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CENTER OF EXCELLENCE

on New Mobility and Automated Vehicles

Will Shared Automated Vehicle Services Fill Transit Service Gaps? (Phase 1)

September 2026

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The Mobility Center of Excellence at UCLA acknowledges the Gabrielino/Tongva peoples as the traditional land caretakers of Tovaangar (the Los Angeles basin and So. Channel Islands). As a land grant institution, we pay our respects to the Honuukvetam (Ancestors), 'Ahihirom (Elders) and 'Eyoohiinkem (our relatives/relations) past, present and emerging.

Disclaimer

Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the Author(s) and do not necessarily reflect the view of the Federal Highway Administration.

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Will Shared Automated Vehicle Services Fill Transit Service Gaps? (Phase 1)

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September 2026



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Executive Summary

Urban residents depend on public transportation to reach essential destinations such as employment, school, and healthcare. While public transit is effective and efficient in high density areas and during peak hours, it often operates inefficiently in low density suburban areas during late service hours, with buses running empty at times. This leads to inefficient resource allocation, particularly since many transit agencies across the U.S. are currently facing significant budget cuts, resulting in service reductions or even route eliminations.

Shared autonomous vehicles (SAVs) present an opportunity to reduce costs and provide service coverage. This study develops a cost-benefit framework to assess the costs and benefits of replacing low-performing transit routes during off-peak hours with SAVs, considering operational and maintenance costs along with mobility, and public health costs. Note that throughout this report, shared denotes shared vehicle assets, not shared or pooled journeys. Pittsburgh, PA, was used as a case study, due to the budget cuts Pittsburgh Regional Transit (PRT) was facing. Cost assumptions were based on publicly available data in the literature. Two scenarios were modeled based on a total of 96 routes: the first focusing on the 9 lowest performing routes (approx. 10%), and the second on the 41 lowest performing routes (approx. 42%), based on the number of routes which were proposed for elimination by PRT. Routes were designated as low performing based on their average cost per passenger during off peak hours.

The findings from this analysis suggest a \$3.75 million net benefit in scenario 1, whereas scenario 2 produced a \$36.2 million net benefit. However, the analysis revealed that there were high costs associated with mobility and public health due to each passenger taking an individual SAV, which resulted in a relatively large increase in the number of trips. Specifically, scenario 1 would require approximately 79.4 thousand SAV trips to replace 10.7 thousand bus trips, while scenario 2 would require approximately 1.79 million SAV trips to replace 150 thousand bus trips. This scale of replacement leads to a negative net benefit within the mobility and public health cost categories in scenario 2. The results emphasize the potential for integrating SAVs into the existing transit system to maintain service coverage while reducing operations and maintenance costs. However, the findings also highlight a tradeoff: as larger-scale replacement scenarios serving higher ridership levels increase the number of individual SAV trips, this leads to negative mobility and public health related costs.

Future research could build on the cost-benefit analysis framework by better understanding the labor costs associated with operating a mature AV service. While labor costs for transit are well established in the literature, labor costs for AV services are not, and AV inspection and maintenance needs may exceed that of human-driven vehicles. The resultant cost-benefit assessments may thus differ based on estimated labor costs. Future research could also include modeling different SAV occupancies and pooling to better reflect real world operations. Sensitivity analyses could be performed on the cost variables to understand the uncertainty associated with the findings. Since SAVs are not currently available for large-scale implementation, analysis results should be compared to scenarios where transportation network companies (TNCs) are serving passengers. Further work may also study induced demand, in which easier and more affordable travel results in increased travel demand. All of

these studies will allow transit agencies to better understand the benefits and costs of integrating current and future ridesharing technologies into transit systems.

Introduction

Public transit is a major component of urban transportation. Many urban residents rely on public transportation to access destinations such as employment, school, and healthcare. For example, in New York City, over 2 million people commute by public transit, and one-third of San Francisco workers do so (1). In addition, it is estimated that over 600,000 older adults in the US depend on public transit as their primary mode to access medical care services (2). In 2019, Americans took more than 9.9 billion trips on public transportation (3). According to the Federal Transit Administration, 8% of the US population is transit-dependent, meaning that 28 million rely on transit (e.g., buses, trains, and ferries) to meet their daily transportation needs (4).

Despite this reliance, public transit systems are sometimes inefficient. In densely populated neighborhoods or during peak hour periods, buses are able to serve a large number of riders. However, buses are often required to run during off-peak or late-night service hours through suburban areas to meet coverage requirements, although they may be serving few to no passengers. This tradeoff between coverage and service quality could lead to inefficient resource allocation. Concurrently, many transit agencies in cities across the U.S. are facing severe budget cuts, including Pittsburgh, Philadelphia, San Francisco, and Chicago. For example, Pittsburgh Regional Transit (PRT) was facing a 35% budget cut, with 41 routes proposed for elimination and others facing major service time reductions in 2025 (5). Given the important role transit plays in providing transportation, these service cuts would negatively affect quality of life for many urban and transit-dependent populations.

Shared mobility services such as shared autonomous vehicles (SAVs) could potentially be integrated into transit operations, helping to reduce costs and preserve service coverage. We develop a framework to better understand the costs and benefits of replacing low-performing transit routes during off-peak hours with SAVs. The cost-benefit analysis framework considers operational and maintenance costs along with public health and congestion costs. The approach involves identifying low performing routes during off-peak hours and understanding the costs and benefits of replacing them with SAVs that provide on-demand services. These services would operate throughout off-peak hours in areas where buses are operating but not serving many passengers, which results in inefficient resource allocation. Our framework is applied to Pittsburgh, PA, as a case study to quantify the associated benefits and costs. Our objective is to identify analysis approaches that help decisionmakers and service providers understand the potential for new mobility services (particularly SAVs) to improve operational efficiency and maintain service coverage. The research question addressed by this analysis is: what are the net benefits of replacing low performing transit routes during off-peak hours with SAVs?

