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Integrating public transportation and shared autonomous mobility for equitable transit coverage: A cost-efficiency analysis

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ABSTRACT

As automated transportation technology advances, public transit agencies could consider how integrating autonomous vehicles and shuttles into existing transit systems affects equity. Capital and operating costs for automated mobility modes managed by public transit agencies are uncertain since few deployments have occurred to date. Automated vehicles and shuttles are agile for dynamic routing and can make use of the existing transportation infrastructure, but operating costs remain uncertain. This study aims to characterize the economic feasibility of improving transit coverage and transit equity of public transportation with shared automated mobility. Cost efficiency analysis compares direct operating costs of shared autonomous vehicles (SAVs) and autonomous shuttles to a conventional transit bus. Using Allegheny County, Pennsylvania as a case study, the analysis considers potentially adding shuttle or SAV service to expand service for the existing public transit system. The results suggest it is feasible to improve transit equity with shared AVs and shuttles at lower costs than buses on average. Revenue kilometers traveled, fleet size, and operating hours are the most important parameters that determine cost-efficiency. Transit planners and policymakers can use this analysis to inform shared autonomous mobility operation guidelines to ensure emerging technology services remain a complement to existing transit.

Introduction

U.S. public transportation agencies are responsible for enabling mobility within their service area by providing transit services. In their role, agencies uniquely serve the transit-dependent population, which relies more heavily on mass transit for social, leisure, and economic opportunities (Litman, 2018a). Transit-dependent populations often overlap with populations that are economically, physically, and socially disadvantaged (Jiao and Dillivan, 2013). So, transit agencies are responsible for maintaining equitable levels of transit service for both choice riders and transit-dependent riders. This requirement for equity in service was formalized in Title VI of the Civil Rights Act of 1964 and now equity analysis is conventional for public transit agencies, although each agency is left to determine its method of analysis. As a result, there are variations in equity analysis from one transit agency to another (Welch and Mishra, 2013). Subsequently, analyses may not completely capture the transit-dependent population. Transit equity analysis is also routinely overlooked in conventional transportation economic evaluation (Litman, 2018b) as it is generally analyzed separately from another measure, transit coverage. Transit coverage analysis serves as an informative indicator of transit service for public transit agencies when making changes to a system (Kittelson & Associates, Inc. et al., 2013). Transit coverage analysis is typically achieved spatially, temporally, or both, which can satisfy different transit agency service objectives. Both analyses are important for agencies in ensuring equitable coverage of transit.

Concurrently, advanced mobility solutions are emerging and expanding the suite of options for transit agencies to enhance services. The timeline for autonomous vehicle (AV) deployment and market acceptance is uncertain; however, shared autonomous vehicles (SAVs), are being deployed in small fleets by private companies (Fagnant and Kockelman, 2018; Feigon et al., 2016; Krafcik, 2018). Also, electric autonomous shuttles are being deployed as a transit solution and hold a larger passenger capacity than traditional cars or SUVs (Center for

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Urban Transportation Research, 2016; U.S. Department of Transportation, U.S., 2017). Operating SAVs and shuttles in public transit systems is uncertain, with few analyses exploring operating costs compared to other forms of mobility. Furthermore, the existing literature has not evaluated how SAVs, or shuttles can affect transit access and equity for transit-dependent populations.

The aim of this study is to characterize the economic feasibility of improving transit coverage and transit equity of public transportation with shared automated mobility. More specifically, this paper attempts to answer the following questions using the Port Authority of Allegheny County transit system:

1. How much does it potentially cost for SAVs and autonomous shuttles to improve public transit access for transit-dependent travelers?
2. Which service parameters are most important for shared automated mobility-public transportation integration to remain complementary?

Transit gap analysis tools that combine transit coverage and equity analysis identify priority services areas in a transit system based on transit dependency. The priority service areas have both unmet transit needs and equity challenges according to the sociodemographic characteristics of a census block group. Then, the priority service areas are used to perform a cost-based analysis for operating shared autonomous vehicles or electric autonomous shuttles as part of a public transit system. This paper makes a contribution to the literature by evaluating the economic and equity outcomes of shared automated mobility vehicles and shuttles operating as a part of an existing public transit system. By prioritizing transit dependent riders, this study also furthers the conversation regarding equity of autonomous vehicle technology. The scenarios presented in this analysis present a path towards AV deployment that furthers transit equity and preserves existing public transportation.

Literature review

Transit equity

Transit equity refers to the distribution of service from public transportation agencies across different populations (Jiao and Dillivan, 2013; Wei et al., 2018). Equity analysis aims to understand whether transit system services are provided in a nondiscriminatory manner (U. S. Department of Transportation, 1964) so that non-white and low-income populations are not worse off than the general public (U.S. Environmental Protection Agency, 2016). Another population of concern in transportation planning, termed transit-dependent, can overlap with populations that are prioritized in equity analysis (Wei et al., 2018). Transit-dependent populations are defined by the American Public Transit Association (APTA) as populations ages 65 or older, children between ages 6 and 12, households without a car, and the population physically unable to drive. Other definitions expand the groups considered transit-dependent, explicitly including populations below the poverty level and non-white populations (Feigon et al., 2016). APTA surveyed transit riders and found that 21.6% of respondents were transit-dependent (Neff and Pham, 2007). The survey results highlight the need for equitable access to public transportation by this subset of riders as respondents reported that they would lose their access to mobility if public transit were no longer available (Chowdhury et al., 2016; Neff and Pham, 2007).

