SAV Fleet Operations with Multiple Service Types: Comparative Analysis of SAV Size, Service Types, and Ride Preferences

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ABSTRACT

Against the backdrop of increasing shared autonomous vehicle (SAV) penetration in the ride-sharing and sourcing markets, this research seeks to address the knowledge gap regarding the impact of users' behavior to pay for various SAV services (provided within the framework of a single shared autonomous fleet operator) on the transportation network. These service choices range from luxury cars and large vehicles to smaller, more economical options, as well as the potential for carpooling with other passengers. A nested service choice model was employed and simulations with different fleet sizes were conducted in the Bloomington region, Illinois, Chicago using the POLARIS software. The comparative analysis of scenarios with and without service options reveals that scenarios with a service choice model resulted in increased daily vehicle miles traveled (VMT) per SAV by 18.4%, empty VMT by 55%, and simultaneously generate 54% more profit. The implementation of dynamic ride-sharing (DRS) led to a significant rise in the average daily profit, increasing from $170 per SAV (without DRS) to $206 per SAV. Results show a clear preference for standard economy services during peak commute hours (8:00 to 9:00 a.m., and 5:00 to 6:00 p.m.) as individuals prioritized time over the quality of service for work trips, whereas demand for luxury services displays minimal fluctuations over the day.

Keywords: Shared autonomous vehicles, demand management, transportation network companies (TNC), Agent-based modeling

BACKGROUND

The rising tide of on-demand ride-sourcing to connect riders and drivers via smartphone applications and sophisticated routing algorithms has had a ripple effect on urban transport systems. As of now, Uber (1) is operating in 900 cities, and Lyft (2) has 29% of the US market share. The inclusion of autonomous vehicles (AVs) in today's transportation network companies (TNCs) by amalgamating car-sharing (e.g., Zipcar, car2go) and ride-sharing (Uber, Lyft) into a unified service of shared autonomous vehicles (SAVs) (3) could provide a more cost-effective transportation option by means of subsidies and potentially supplant a substantial portion of privately and publicly owned-conventional vehicles (4). Waymo and Cruise have already initiated a self-driving taxi service utilizing autonomous technology in different US cities (5; 6), and several other companies, including Baidu, Aurora, and Zoox are also operating in this field. Uber has recently announced a strategic collaboration with Waymo, aiming to incorporate autonomous driving technology into Uber's extensive ride-sharing and delivery networks (7). Existing TNCs like Uber and Lyft provide customers with choices between standard-sized economy vehicles (Like UberX and Lyftline) and premium vehicles (like LyftLux and Uber Black), as well as extra-seating (XL) options. In contrast, Cruise has faced challenges in developing and producing autonomous vehicles (AVs), resulting in their reliance on standard makes such as Chevy Bolt electric vehicles (8). The intricate nature of AV design and manufacturing has contributed to the limitations of using standard-sized autonomous vehicles. Consequently, companies that possess SAV fleets face limitations in their ability to provide a diverse array of services to their customers. Currently, Cruise possesses a six-passenger, all-electric vehicle named "Origin" that is prepared for production, and is now awaiting approval from the United States National Highway Traffic Safety Administration (NHTSA) to proceed (9). Waymo's (10) fleet offers the world's first premium electric autonomous service with the Jaguar I-PACE vehicle type. Hence, it is merely a question of time until these SAV fleet operators undergo further expansion, thereby presenting their users with a range of choices encompassing standard SAVs (existing service), luxury SAVs, and large vehicle SAVs, all accessible through a single smartphone app.

Although there exists a substantial body of literature focusing on standard-sized AV simulations aiming to analyze the impacts of ride-sharing, the provision of PUDOs, and optimized SAV repositioning (11; 12; 13; 14; 15; 16), there is a little of research specifically examining the impacts of various SAV service options, such as the choice between economy and premium offerings or the provision of standard (4-seater) versus large/ XL (5+ seater) vehicles on the traffic network. This limitation in research is primarily attributed to the scarcity of data, which is a consequence of the fact that these scenarios are still anticipated to occur in the future. Therefore, in order to analyze individuals' behavior towards the services provided, this study relies on the existing literature on service choice modeling in the context of human-driven ride-hailing services. There exists some literature that compares services offered by Uber over conventional taxis such as Paronda et al. (17) who analyzed the operations of Uber and GrabCar in the Philippines and observed that Uber provided a service with enhanced speed, affordability, and superior quality when compared to traditional taxi services. Nevertheless, the research failed to consider distinct Uber services such as UberX, UberXL, or premium alternatives. Schwieterman (18) conducted a study that investigated the influence of service attributes, specifically Lyft Line, UberPool, Lyft, and UberX, on user preferences when choosing between transportation network companies (TNCs) and public transit. Several studies have been conducted to examine the sociodemographic characteristics of users of TNCs (19; 20; 21). Yet, the prior research failed to examine the effects of users' service preferences on the wider transportation system.