Literature Review

Several researchers have estimated the costs and benefits of integrating shared mobility services into transit operations across a number of scenarios (see Table 1). For example, Hanig et al. (2023) (6) developed a framework to assess the costs and benefits of using transportation network companies (TNCs) and SAVs as an alternative to alleviate overcapacity on buses during

the COVID-19 pandemic. Hanig et al. (2023) (6) concluded that dispatching single-occupancy AVs could lower the cost of allowing overcrowding by about \$13 million, mainly attributed to reduction in COVID-19 related deaths from people having increased physical distancing space from other passengers.

Table 1: Examples of research which assess the costs and benefits of integrating shared mobility services into transit operations.

Study	Role of Shared Mobility Services in Transit Operations	Transit Level	Operating Condition
Hanig et al. (2023)	TNCs and AVs to reduce bus overcrowding	Local	Covid-19
Imhof et al. (2020)	AVs to replace all buses	Regional	Normal
Shariat et al. (2025)	TNCs to replace low demand or off-peak bus segments	Local	Normal
Whitmore et al. (2022)	AVs as transit feeder in low transit coverage areas	Local	Normal
Grahn et al. (2023a)	On-demand shuttles and TNCs as transit feeders in low density areas	Local	Normal
Grahn et al. (2023b)	On-demand shuttles, TNCs, and SAEVs as transit feeders in low density areas	Local	Normal
This study (2025)	AVs to replace low performing routes	Local	Normal

Dispatching TNCs, however, resulted in increased societal costs of \$5 million compared to allowing overcrowding. Imhof et al. (2020) (7) examined the costs and benefits of replacing an entire regional public transportation system with AVs but did not account for mobility and public health costs in their cost-benefit framework. Their analysis shows that SAVs could result in revenues 11% higher than total costs, compared to the revenue from the current bus system which only covers 57% of total costs. Shariat et al. (2025) (8) developed a decision-making framework to evaluate whether low demand or off-peak bus segments could be substituted with TNC services along existing fixed bus routes. Shariat et al. (2025) (8) considered both

operational costs and passenger related costs, including walking, waiting, and in-vehicle travel time. The results indicate that TNC substitution is most suitable under low-demand conditions, specifically when passengers per stop are less than 1.2 and passengers per mile are less than 3.56.

Whitmore et al. (2022) (9) assessed the costs and benefits of expanding transit service coverage using SAVs as a first- and last-mile service for transit-dependent riders. Whitmore et al. (2022) (9) found that SAVs and autonomous shuttles could be a cost-effective way for transit agencies to improve public transit access. Grahn et al. (2023a) (10) developed an optimization framework for integrating on-demand shuttles and TNCs as first- and last-mile services. They evaluated operational costs, as well as wait time and in-vehicle time, to assess impacts on service performance within a low-density residential area. Their findings highlight that a hybrid system with on-demand shuttles and TNCs can improve reliability by 40% and reduced generalized travel costs. Grahn et al. (2023b) (11) expanded on the analysis by applying a real-time operations framework to quantify environmental impacts of on-demand shuttles, TNCs, and shared autonomous electric shuttles as first- and last-mile services. Their results highlight that while an on-demand shuttle and TNC hybrid scenario increased VMT by 60% to 156% compared to only shuttle operations, fuel consumption was reduced by 12% to 45%. Additionally, autonomous electric shuttles reduced fuel consumption by 82% but increased operational costs due to battery range restrictions which required more vehicles to operate.

The study most similar to this report is Hanig et al. (2023) (6). However, their work focuses on understanding the costs and benefits of integrating AVs into transit to reduce overcrowding on buses and limit the spread of COVID-19. Given the unique challenges presented by COVID-19, the applicability of their insights and results to transit operations and decision-making under normal conditions is limited. Hence, a framework is needed at the local level to help transit agencies identify a subset of candidate routes that could be replaced by AVs and better understand the costs and benefits of replacing these routes during off-peak hours with SAVs under typical, non-pandemic operating conditions.

Methodology

Study Area

Pittsburgh, PA, was selected as the case study because it has a public transit system, Pittsburgh Regional Transit (PRT), that recently proposed eliminating 41 routes and reducing bus service on 54 routes in response to budget shortfalls (5). As such, a goal of this study is to better understand the costs and benefits of replacing low performing bus routes with SAVs during off-peak hours. Additionally, the PRT bus system includes both high- and low-density routes, providing a useful context for assessing the cost-effectiveness of such replacements. Finally, 17% of Pittsburgh, PA residents commute to work via public transit, meaning that disruptions to transit service availability would affect mobility and accessibility for many of its residents (12). These characteristics make Pittsburgh the ideal case study for applying our proposed cost-benefit analysis framework.

Data

Our study uses bus ridership data from January 2022 to December 2022 provided by PRT, which is collected on a daily basis. The dataset includes daily information for all PRT routes, recording the time and number of passengers boarding at each bus stop, and the trip direction (inbound or outbound). The data allows us to calculate the average passenger load for each route throughout the year to identify low performing routes. Access to PRT ridership data was obtained through a non-disclosure agreement and therefore cannot be publicly shared.

The dataset provided by PRT does not include individual trip distances for passenger. Specifically, passengers are only required to scan their travel card when boarding a vehicle and not when exiting, which prevents the collection of individual passenger trip lengths. Therefore, the exact length of trip for each transit rider is not known. To estimate realistic trip distances for passengers, we employ data from the Make My Trip Count survey, conducted in 2018 by the Green Building Alliance. This latest survey collected information on travel lengths by bus for residents across Allegheny County, which covers Pittsburgh and surrounding areas, enabling us to draw trip distances for SAVs from a distribution. Access to the 2018 Make My Trip Count Survey was obtained through a non-disclosure agreement and therefore cannot be publicly shared¹.