Transit planning has responded and organized operations around the commuting population at the expense of transit dependent riders who rely on public transport to meet multiple needs on a daily basis (Jiao and Wang, 2021; Lubitow et al., 2017). The assumption about mobility patterns in tangent with the promotion of and investment in private vehicle ownership has resulted in declining public transit service and access for transit dependent riders. Studies also suggest transit systems that are planned around commuter or choice riders contribute to the social exclusion of transit dependent riders who may be a part of low-income, disabled or racial minority populations (Chen et al., 2021; Lubitow et al., 2017; Merlin et al., 2021).

Transport equity analysis is challenging because there are several types of equity issues, with varying impacts to consider and several ways to measure those impacts (Twaddell et al., 2019). Some approaches are customized to identify areas with a high concentration of multiple types of underserved populations (Feitelson, 2002; Twaddell et al., 2019), like those of interest in this study. Several qualitative studies assess the implications of changes to transit service on the mobility of the transit-dependent population (Fagnant and Kockelman, 2018; Wei et al., 2018). Alternatively, quantitative studies have performed transit equity analysis via transit coverage (Litman, 2018b; S. A. Mamun and Lownes, 2011) as well as the costs of achieving social equity from both the agency and rider perspective (Carleton and Porter, 2018; Feitelson, 2002, 2002; Garrett and Taylor, 1999; Wei et al., 2018). These studies examine the status quo modes of public transportation: rail, bus, rapid service. As new technology emerges in the transportation sector, achieving or improving equity in access is still important to consider. Changes to transit will occur as more systems implement advanced mobility solutions like shared autonomous vehicles and electric autonomous shuttles.

Transit coverage

Transit coverage is a level-of-service measure that evaluates spatial transit availability across a large-scale network (Ding et al., 2018; Fayyaz et al., 2017). Coverage measures are especially useful for revealing latent or unmet transit needs in a transit system (Kittelson & Associates, Inc. et al., 2013). Transit coverage analysis output is the percentage of a population that can potentially be served by the transit system (Fayyaz et al., 2017; Jiao and Dillivan, 2013). For example, systems might provide service to 80% of the service area or 65% of the population. Evaluating transit coverage typically requires spatial or temporal data to indicate service coverage across a system, satisfying different transit agency service objectives. Transit planning and service analysis typically include a coverage service objective for trips such as short passenger wait times, which is evaluated using temporal data (Fayyaz et al., 2017; Kittelson & Associates, Inc. et al., 2013). Alternatively, spatial and population data can be used to establish the percentage of the area that can access a transit stop (Fadaei and Cats, 2016).

Time-of-Day, Local Index of Transit Availability (LITA), and the Transit Capacity and Quality of Service Method (TCQSM) are three conventional approaches used for evaluating system-level coverage (Carleton and Porter, 2018; M. Mamun and Lownes, 2011). The Time-of-Day approach is an evaluation tool that uses a relative value of transit service across time in a day (S. A. Mamun and Lownes, 2011), producing a score for level-of-service during peak and off-peak hours. The Time-of-Day tool uses temporal transit demand data to make clear where transit demand is unmet, which can lead to changes in frequency or transit capacity to meet the demand (Ibarra-Rojas et al., 2015; Polzin et al., 2002). While adjusting transit service based on the temporal need will improve the riding experience, studies that only employ temporal analysis evaluate service for the population currently with transit access instead of the population that may still require service. Spatial methods for evaluating transit coverage are more robust in that they can capture the demographic information (Jiao and Dillivan, 2013), although the emphasized indicators can still vary.

The Local Index of Transit Availability (LITA) approach measures the service intensity based on the capacity, frequency, and service coverage of a system (Rood and Sprowls, 1998). The service intensity is related to the population of smaller areas of measures such as traffic analysis zones or census block groups which yield scores for the system (S. A. Mamun and Lownes, 2011; Rood and Sprowls, 1998). The LITA scores combine spatial and temporal coverage, unlike the Time-of-Day tool which only examines the temporal coverage of a transit system. This approach also uniquely evaluates passenger comfort and convenience by incorporating transit vehicle capacity (Rood and Sprowls, 1998). Although developed by transit planners Rood and Sprowls (Rood and Sprowls, 1998), this tool is better suited for use in coordinated land use and transit planning, or transit-oriented land development, rather than solely transit planning (M. Mamun and Lownes, 2011).