There exist a multitude of extensive datasets that shed light on the level of demand for rideshare services offered by companies such as Uber and Lyft. A prominent dataset, which can be accessed through the official website of the New York City Government, provides comprehensive records of yellow and green taxi trips (22). The dataset encompasses detailed information regarding the timing and locations of pick-up and drop-off, distances traveled during the trip, breakdown of fares as per service type, the range of payment methods available, and passenger numbers as reported by the drivers. In addition, the Massachusetts Government's official website provides access to valuable rideshare data pertaining to the Boston region (23). Since 2017, the Department of Public Utilities (DPU) has consistently released annual reports containing data on rideshare services. In 2021, TNCs, also known as rideshare enterprises, were responsible for approximately 39.7 million rides in Massachusetts. Furthermore, the City of Chicago provides access to a dataset specifically centered on the Chicago area via its official data portal (24). Several studies have employed the previously mentioned datasets to analyze dynamic ride-sharing behavior and competitive dynamics among TNC companies and to predict their pick-up and drop-off locations (25; 26; 27; 28).

Despite the existence of diverse services, such as UberPool, UberXL, LyftLux, and LyftPlus, offered by TNCs like Uber and Lyft, there is a shortfall of academic research pertaining to the public's perception of these services with respect to fare rates and waiting durations. Furthermore, little in the way of research exists regarding the effects of these services on the transportation network (such as VMT and average trip-length changes within the network), the operations of Transportation TNC fleets, and the wider transportation network. This study aims to conduct a pioneering analysis that simulates the effects of users' SAV service choices aiming to lead SAV-owned companies to develop strategies for determining optimal fares and SAV fleet sizes while maintaining acceptable levels of empty vehicle miles traveled (empty VMT) and operational costs. The remainder of the paper is arranged as follows: we commence with an explanation of simulations in POLARIS, followed by a comprehensive description of the dataset and case study region chosen for the analysis. Subsequently, we present a detailed account of the service choice implemented along with different scenarios that were simulated. The penultimate section discusses the results derived from these scenarios, and the paper concludes with a summary of the findings and implications thereof.

MODELLING IN POLARIS

This study leverages the Polaris software, developed by Argonne National Laboratory, that facilitates the micro-simulation of SAV operations with and without DRS (29; 30). The travel demand simulator is capable of performing comprehensive simulations, thanks to its integration of a population synthesizer that can iteratively adjust the agent population averages across various categories in order to align them with the regional cross-tables. The synthetic population is subjected to a series of activity models that enable the generation, scheduling, and allocation of hours for each individual. The synthesizer enables the efficient scaling of simulated individual agents, while POLARIS is a resilient C++ framework capable of simulating nearly all regional populations with great efficiency. Utilizing dynamic traffic assignment (31), network traffic is balanced to achieve a dynamic user equilibrium.

DATA SETS USED AND CASE STUDY REGION

The region under consideration for this study is Bloomington, located in the state of Illinois, United States of America. 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 around 120,000 individuals. For SAV simulations, it is proposed that economy fares commence at a base fare of \$2, accompanied by supplementary charges of 90 cents per mile traveled and 25 cents per minute. The projected operational costs for a typical SAV were hypothesized to amount to \$10 per day per SAV, along with an additional charge of 30 cents per mile. In contrast, XL vehicles were anticipated to incur a cost of \$25 per day per SAV, in addition to an extra fee of 40 cents per mile. Luxury vehicles are priced 50 percent more than the number of economy service vehicles, whereas the ride-sharing provisions were specifically devised to decrease the total fare by 40% to promote pooling (32). This study employs high volume for-hire vehicle (FHV) trip data from New York City to develop a model for individual service choice. The dataset consists of 693,072 rides provided by Uber, Lyft, and traditional taxi services (22). The extensive dataset encompasses detailed information regarding the type of service selected (such as Lyft Line, Lyft Premier, Lyft Lux SUV, UberXL, UberX, UberPool, etc.), the amount paid for the service, the starting and ending locations, the distance traveled, and the prevailing weather conditions during each individual trip.