Methods

This section details our methods for evaluating the costs of integrating SAVs into the public transit system. We begin by identifying low-performing routes based on average operational costs per passenger during weekday off-peak hours. Next, we describe the cost-benefit analysis

¹ A previous version of this survey is publicly available online:
<https://data.wprdc.org/dataset/make-my-trip-count-2015>

framework used to estimate operational, mobility, and public health costs and benefits for both modes.

We use data from PRT covering a 12-month period to model bus loads for all routes. To estimate trip distances per passenger, we generate simulated distances using the probability distribution of trip distances from the Make My Trip Count survey data. This approach allows us to capture the varying passenger trip distances and better estimate the costs and benefits of replacing low-performing routes with non-electric SAVs. While most AV deployments are using electric vehicles, assuming non-electric SAVs in this analysis allows the framework to be applied in future work to compare results with other shared mobility services such as TNCs, which are mostly non-electric. This better isolates the effects of automation on the final net benefit.

Identifying Low Performing Transit Routes

We focus our analysis on weekday off-peak hours, with the morning peak period defined from 6:00 to 9:00 AM and the afternoon peak period from 3:00 to 6:00 PM. All weekday trips outside of the morning and afternoon peak periods are considered off-peak. Trips within the off-peak periods were extracted based on departure times at each stop. For this analysis, the metric used to identify low performing routes is the average operational cost per passenger, which takes into account the cost to operate each transit route relative to the number of passengers using the route. This metric effectively captures operational efficiency and demand, identifying routes which have disproportionately high operating costs corresponding to their low ridership.

The average operational cost per passenger (C_r) was computed for each trip (i) using the operating cost per kilometer ($O_{BUS} = \$14.64/\text{km}$), which includes labor, fuel and any associated taxes, insurance, and maintenance services (13, 14). Labor and wages, maintenance, and insurance costs were derived from the PRT budget using the FY 2022 actual expenditures (13), while fuel costs were derived from the 2022 National Transit Database Annual Data on operating expenses (14). The operating cost per kilometer represents the total cost incurred by an agency to operate buses divided by the total revenue kilometers traveled. The total distance traveled by a bus for a single trip ($D_{BUS,i}$), the operating cost per kilometer (O_{BUS}), and the total ridership (R_i) were used to calculate the operating cost per passenger for each route (r) as shown in Eq. (1).

$$C_r = \frac{O_{BUS} \times \sum_{i \in r} D_{BUS,i}}{\sum_{i \in r} R_i} \quad (1)$$

If no passengers were recorded for a trip, the operational cost was set to the maximum value of \$14.64/km multiplied by the trip distance representing the full cost of operating the trip. Routes were ranked in descending order based on their average operational cost per passenger, with higher costs indicating lower performance. The lowest-performing routes were selected for further analysis.

Cost-Benefit Analysis Framework

The total benefit (T_b) of removing low-performing routes during off-peak hours include mobility, and public health, as well as avoided bus operation and maintenance cost. This is calculated by multiplying the operational cost per kilometer for buses (O_{Bus}) by the total distance traveled on the low-performing routes selected for removal (D_{Low}). Similarly, the externalities were estimated using the total distance traveled and corresponding mobility ($M_{Bus} = \$0.212/km$), and public health ($P_{Bus} = \$0.022/km$) factors (15), as shown in Eq. (2). The mobility factor is based on the U.S. Department of Transportation's recommended monetized value for bus congestion and traffic in urban areas, which are derived from the Highway Cost Allocation Study and account for factors such as traffic volumes, vehicle occupancy, and the value of travel time per person-hour (15). Because buses are substantially larger than SAVs, they occupy more roadway space and have a higher passenger-car equivalent, and therefore a higher per-kilometer congestion cost than light-duty SAVs (16, 17). Public health factor corresponds to the monetized cost of emission damages associated with bus operations and is estimated using the U.S. Environmental Protection Agency MOVES model, which estimates emissions generated by on-road vehicles under different operating conditions (15).

$$T_b = \sum_{Low} D_{Low} \times (O_{Bus} + M_{Bus} + P_{Bus}) \quad (2)$$

To estimate the total costs (T_c) of substituting trips originally done by bus with SAVs, trip distances were simulated using passenger bus commute distance data from the Make My Trip Count survey. The probability distribution of the bus commute distances was used to simulate realistic passenger trip distances. For each boarding passenger within the transit data, the travel distance is drawn from a lognormal probability distribution parameterized by μ and σ , which are the mean and standard deviation of the natural logarithm of the variable, respectively. The lognormal distribution is chosen as it ensures strictly positive travel distances and captures the right-skewed distribution of observed trip lengths. The fitted lognormal distribution resulted in a mean of 11.18 km, a median of 6.68 km, and a standard deviation of 14.99 km (refer to Figure 1 and Figure 2). The number of simulated trips is equivalent to the total ridership on the low-performing routes, assuming each passenger takes an individual SAV trip. It should be noted that pooling is not considered as part of this analysis.

Vehicle purchase costs were excluded, assuming that PRT would partner with an SAV dispatcher to service trips. The cost of SAVs was then estimated using the simulated trip distances (D_{SAV}), the SAV operating cost per kilometer ($O_{SAV} = \$1.117/km$) (18) as well as the mobility ($M_{SAV} = \$0.085/km$), and public health ($P_{SAV} = \$0.008/km$) factors (15), as shown in Eq. (3). The SAV operating cost includes insurance, fuel and any associated taxes, maintenance, and labor costs (18). SAV insurance, fuel, maintenance (including inspection costs), and labor costs were obtained from a study done by Nunes and Hernandez (2020) (18) who estimated SAV operating costs per mile in San Francisco. Labor cost for SAVs include the cost of remote human supervisors responsible for monitoring fleet operations and intervening as needed to ensure the safe operations of driverless taxis (18). We estimate a labor cost of \$1.117/km, which corresponds to one safety operator for every 25 SAVs deployed. Any labor costs from SAV inspection and maintenance are included in the Maintenance and Wear cost category. The

mobility and public health factors were based on the U.S. Department of Transportation's recommended monetized values for light-duty vehicles (15), as the analysis assumes the use of non-electric autonomous vehicles.

$$T_c = \sum_{SAV} D_{SAV} \times (O_{SAV} + M_{SAV} + P_{SAV}) \quad (3)$$

The net benefit (N_b) is the difference between the total costs and benefits of removing low performing bus routes and replacing them with SAVs during off-peak hours, shown in Eq. (4).

$$N_b = T_b - T_c \quad (4)$$

Table 2 provides a summary of the cost variables for buses and SAVs.

