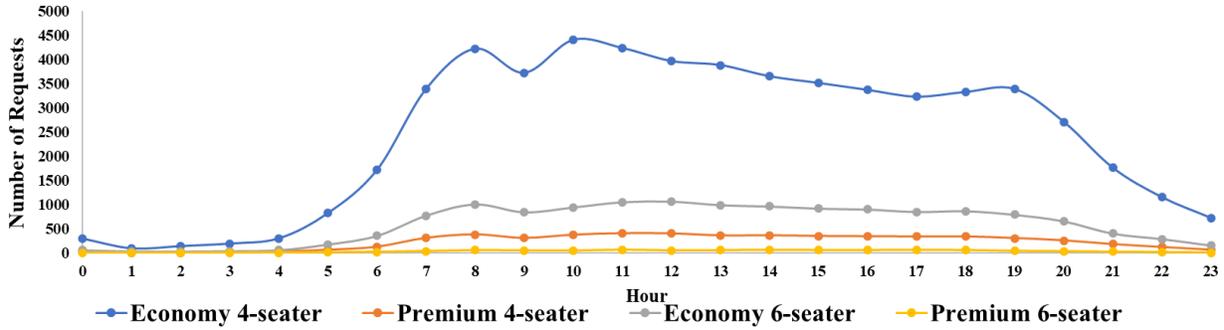


Figure 2 Endogenous Demand Distribution by Service and Seating Type Across the Day

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.

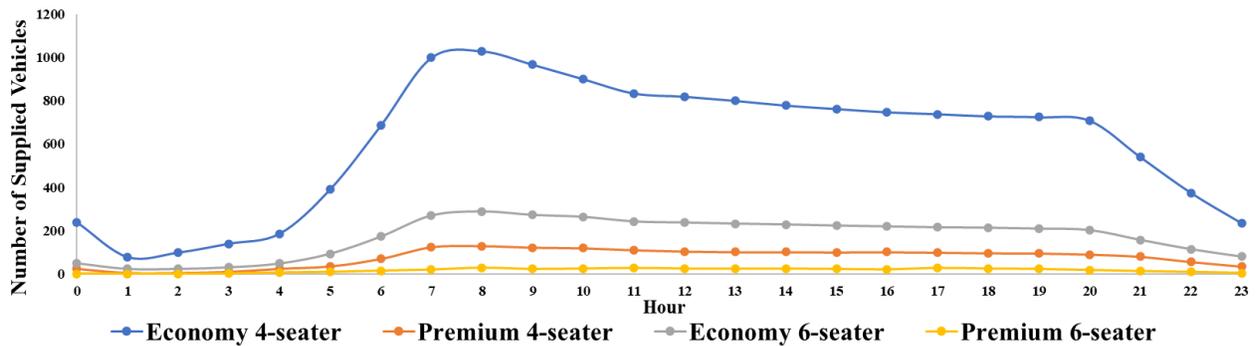
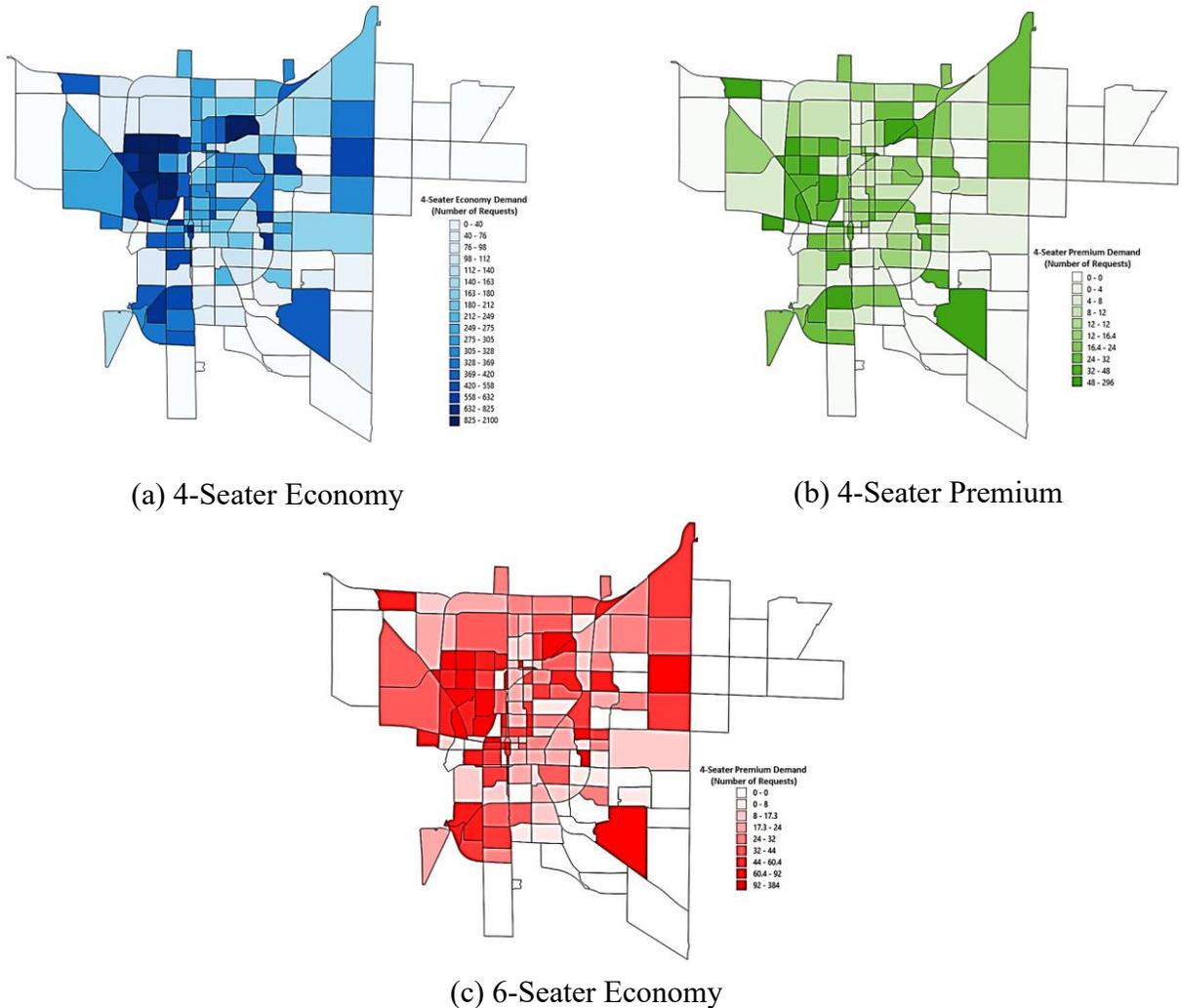