SERVICE CHOICE MODEL

The nested model choice model implemented in Polaris (30) posits that individuals who opt for TNCs instead of alternative modes will exclusively use SAVs. This study expands upon the existing mode choice model by incorporating a service choice model that assumes a complete monopoly in the market, where all the SAV services are provided by a single operator. The operator is responsible for the centralized assignment and monitoring of requests and may reposition resources as necessary in response to changes in the demand-supply ratio. The SAV operator carries out repositioning tasks, while also 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 incorporates a heuristic approach to effectively handle travel delays encountered at various points during the trip, as discussed in the study done by Gurumurthy and Kockelman (13). Upon an SAV trip request, the operator assigns it to the nearest vehicle to lower the total empty VMT and decrease wait times using a zone-based structure. POLARIS sorts pool of people who selects an SAV as their preferred mode of transportation (after the nested mode choice model is implemented), and subsequently provides the spectrum of services that are nested within a single operator platform. When individual prefers a pooled service, a standard economy vehicle (4-seater) is assigned, drawing inspiration from Uber and Lyft operations for pooled rides. However, if a passenger prefers not to share their ride with unknown co-passengers, they have the option to select from either a standard (4-seater) or an XL (6-seater) vehicle, based on their party size, as shown in Figure 1 Mode choice model with integrated service choice. Following this selection, the service choice comes into play. Given the choice of vehicle type, the passenger is then presented with two service options: economy and premium. It is assumed that the passenger's service choice is primarily influenced by fare and in-vehicle travel time.