Table 2: Summary of cost variables.

Item	Bus	SAV
Operations & Maintenance	\$14.64/km (13, 14)	\$1.117/km (18)
Labor and Wages	\$12.86/km (13)	\$0.888/km (18)
Insurance	\$0.21/km (13)	\$0.081/km (18)
Fuel & Taxes	\$0.66/km (14)	\$0.052/km (18)
Maintenance and Wear	\$0.91/km (13)	\$0.096/km (18)
Mobility (i.e., congestion)	\$0.212/km (15)	\$0.085/km (15)
Public Health (i.e., pollution)	\$0.022/km (15)	\$0.008/km (15)

Note: All costs were converted to 2022 dollars using the Consumer Pricing Index (19).

Results

Performance Statistics for Different Bus Routes

Tables 3 and 4 present descriptive statistics for the 96 PRT transit routes, classified into three groups based on their average operational cost per passenger: highest performing routes, middle performing routes, and lowest performing routes, all during off-peak hours. Two scenarios were analyzed. The first scenario focuses on the 10% of buses with the highest average cost per passenger, as shown in Table 3. The second scenario models the total routes focuses on the 41 lowest performing routes in terms of average cost per passenger during off-peak hours, as shown in Table 4.

Table 3: Descriptive statistics for scenario 1.

Statistic	Highest Performing Routes	Middle Performing Routes	Lowest Performing Routes
Number of Routes	43	44	9
Average number of passengers per off-peak trip	17	12	7
Average off-peak cost per passenger	\$12.93	\$31.37	\$64.18
Average route distance (km)	14.69	26.99	30.21
Percentage of routes traveling inbound	48.52%	50.06%	47.80%
Percentage of off-peak service empty ridership	2.28%	3.93%	11.51%
Local bus service type	84.94%	68.87%	8.19%
Commuter bus service type	2.51%	12.42%	49.49%
Coverage bus service type	4.76%	18.71%	42.32%
Rapid bus service type	7.78%	0.00%	0.00%

Across the groups, the statistics revealed distinct differences in service patterns and ridership. The average number of passengers per off-peak trip indicates demand during off-peak periods, with the highest performing routes carrying the most passengers, followed by the middle

performing routes, and lowest performing routes serving the least number of passengers. The average off-peak cost per passenger reflects operational efficiency in terms of passenger demand, where the lowest performing routes had the highest costs due to low ridership per trip. The percentage of off-peak service empty ridership highlights inefficient usage of buses, with lowest performing routes running empty buses more frequently than higher performing routes. In scenario 1, the lowest performing routes were empty (i.e., without a passenger) 11.5% of the time compared to 4.9% in scenario 2.

Table 4: Descriptive statistics for scenario 2.

Statistic	Highest Performing Routes	Middle Performing Routes	Lowest Performing Routes
Number of Routes	27	28	41
Average number of passengers per off-peak trip	22	13	10
Average off-peak cost per passenger	\$9.94	\$20.40	\$40.84
Average route distance (km)	15.05	19.20	27.04
Percentage of routes traveling inbound	48.08%	50.43%	49.29%
Percentage of off-peak service empty ridership	1.89%	3.18%	4.93%
Local bus service type	91.18%	69.98%	61.23%
Commuter bus service type	3.00%	1.27%	20.57%
Coverage bus service type	0.00%	20.66%	18.20%
Rapid bus service type	5.83%	8.09%	0.00%

The average distance traveled by routes provides an understanding into how much area the routes cover. Lowest performing routes travel longer distances, while serving fewer passengers, contributing to higher operational costs. The percentage of inbound trips is relatively consistent across low, middle, and high performing routes.