Figure 3 Hourly Supply of SAVs by Service and Seating Type



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

1  
2

3 The VOTT and fares for SAVs were tailored to reflect a range of service levels and pricing  
 4 structures similar to those of Uber and Lyft in U.S. cities (Lyft, 2024; Majaski, C., 2024). Economy  
 5 4-seater (standard) SAV fares were assumed with a base fare of \$2 plus \$1.00 per mile and \$0.25  
 6 per minute. A typical (4-seater standard) SAV's ownership cost was assumed to be \$40 per day,  
 7 plus another \$1.00 per mile (Loeb and Kockelman, 2018; Bösch et al., 2018; Arbib and Seba,  
 8 2017). For economy XL SAVs, a higher cost structure was applied, with \$60 per day and \$1.50  
 9 per mile, with fares priced 50% higher than those for economy SAVs (Lyft, 2024). Premium  
 10 (luxury) SAVs, intended for a more upscale service level, were assumed to incur twice the  
 11 operating costs and fares of economy SAVs. Ride-sharing fares were reduced by 40% to encourage  
 12 pooling (Gurumurthy et al., 2019), but DRS is allowed/assumed only in the 4-seater economy  
 13 service type. The 100% endogenous demand was then reduced to 25% of the total to compare SAV  
 14 operations across different fleet sizes, with and without service offerings. A fixed party size  
 15 distribution adopted by Huang et al. (2024) was applied to this fixed demand. It assumes that 65%  
 16 of trips involve solo riders, 25% involve two-person parties, and 10% include three or more parties.  
 17 Three different fleet sizes of SAVs were tested with the DRS (pooling) option.