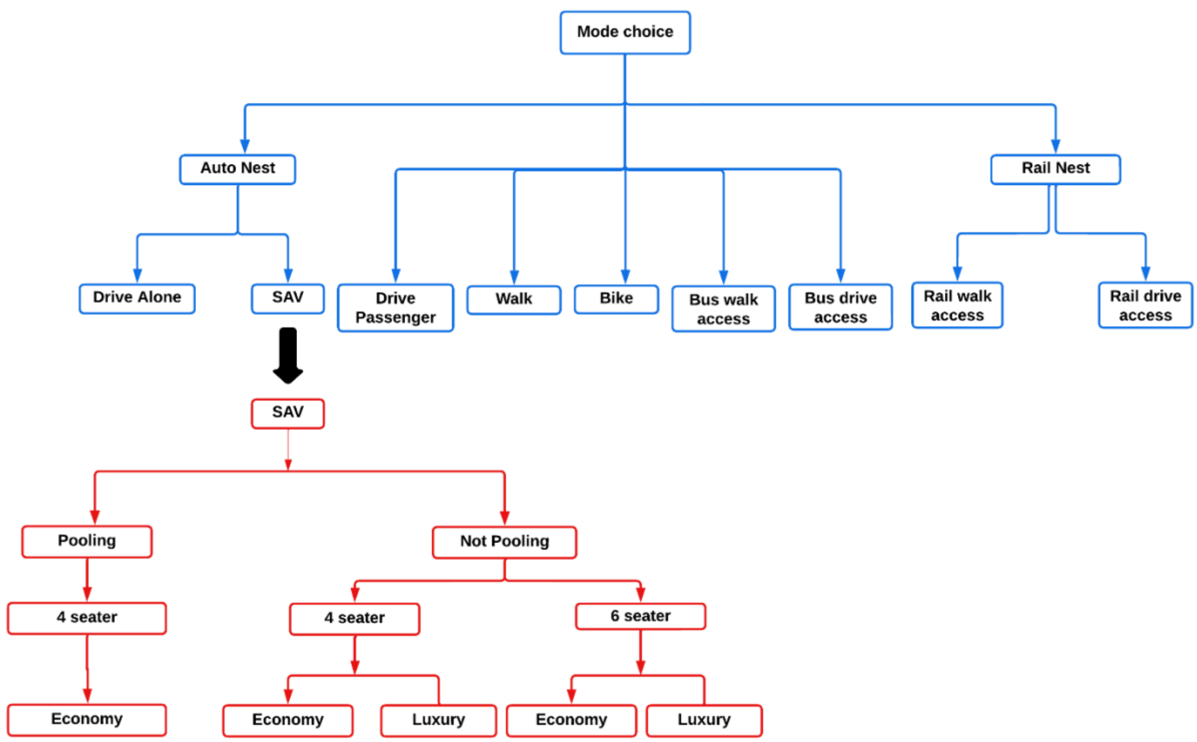

Figure 1 Mode choice model with integrated service choice

RESULTS

The nested logit model explained above was tested in the Bloomington region of Illinois, Chicago. The service choice parameters are tuned to current travel trends that yielded around 20,579 trip requests in a 24-hour simulation period when 25% of the population was synthesized. Three different fleet sizes of SAVs were tested with and without dynamic ride-sharing. In all cases, the highest waiting time is established at 15 minutes. This signifies that the maximum duration for an SAV to arrive for pickup is estimated to be 15 minutes prior to the commencement of the pickup trip. The travel time may increase if there are changes in traffic conditions. It was posited that the fare for an SAV varies solely based on service type, implying that a 6-seater vehicle would have the same pricing as a 4-seater vehicle. Furthermore, in the process of matching the trip request from the demand side to the supply side by the operator, if a service type requested is not available within a 15-minute range, then the vehicle is not assigned. In order to conduct a comparative analysis of three scenarios (with different fleets), the initial step involved simulating traffic to establish demand within the Bloomington region. Subsequently, the demand was fixed at 25% of the total to compare SAV operations across various fleet sizes, both with and without the inclusion of a dynamic ride-sharing option. On the supply side, the distribution of vehicles was such that the fleet operator allocated 75% of its vehicles for economy requests, while the remaining 25% were designated for premium services. In relation to the distribution of vehicle types, it can be observed that 88% of the fleet consists of 4-seaters, while the remaining portion comprises 6-seaters. The prevalence of standard 4-seater vehicles can be attributed to their high demand, driven by their comparatively lower cost. Additionally, a significant proportion of trip requests, approximately 60%, involve solo drivers, while nearly 15% of these requests explicitly express a willingness to share rides. Therefore, there was a higher demand for 4-seater economy vehicles in comparison to other types of service vehicles.

The scenario results where people were offered dynamic ride sharing (Table 1) indicate that individuals opting for economy vehicles tend to travel longer distances on average compared to those choosing premium vehicles. Nonetheless, no discernible disparity in the mean trip distance covered by an individual is observed between a standard and an XL, as both options have the same fares when opting for the economy service. It seems likely that the implementation of dynamic ride-sharing will lead to an increase in both the total distance covered and the number of unoccupied vehicles operated by SAVs within the network. This can be attributed to the increased circulation of these vehicles, as they will need to traverse longer distances to accommodate passengers of diverse origins who have opted for ride pooling.

Table 2 Fleet performance metrics for the Bloomington region with service choices, NO DRS contains scenario results where the service choice did not offer dynamic ride-sharing. Results indicate that the average vehicle miles traveled (VMT) by standard vehicles with economy service increased by an average of 6% across all scenarios as compared to a strategy where ride pooling was allowed.

As anticipated, there exists an inverse relationship between vehicle utilization and idle time. As the size of the fleet increases, the average number of trips served per vehicle decreases. In contrast, the expansion of the SAV fleet resulted in a reduction in the mean duration of users' waiting periods. In particular, the mean duration of waiting time experienced by individuals does not vary much with DRS strategy (3.8 min), and without the DRS strategy (3.9 min) in the stimulation. This is primarily due to the fact that our simulation represents a quarter of the total population, with approximately 15% of individuals opting for the pooling option. There is a limited amount of data available to analyze the impact of pooling on waiting times compared to events where pooling is not offered. The idle time that exceeds 15 hours can also be attributed to the difficulties encountered in aligning particular service types with their corresponding requests, as the positioning of vehicles plays a substantial role in this regard. In the event that a customer expresses a preference for a premium vehicle as opposed to an economy vehicle, and if the premium vehicle cannot be provided within a 15-minute waiting period, the trip will not commence.

Table 1 Fleet performance metrics for the Bloomington region with service choices, DRS

	Scenario 1				Scenario 2				Scenario 3			
	Standard		XL		Standard		XL		Standard		XL	
	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux
SAV fleet size (100% population)	2200				2000				1800			
Population per SAVs	54				60				66			
SAVs per service type (%)	33	13	39	15	35	14	37	14	35	14	39	12
Demand (100% population)	37,312 trips	9,308	29,080	6,616	37,356	9,580	28,720	6,660	37,620	9,288	28,900	6,504
Avg wait time (min)	3.9 min	3.9	3.4	3.8	4.1	3.9	3.5	3.7	4.2	3.8	3.7	3.6
Avg traveled distance per person (mi)	4.05 mile	3.36	3.95	3.58	4.07	3.37	3.95	3.55	4.08	3.33	3.90	3.58
Avg VMT per SAV (mi)	286.6 mile	178.6	185.2	117.6	297.3	180.5	215.6	139.0	345.6	194.6	234.2	159.2
% eVMT	30	37	29	35	31	35	29	35	32	36	31	35
SAV trips/vehicle/day	51.54 trips	33.72	33.50	19.93	52.76	34.71	38.81	24.13	59.53	37.45	41.52	29.04
Avg party size	1.61 occupants	1.60	1.60	1.58	1.58	1.59	1.59	1.59	1.60	1.57	1.57	1.57
Idle time per day (hour /vehicle)	15.26 hours	18.49	18.37	20.41	14.95	18.45	17.45	19.76	13.45	18.00	16.85	19.10
AVO (per revenue-mile)	1.67 occupants per revenue-mile	1.60	1.61	1.57	1.64	1.60	1.58	1.58	1.65	1.58	1.56	1.56