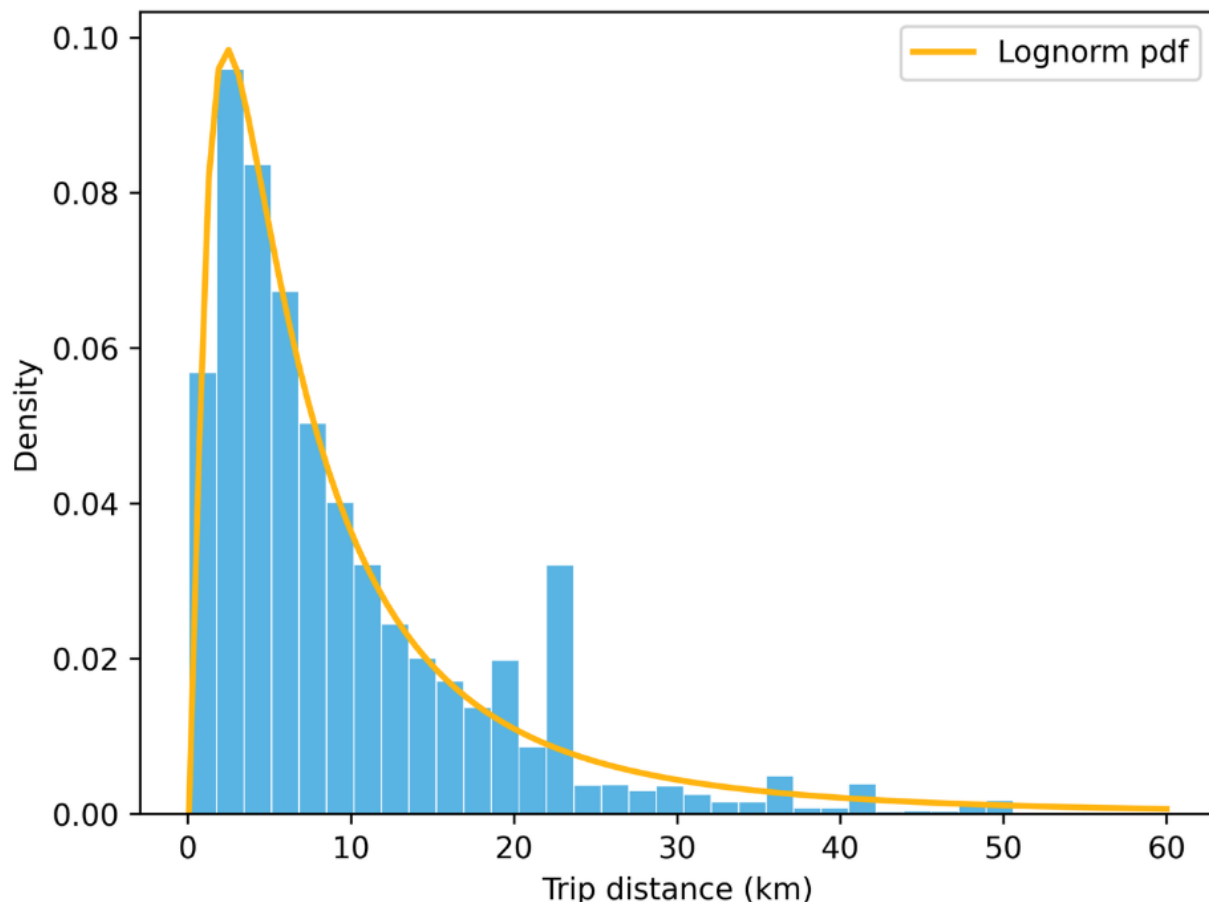
The bus service type provides insight into the areas the routes serve. Local routes focus on access, speed, and reliability by serving a higher number of stops along the route. In comparison, commuter routes provide faster, limited-stop service between downtown and suburban destinations, but may operate similar to local routes during peak hours. Coverage routes cover low-density areas to provide access in areas with low demand. Lastly, rapid routes feature limited stops and higher-capacity vehicles and may operate along local bus service routes.

In scenario 2, while all three groups consisted of mostly local bus services which operate in urban areas with higher ridership, the lowest performing routes tended to cover commuter and coverage services, which operate in suburban and low-density areas with infrequent service. In scenario 1, the lowest performing routes were mostly commuter bus services, whereas the highest performing routes included the only rapid bus services, which usually run along local service routes and serve high-demand urban areas. These results suggest that low performing routes averaged longer route distances, lower passenger demand, and service types which operate in less dense areas, contributing to operational inefficiencies.

Cost-Benefit Analysis

Figures 1 and 2 show the distribution of generated passenger trip distances for scenarios 1 and 2, respectively. A total of 79.4 thousand passenger trip distances were generated for scenario 1, while 1.79 million passenger trip distances were generated for scenario 2.

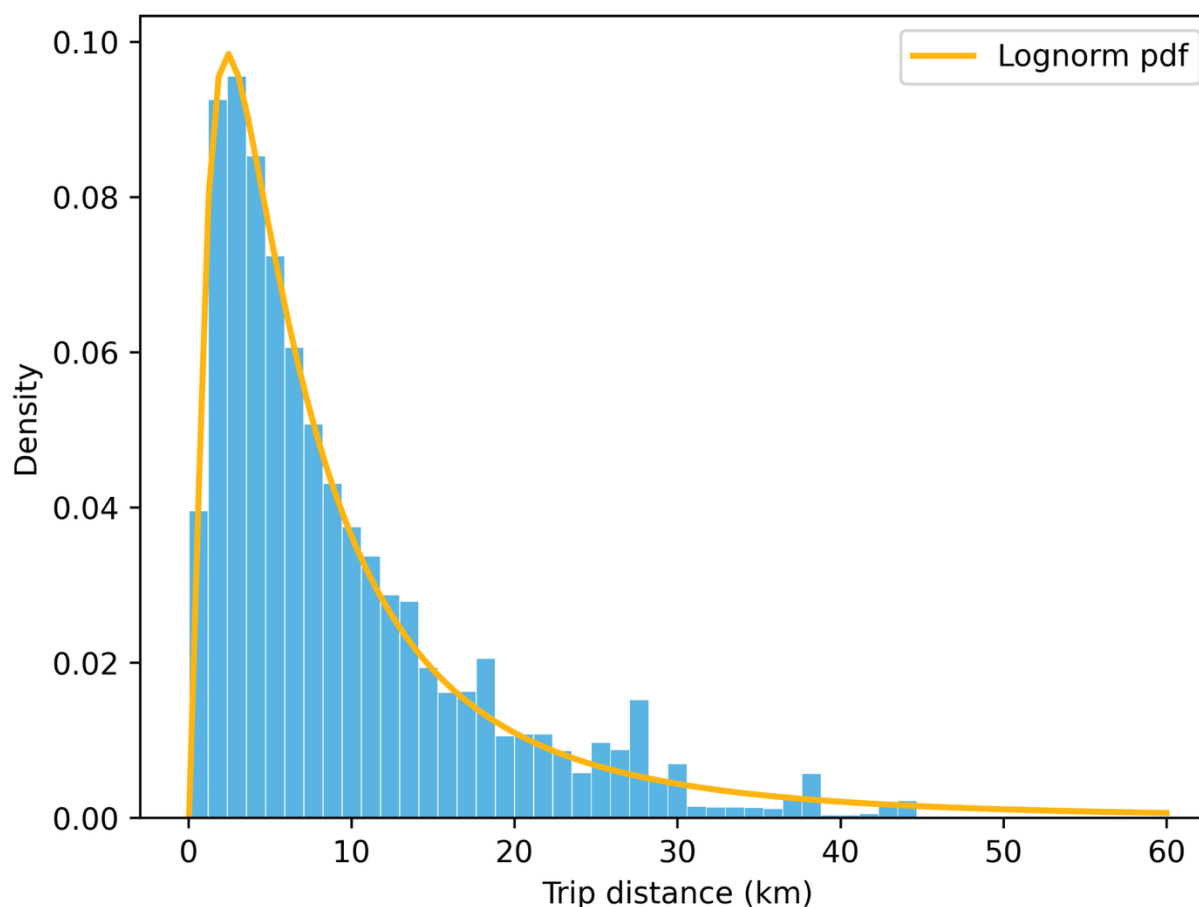
Figure 1: Distribution of generated passenger trip distances for scenario 1.