## 1 **RESULTS**

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

19 Revenue per SAV values indicate a better financial viability of economy services than luxury  
20 options. In Scenario 1, 4-seater economy SAVs generated \$257 per SAV, more than triple the  
21 revenue of luxury SAVs (approximately \$188 per SAV). Similarly, 6-seater economy SAVs  
22 earned \$277 per SAV, outperforming luxury services. In Scenario 3 (250 people per SAV), the  
23 revenue for 4-seater economy SAVs increased to \$445 per SAV, while luxury services showed  
24 slight improvement but still lagged at \$256 per SAV due to lower demand. Profit per SAV values  
25 further showed the economic advantage of economy SAVs over luxury services. In Scenario 1, 4-  
26 seater economy SAVs achieved a profit of \$59 per SAV, whereas luxury services operate at a loss  
27 of - \$209 per SAV. For 6-seater economy SAVs, the profit is modest at \$69 per SAV. In Scenario  
28 2, as fleet sizes shrink, profitability for 4-seater economy SAVs remains at \$115 per SAV, while  
29 luxury services improve marginally but remain uncompetitive, with a profit of only - \$260 per  
30 SAV in the smallest fleet.

31 Table 2 presents fleet performance metrics when riders were presented with just single standard  
32 service, with the choice of dynamic ride-pooling across three fleet sizes: 500 SAVs (Scenario 1),  
33 375 SAVs (Scenario 2), and 250 SAVs (Scenario 3). The results indicate that median peak-hour  
34 wait times increase as fleet size reduces, rising from 4.2 minutes in Scenario 1 to 4.5 minutes in  
35 Scenario 2 and further to 5.3 minutes in Scenario 3, reflecting the reduced availability of SAVs to  
36 meet demand. Average VMT per SAV rises significantly as fleet size reduces, growing from 164  
37 miles in Scenario 1 to 212 miles in Scenario 2 and 279 miles in Scenario 3. The percentage of  
38 eVMT rises slightly across scenarios, from 25.6% in Scenario 1 to 27.5% in Scenario 2 and 28.9%  
39 in Scenario 3. Despite this, AVO per revenue mile and revenue minute, remains consistent across  
40 scenarios. AVO per revenue-mile ranges between 1.89 and 2.19 occupants per mile, while AVO  
41 per revenue-minute varies slightly from 1.91 to 2.23 occupants per minute. Profitability improves  
42 significantly as fleet size decreases. Revenue per SAV increases from \$322 in Scenario 1 to \$445  
43 in Scenario 2 and \$649 in Scenario 3. Correspondingly, profit per SAV rises from \$156 to \$229  
44 and ultimately to \$344 in the third fleet scenario, driven by improved vehicle usage, though at the  
45 cost of higher eVMT and longer wait times.