Table 2 Fleet performance metrics for the Bloomington region with service choices, NO DRS

	Scenario 1				Scenario 2				Scenario 3			
	Standard		XL		Standard		Standard		XL		Standard	
	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Eco	Lux	Eco
SAV fleet size (100% population)	2200				2000				1800			
Population per SAVs	54				60				66			
SAVs per service type (%)	33	13	39	15	35	14	37	14	35	14	39	12
Demand (100% population)	36,036 trips	9,712	29,536	7,032	35,296	9,808	30,400	6,812	35,520	10,008	29,904	6,884
Avg wait time (min)	3.6 min	3.7	3.6	3.7	3.7	3.9	3.8	3.7	3.9	3.6	3.7	3.6
Avg traveled distance per person (mi)	3.8 mile	3.4	4.0	3.5	3.8	3.4	3.9	3.6	3.9	3.4	3.9	3.4
Avg VMT per SAV (mi)	276.3 mile	185.0	191.9	124.1	306.3	227.1	254.8	154.0	293.3	180.3	221.9	135.6
% eVMT	31	36	30	33	32	37	31	34	32	35	30	35
SAV trips/vehicle/day	49.8 trips	35.2	34.0	21.2	54.5	42.3	44.7	28.4	51.6	34.8	39.3	26.1
Avg party size	1.58 occupants	1.58	1.60	1.57	1.58	1.59	1.59	1.58	1.59	1.55	1.59	1.60
Idle time per day (hour/vehicle)	15.6 hours	18.3	18.2	20.2	14.7	17.0	16.2	19.3	15.1	18.4	17.3	19.9
AVO (per revenue-mile)	1.57 occupants per revenue-mile	1.58	1.60	1.56	1.58	1.58	1.58	1.58	1.59	1.55	1.58	1.59

Table 3 Fleet performance metrics for the Bloomington region without service choices

	DRS			NO DRS		
	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
SAV fleet size (100% population)	2,200	2,000	1,800	2,200	2,000	1,800
Population per SAVs	54	60	66	54	60	66
Demand (100% population)	82,320 trips	82,320	82,320	82,280	82,284	82,276
Avg wait time (min)	3.19 min	3.25	3.29	3.15	3.16	3.19
Avg traveled distance per person (mi)	4.48 mile	4.47	4.54	4.33	4.34	4.36
Avg VMT per SAV (mi)	173.7 mile	191.3	213.8	177.5	195.9	218.4
% eVMT	23	23	24	25	25	25
SAV trips/vehicle/day	37.42 trips	41.16	45.73	37.40	41.14	45.71
Avg party size	1.59 occupants	1.59	1.59	1.59	1.59	1.59
Idle time per day (hour/vehicle)	18.68 hours	18.12	17.45	18.55	17.99	17.31
AVO (per revenue-mile)	1.96 occupants per revenue-mile	1.96	1.99	1.88	1.89	1.90

In general, the profitability of SAVs decreases with 6-seater vehicles, including both economy and premium options, offering fares equivalent to those of standard-sized SAVs as shown in Table 4 Fleet Costs and revenue metrics for the Bloomington region with service choices, DRS**.** This is due to the higher operational and purchase costs associated with the 6-seater vehicles. The decrease in fleet size (from 2200 to 1800) resulted in an increase in the average daily profit per SAV by 21.2% across all the services ($170/SAV/day to $206/SAV/day) with DRS**.** When performing a comparison of the average daily profit per SAV across all scenarios and services, it is observed that the model with DRS (shown in Table 4 Fleet Costs and revenue metrics for the Bloomington region with service choices, DRS and Table 5 Fleet costs and revenue metrics for the Bloomington region with service choices, NO DRS) yields higher profit than the model using DRS. To analyze the financial viability of offering specialized services as opposed to offering a standard Shared Autonomous Vehicle (SAV) service. In the Bloomington region, we conducted SAV operations in the absence of a service choice model. The findings, as presented in Table 3 Fleet performance metrics for the Bloomington region without service choices demonstrate a 15.5% decrease in the average VMT and 35% in the empty VMT per SAV per day and a consistent reduction in the average waiting time across all the scenarios when services are not provided. The observed event can be attributed to the process of efficiently pairing trip requests with the best-suited and nearest vehicle, resulting in a natural augmentation of circulation within the network and thus adding more wait time and vehicle miles to the network. The reduction in the number of unoccupied vehicle miles is due to the fact that the operator opts for the closest vehicle to the passenger's location, thereby eliminating the necessity to match specific services.