The average trip distances were 9.60 km and 9.50 km in scenarios 1 and 2, respectively. Excessively long simulated trips were capped for each passenger according to the length of their original bus route. For example, if the distribution generated a trip length of 25 km but there was only 10km remaining between the stop where the passenger boarded and the last stop on

the route, the length of this trip would be capped to 10km. It should be noted that in this analysis, we model SAVs as a stop-level service where SAVs directly replace buses and transport passengers between bus stops.

Figure 2: Distribution of generated passenger trip distances for scenario 2.



Figures 3 and 4 present the net benefit of replacing the lowest performing routes with SAVs for scenarios 1 and 2, respectively, while Table 5 summarizes the corresponding values.

Scenario 1 modeled a scenario where a small portion of low-performing routes were replaced by SAVs during off peak hours. The number of SAV trips taken was found to be 79.4 thousand, traveling a total distance of 762 thousand km, compared to 10.7 thousand bus trips traveling 324 thousand km. This resulted in a net benefit of \$3.75 million due to slightly improved mobility and public health and mostly from reduced operating and maintenance costs. Mobility impacts remained slightly positive because the ratio of SAV vehicle-kilometers traveled (VKT) to removed bus VKT traveled was 2.35, which was below the mobility breakeven threshold of 2.50 based on the mobility factors between the two modes. Similarly, the SAV to bus distance traveled ratio remained below the breakeven threshold of 2.92 for public health costs. As highlighted within the descriptive statistics, the lowest 9 routes operated with no passengers 11.5% of the time during off-peak hours, indicating that these buses generate externalities while serving no passengers, compared to SAVs, which is an on-demand service and only generates VKT when there is passenger demand.

Table 5: Net benefit for scenarios 1 and 2.

Scenario 1: 9 routes replaced			
	Cost	Benefit	Net Benefit
Operations & Maintenance	\$994,660.39	\$4,741,797.54	\$3,747,137.15
Mobility	\$64,779.73 (traffic and congestion)	\$68,683.02 (economic activity)	\$3,903.29
Public health	\$5,728.82 (pollution)	\$7,111.59 (access to healthcare)	\$1,382.77
Total	\$1,065,168.93	\$4,817,592.15	\$3,752,423.22
Scenario 2: 41 routes replaced			
	Cost	Benefit	Net Benefit
Operations & Maintenance	\$22,401,928.14	\$59,279,207.69	\$36,877,279.54
Mobility	\$1,442,826.41 (traffic and congestion)	\$858,635.35 (economic activity)	-\$584,191.06
Public health	\$127,596.89 (pollution)	\$88,905.02 (access to healthcare)	-\$38,691.87
Total	\$23,972,351.45	\$60,226,748.06	\$36,254,396.61

Because buses have higher mobility and public health costs per kilometer than SAVs and travel empty a relatively high portion of the time, replacing the empty bus VKT with on-demand SAV trips contributed to slightly positive mobility and public health impacts. Low performing routes averaged 30.2 km in length in scenario 1, whereas most passenger trips were substantially shorter, as shown in Figure 1, implying that individual passengers traveled shorter distances while buses may have continued operating empty during portions of the route. In comparison, scenario 2 was modeled to reflect the situation faced by PRT, representing the potential benefits of substituting SAVs for 41 of the lowest financially performing bus routes. For scenario 2, the number of SAV trips taken was computed to be 1.79 million trips, traveling a total distance of 16.9 million km, compared to 150 thousand bus trips traveling 4.05 million km. This yielded a benefit approximately 2.5 times greater than the cost. The net benefit for scenario 2 amounted to \$36.2 million, primarily due to assumed reductions in labor for operations and maintenance.

Mobility and public health both resulted in a negative net benefit, as replacing a higher share of bus trips with a greater number of SAV trips increased mobility costs that outweighed the benefits. The ratio of SAV VKT to removed bus VKT was 4.20, exceeding the breakeven for both mobility and public health. Unlike scenario 1, the lowest 41 routes only operated empty during off-peak hours 4.93% of the time, implying that fewer buses were generating externalities while carrying no passengers, resulting in negative mobility and public health net benefits for this scenario.

Figure 3: Net benefit for scenario 1.