1

**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  | -   |

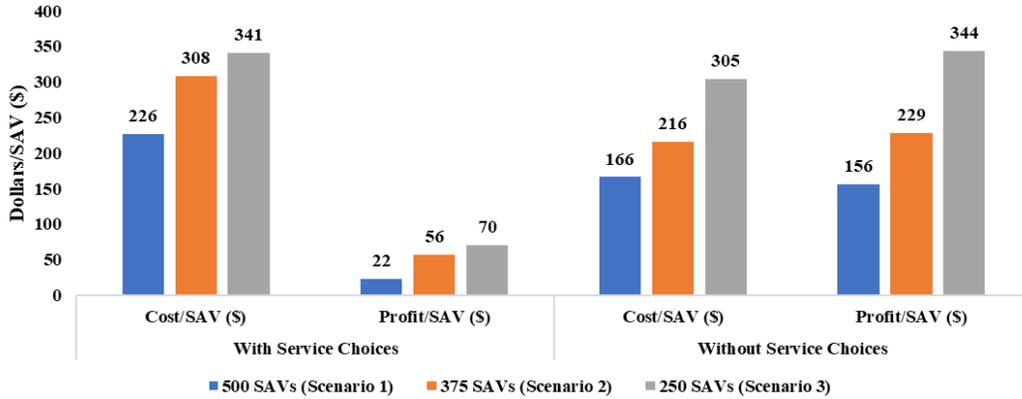
2

1 Figure 5 illustrates the economic performance of SAV fleets across three fleet sizes (500, 375, and  
 2 250 SAVs) under two operational scenarios: fleets with service choices (offering both economy,  
 3 premium, and XL SAV services) and fleets without service choices (offering a single economy  
 4 service). The metrics compared include cost and profit per SAV. Fleets with service choices  
 5 experience higher costs, rising from \$226 per SAV in Scenario 1 to \$341 per SAV in Scenario 3.  
 6 Despite this, profit per SAV remains low, increasing modestly from \$22 in Scenario 1 to \$70 in  
 7 Scenario 3. In contrast, fleets without service choices showed superior financial performance.  
 8 Costs per SAV remain relatively lower than those with service choices, rising from \$166 in  
 9 Scenario 1 to \$305 in Scenario 3. Profit per SAV rises substantially from \$156 in Scenario 1 to  
 10 \$344 in Scenario 3, indicating the financial advantage of single-service fleets and improved  
 11 operational efficiency as fleet sizes shrink.

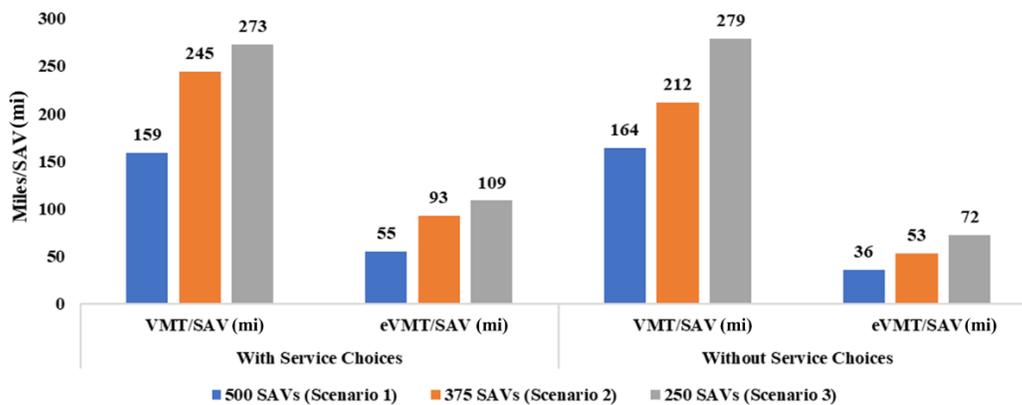
12 The operational inefficiencies of multi-service fleets are further evident in the eVMT values (see  
 13 Figure 6). Fleets with service choices experience higher VMT per SAV as fleet sizes reduce, rising  
 14 from 159 miles in Scenario 1 to 273 miles per SAV in Scenario 3. Similarly, eVMT per SAV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

20 **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        |



1  
2 **Figure 5 Comparison of Costs and Profits per SAV Across Fleet Sizes and Service Choices**



3  
4 **Figure 6 Comparison of VMT and eVMT per SAV Across Fleet Sizes and Service Choices**

5 **CONCLUSIONS**

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

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

1 \$50 per SAV (with no services offered) to \$27 per SAV (with services offered). Fleets with diverse  
2 service offerings showed an average increase of just 4% in VMT per SAV, rising from 206 miles  
3 per SAV (without service) to 213 miles per SAV (with service). However, empty VMT increased  
4 significantly, from 50 miles per SAV to 80 miles per SAV, representing a 60% increase when  
5 services are offered. 6-seater premium SAV services were significantly underutilized due to a lack  
6 of demand. Both economy XL and premium services incurred losses across all fleet sizes,  
7 primarily due to their higher operational costs and limited demand. In contrast, 4-seater economy  
8 SAVs consistently outperformed in financial metrics due to higher trip volumes and lower  
9 operational costs, benefiting from streamlined fleet management and reduced repositioning trips.

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

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## 30 **AUTHOR CONTRIBUTIONS**

31 The authors confirm the contribution to the paper as follows: Conceptualization, data curation,  
32 formal analysis, investigation and methodology: Priyanka, P.; Gurumurthy, K.M; and Kockelman,  
33 K.; Resources and Software: Gurumurthy, K.M, Jayashankar, N; and Priyanka, P.; Project  
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