Table 4 Fleet Costs and revenue metrics for the Bloomington region with service choices, DRS

	Scenario 1				Scenario 2				Scenario 3			
	Standard		XL		Standard		XL		Standard		XL	
	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux
SAV fleet size (100% population)	2200				2000				1800			
Population per SAVs	54				60				66			
Total cost ($)	17,369	8,770	23,345	11,540	17,550	8,852	22,709	11,103	17,959	8,477	22,977	10,591
Total revenue ($)	66,811	22,932	53,295	16,964	67,025	23,592	52,614	16,998	67,926	22,733	52,532	16,741
Profit (%)	284.7	161.5	128.3	47.0	281.9	166.5	131.7	53.1	278.2	168.2	284.7	161.5
Net profit across service types (%)	162%				166%				167%			
Profit per passenger served ($)	$3.0	3.8	2.6	2.1	3.0	3.9	2.6	2.2	3.1	3.9	3.0	3.8
Profit per trip ($)	$2.7	3.0	2.1	1.6	2.6	3.1	2.1	1.8	2.7	3.1	2.7	3.0
Revenue per SAV ($)	$369	332	246	204	379	342	284	246	430	367	302	299
Profit per SAV ($)	$273.2	205.2	138.0	65.3	279.5	213.6	161.6	85.4	316.2	229.9	169.9	109.8

Table 5 Fleet costs and revenue metrics for the Bloomington region with service choices, NO DRS

	Scenario 1				Scenario 2				Scenario 3			
	Standard		XL		Standard		XL		Standard		XL	
	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux	Eco	Lux
SAV fleet size (100% population)	2200				2000				1800			
Population per SAVs	54				60				66			
Total cost ($)	$16,808	9,036	24,072	11,674	16,502	9,063	24,202	11,038	16,849	9,225	23,922	10,930
Total revenue ($)	$64,718	23,866	54,248	17,818	63,373	24,318	55,634	17,572	64,298	24,634	54,685	16,989
Profit (%)	285	164	125	53	284	168	130	59	282	167	129	55
Net profit	161%				164%				163%			
Profit per passenger served ($)	$3.4	3.9	2.6	2.2	3.4	3.9	2.6	2.4	3.4	4.0	2.6	2.2
$ Profit per Trip	$2.7	3.1	2.0	1.7	2.7	3.1	2.1	1.9	2.7	3.1	2.1	1.8
Revenue per SAV ($)	$358	346	250	215	391	419	327	293	374	342	288	257
Profit per SAV ($)	$265	215	139	74	289	263	185	109	276	214	162	92

Table 6 fleet costs and revenue metrics for the Bloomington region without service choices

	DRS			NO DRS		
	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
SAV fleet size (100% population)	2200	2000	1800	2200	2000	1800
Population per SAVs	54	60	66	54	60	66
Total cost ($)	$34,151	33,692	33,356	34,782	34,377	33,972
Total revenue ($)	$99,912	99,794	100,965	97,395	97,530	97,780
Profit (%)	193	196	203	180	184	188
Net profit	197%			193%		
Profit per passenger served ($)	$1.32	1.32	1.31	1.34	1.33	1.34
$ Profit per Trip	$1.60	1.61	1.64	1.52	1.53	1.55
$ Revenue per SAV	$181.7	199.6	224.4	177.1	195.1	217.3
$ Profit per SAV	$119.6	132.2	150.2	113.8	126.3	141.8

Figure 2 temporal distribution of average SAV trip requests with service types across all scenarios – DRS illustrates the temporal distribution of SAV demand for all service types over a simulation period. The figure presented displays the data obtained from averaging the number of trip requests across three different scenarios, involving fleets of sizes 2200, 2000, and 1800, all of which had the DRS strategy enabled. The peak demand for standard economy service requests occurs during the time periods of 8:00 and 9:00 a.m., and 5:00 and 6:00 p.m. In contrast, the highest number of XL economy service requests is observed between 7:00 to 8:00 a.m., and 2:00 to 3:00 p.m. The demand for luxury services exhibits minimal temporal fluctuations. The demand for standard luxury experiences exhibits a notable increase after 8 AM, maintains a relatively stable level until 6 PM, and subsequently experiences a gradual decline.