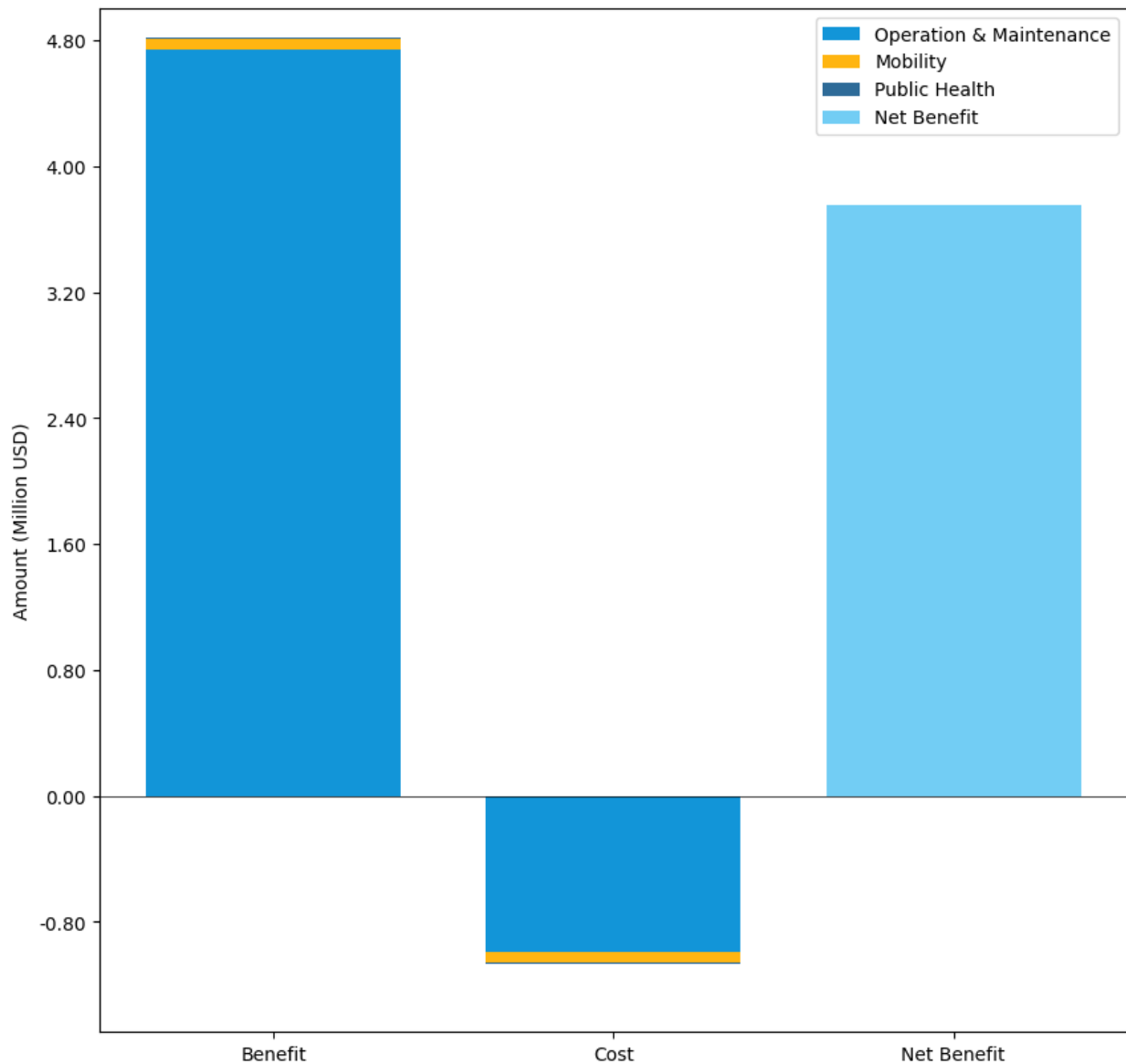
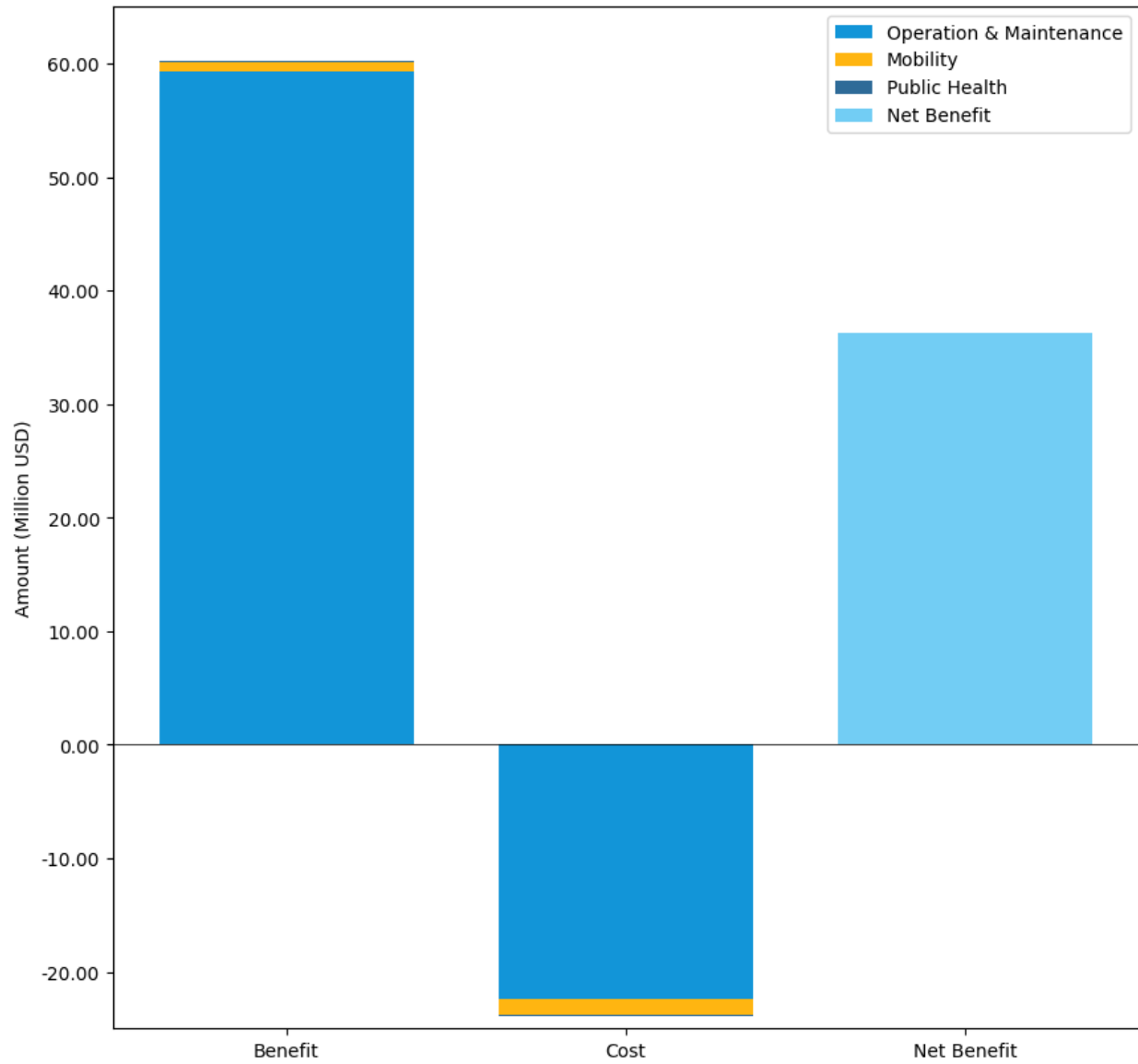


Figure 4: Net benefit for scenario 2.



Discussion

We investigate the costs and benefits of replacing low performing routes with SAVs during off-peak hours. Our cost benefit analysis suggests a \$3.75 million net benefit for scenario 1 where 9 routes were replaced, and a \$36.2 million net benefit for scenario 2 where 41 routes were replaced over a 12-month period.

The estimated benefits are dominated by the assumed labor cost savings, so the analysis is highly sensitive to these parameters. Secondary to that, there are mixed benefits due to increased VKT, which can have both positive (greater access) and negative impacts (more congestion and associated pollution). Because passengers that once took a bus are now taking an individual SAV, VKT increases, resulting in a negative benefit in scenario 2 for both mobility (congestion) and public health (pollution). A comparison of VKT shows that in scenario 1, the 9 lowest performing bus routes totaled 10.7 thousand bus trips and traveled 324 thousand km across all replaced routes, amounting to \$4.81 million in benefits due to avoided operations and maintenance, mobility, and public health costs. These routes were replaced by 79 thousand individual SAV trips, where the number of SAV trips generated was equivalent to the total number of passengers boarding the low performing bus routes. The generated SAV trip distances totaled 762 thousand km, contributing to \$1.06 million in SAV costs. In scenario 2, the 41 lowest performing routes traveled a total distance of 4.05 million km across 150 thousand bus trips, contributing to \$60.2 million in benefits. Replacing the trips served by these routes required 1.79 million SAV trips traveling 16.9 million km, with associated SAV costs amounting to \$23.9 million.

Scenario 1 focuses only on a small subset of routes with limited operations outside of peak periods. Implementing SAVs would more realistically occur on a larger scale; thus, scenario 2, which models replacement of 41 low performing routes, better reflects the number of routes affected by budget cuts and, therefore, may better represent operational decisions transit agencies face.

Allowing for pooled SAV trips would reduce the number of vehicles operating, lowering traffic and congestion costs and reducing overall trip distances, therefore improving the net benefit. Furthermore, the model assumes all trips are non-pooled. In practice, most SAVs have 4-passenger occupancy, although larger vehicles could be used to maximize passenger capacity while deploying fewer vehicles. Additionally, other costs and benefits that could be incorporated into the model include crash costs and safety benefits, which could be evaluated in the future.

Our results highlight the potential for significant benefits from replacing low performing routes with SAVs. The increased mobility and public health costs in scenario 2 emphasizes the importance of operational strategies that could mitigate negative outcomes, such as allowing pooled trips, which would need to be evaluated in future work. Overall, the cost-benefit analysis offers a framework for service providers and decisionmakers to evaluate whether SAV integration into the public transit system is a viable alternative to maintain quality of service while reducing or eliminating low performing routes. By strategically integrating SAVs, agencies could still provide service coverage during off-peak hours while improving operational efficiency.

Future Research Needs

This study identifies many areas for potential future research. First, the cost assumptions for running an AV service were estimated in 2020, and both commercial and public sector AV deployments have increased significantly since then. These assumptions could be updated based on more real-world experience. Second, a scenario including pooled trips could be considered in future analysis. Expanding the model to include pool trips could provide a more comprehensive understanding of the costs and benefits of integrating SAVs into the public transit system. Simulating other service designs (e.g., door-to-door services) could also be another direction for future work as this would affect the number of miles traveled by SAVs and the overall net benefit.

Another area for potential future work includes conducting a sensitivity analysis on the cost variables used within the cost-benefit analysis framework. This will provide a more robust understanding of the results based on the assumptions, while also accounting for uncertainty as these factors can vary across regions and under different policies. Future work could also expand the analysis to incorporate road use charges based on travel distance rather than representing roadway costs through fuel taxes. However, road use charges are not fully implemented yet, and exact prices may vary, particularly since most existing programs are designed for electric vehicles (20). In addition, future research could extend the framework to evaluate electric SAVs, which would incorporate road use charges to account for roadway costs since fuel taxes would not be applicable.

Since SAVs are not yet available for large-scale deployment, future research could also evaluate a near term solution. This additional analysis could focus on integrating existing ride share vehicles from TNCs into the public transit system for low performing routes during off-peak periods. The analysis could be conducted using the same framework applied in this study for SAVs, allowing for a direct comparison of cost-benefit outcomes. This approach would allow us to evaluate the feasibility of TNC services as a near-term solution, while considering that SAVs could provide additional benefits, including potentially lower labor costs, more efficient operations, and potentially reduced fuel consumption due to optimized driving (21).

Longer-term research could focus on deploying pilot programs to test the assumptions in the model, as well as to better understand passenger travel behavior, such as how demand may change due to the integration of SAVs into transit services. Furthermore, future studies could examine how the outcomes may vary over time, including impacts on service frequency and spatial coverage. Ultimately, these assessments would support transit agencies in using this cost-benefit framework to make strategic decisions about AV deployments that complement and strengthen transit services and coverage.

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