Figure 3 Profit per SAV for each scenario with and without service choices shows that the average daily profit (in dollars) per SAV with service choices goes up in the scenarios with larger SAV fleets (one SAV for 54 people and one SAV for 60 people) and has equivalent profits compared to the operator without service choices when the fleet size is reduced to one SAV for 54 people. The reason for this trend in the first two scenarios is that a larger fleet size leads to a decrease in the number of empty VMT, resulting in lower operational costs. Additionally, the inclusion of premium services contributes to the overall profit by generating additional marginal profit (due to its higher fares). However, in the latter case, the operational costs offset the additional marginal profit generated by luxury services, resulting in an equivalent level of profitability compared to a scenario where only economy services are provided to customers. The average percentage increase in VMT and empty VMT per SAV post implementation of the service choice model was 18% and 55% respectively as depicted in Figure 4 Percentage change in average VMT, empty VMT and profit per SAV .

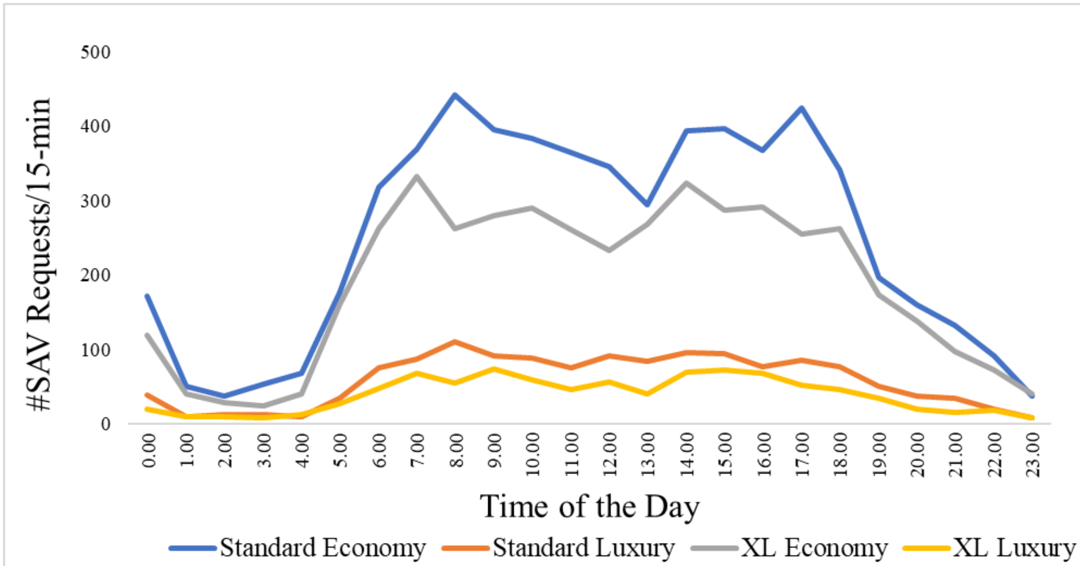

Figure 2 temporal distribution of average SAV trip requests with service types across all scenarios – DRS

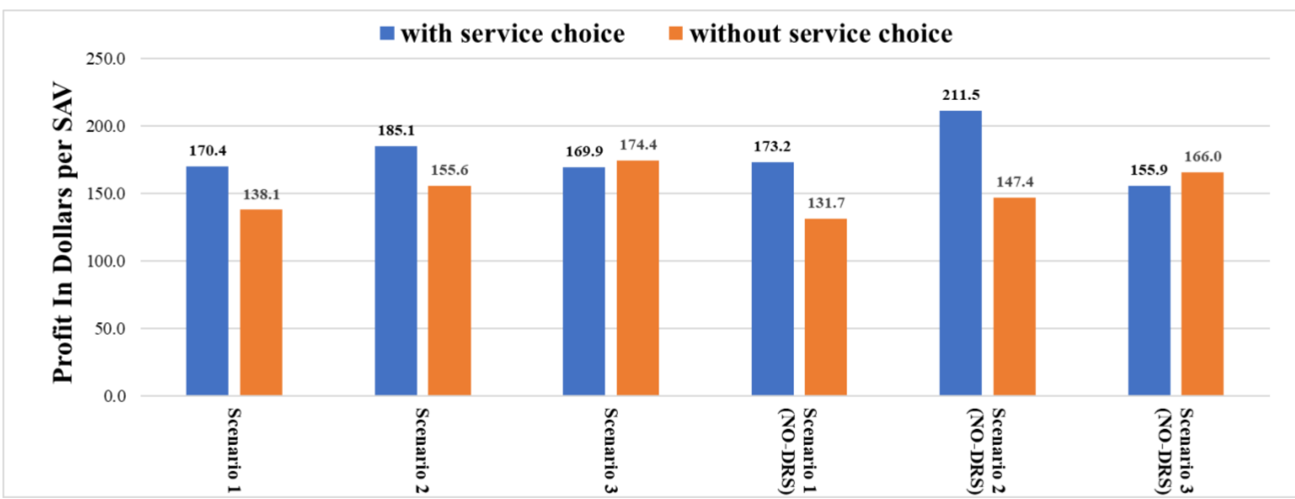

Figure 3 Profit per SAV for each scenario with and without service choices

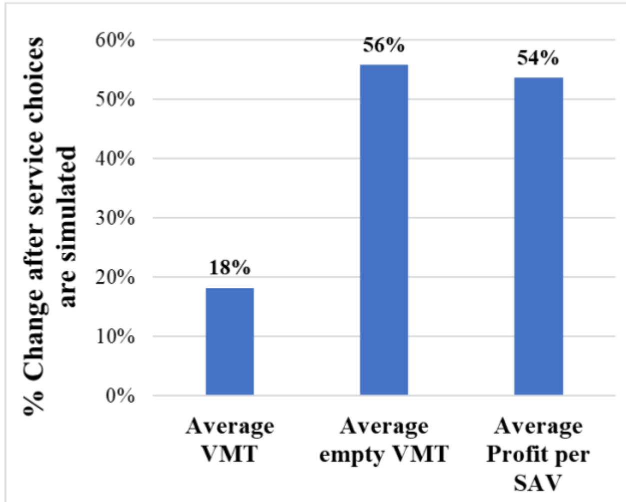

Figure 4 Percentage change in average VMT, empty VMT and profit per SAV after implementation of service choice model.

CONCLUSIONS

This research investigates the relative effects of providing various service options within a single SAV fleet, both with and without the implementation of a dynamic ride-sharing strategy. A comparison was conducted between two scenarios, one involving service offerings and the other without, using the POLARIS, which is an agent-based simulator. In the initial scenario, individuals were provided with a choice between two categories of services: luxury and economy. Additionally, they were given the option to select between two types of vehicles: standard (4-seater) and XL (6-seater). The application of fares was determined based on the specific service type that was requested. In the second scenario, people were exclusively provided with a standard economy vehicle. SAV services on a sample representing 25% of the population in the Bloomington region, which covers an area of 74 square miles. The analysis of various fleet sizes and service options reveals that the implementation of DRS led to a 21.2% ($170/SAV/day to $206/SAV/day) increase in the average daily profit per SAV as compared to the scenarios without DRS. Results show a clear preference for standard economy services during peak commute hours (8:00 to 9:00 a.m., and 5:00 to 6:00 p.m.). This demand stems from individuals who tend to prioritize time over quality of service for work trips. Furthermore, the mean daily profit (measured in dollars) per SAV with service options exhibits a 23% and 19% increase in scenarios with fleet sizes of 2200 and 2000, respectively. However, when the fleet size is reduced to 1800, the operator without service choices still generates equivalent profits. This is because fewer vehicles had to serve a larger population, resulting in increased circulation within the network and subsequently contributing to higher operational expenses. Additionally, scenarios offering different services show an average rise of 55% in empty VMT but simultaneously generate 54% more profit than scenarios where service choices are not available. Thus, it is necessary to enact policies on SAV fleet operators in the future to curb empty VMT in the traffic network.

The inherent complexity of AV design and manufacturing has resulted in constraints that hinder SAV fleet operators from providing a diverse range of services to their customers. Therefore, it is recommended that these SAV services be taken into account for future fleet operations. The present study has certain limitations that may be subject to further investigation in future studies.

For example, it is critical to consider adapting fares based on the type of vehicle utilized. In this study, it is argued that XL vehicles should be priced higher than standard vehicles, despite the current situation where both types of vehicles have the same cost. Utilizing empirical data from real-world scenarios, specifically pertaining to individuals' selection of services for SAVs, is imperative in constructing accurate models of service preferences. This approach is particularly important due to the potential divergence in service choices between SAVs and traditional TNC services, primarily stemming from the relatively low likelihood of individuals initially favoring SAVs as their primary mode of transportation.

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AUTHOR CONTRIBUTIONS

The authors confirm the contribution to the paper as follows: study conception and design: Gurumurthy, K.M; Priyanka, P., and Kockelman, K.; Data and results analyses: Gurumurthy, K.M; Priyanka, P., and Kockelman, K.; Draft manuscript preparation: Priyanka, P., Gurumurthy, K.M; and Kockelman, K.; All authors reviewed the results and approved the final version of the manuscript.

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