The Transit Capacity and Quality of Service Manual (TCQSM) uses temporal and spatial data to determine system coverage (Ding et al., 2018; Kittelson & Associates, Inc. et al., 2013; Wei et al., 2018). The systematic approach measures temporal accessibility at transit stops with various temporal measures such as dwell time, speed, and reliability (Kittelson & Associates, Inc. et al., 2013). This method also evaluates spatial service coverage in an area using proximity-based analysis. Areas with population density sufficient for hourly transit service are emphasized so the more a system provides service to high-density areas, the higher transit coverage it has according to the TCQSM. The TCQSM approach is useful; however, the focus on high-density areas does not necessarily capture a high density of demand by the transit-dependent population (Jiao and Dillivan, 2013). The TCQSM approach is used in this study, refocusing coverage analysis on the transit-dependent population specifically.

Shared autonomous mobility

Emerging mobility solutions seek to use automated technology to transition from a human-driven vehicle ecosystem to a computer-driven environment (Litman, 2018b). Previous studies note an array of potential societal benefits like fewer crashes (Anderson et al., 2014; Fagnant and Kockelman, 2018; Greenblatt and Saxena, 2015; Harper et al., 2016; Khan et al., 2019; Metz and Metz, 2018) less congestion (Fagnant and Kockelman, 2018; Greenblatt and Saxena, 2015; Metz and Metz, 2018) reduced vehicle energy and emissions (Fagnant and Kockelman, 2018; Greenblatt and Saxena, 2015; Litman, 2018b; Mersky and Samaras, 2016; Taiebat et al., 2018; Vahidi and Sciarretta, 2018), reduced urban parking requirements (Harper et al., 2018), and increased productivity (Fagnant and Kockelman, 2018) although the magnitude and even the sign of these impacts depend on assumptions, technologies, and policies (Anderson et al., 2014; Taiebat et al., 2018; Wadud et al., 2016). Auto manufacturers are increasingly adding partially automated features to their vehicles and policymakers are outlining regulations anticipating the deployment of highly automated vehicles. Yet, full-scale deployment of privately-owned AVs brings about a new set of risks, creating barriers to adoption (Bezai et al., 2021). Evaluating risks using on-road testing could take up to hundreds of years to reach a level of certainty equivalent to conventional vehicle safety tests (Kalra, 2017). Postponing deployment to accumulate the hundreds of millions of miles is not considered prudent because avoidable vehicle fatalities would continue in the meantime (Kalra, 2017). As a result, policymakers are working to develop a flexible regulatory framework to work around these risks to facilitate the successful adoption of the technology. Testing deployments have occurred with and without the shared use of autonomous technology in the U.S. and throughout the world (U.S. Department of Transportation, 2017).

To date, numerous studies have estimated costs for automated vehicles and shuttles in a variety of sharing scenarios. The cost associated with operating shared automated vehicles is an important factor in decision-making, regardless of private or public operation management. All dollar values of past studies are converted into $2019 for comparison, using the Consumer Price Index. Automated taxis (Bauer et al., 2018; Bösch et al., 2018; Fagnant and Kockelman, 2018) and AV ride-sharing (Fagnant and Kockelman, 2018; Fulton et al., 2020; Narayanan et al., 2020; Turoń and Kubik, 2020) were more prominent scenarios in existing literature, reporting a range of operating costs from $0.11/km to $1.02/km. The range of results could be attributed to some studies omitting overhead, parking, maintenance, and cleaning in cost analysis, which may overstate the cost benefits of SAVs (Narayanan et al., 2020). Also, because automated technology is still under development, the associated costs vary between studies over time while deployments provide pragmatic acquisition and operational costs for AVs and shuttles. Many studies explore costs associated with AVs used for ride-hailing and as taxis, resulting in a gap in the literature on costs for integrating shared automated mobility into public transit (Golbabaei et al., 2021).

Although automated vehicle-public transit operational feasibility is being established (Levin et al., 2019; Mo et al., 2021; Pinto et al., 2020; Wei et al., 2018), cost analysis studies have reported costs between $0.19/km and $0.30/km and up to $0.39/km for SAVs providing first and last-mile service in a public transit system (Moorthy et al., 2017). Shared automated mobility is still evolving to provide pragmatic information for future transportation policymaking but is still grappling with uncertain technology costs, fleet sizing, regulatory requirements, and other factors (Narayanan et al., 2020). Meanwhile, more than one hundred testing deployments of autonomous shuttles have taken place globally as they are well-suited to provide service for short-distance trips like tourist destinations and university campus transit routes (Iclodean et al., 2020; Smith, 2014). Shuttles operate at lower speeds and their predictability reduces risks that act as a barrier for private autonomous vehicles (Hunter, 2018). Some pilot programs for shuttles include service to the existing public transit system (Smart Columbus, 2021; The Swiss Transit Lab, 2018) in the form of first-mile, last-mile transit access.

Cities that tested AV technology have found that publicly-led testing and pilots provide the best opportunity to shape local AV deployment (Chatman and Moran, 2019), incentivizing transit agencies to provide shared autonomous mobility. If shared autonomous mobility is only available through private companies, the potential decline in transit ridership could lead to reduced levels of service (Litman, 2020), which would affect transit-dependent riders acutely. Also, ensuring equitable service from mobility-as-a-service companies is an ongoing concern. Unlike public transit agencies, privately-owned companies are not mandated to operate equitably at this time. However, public transit agencies can expand their transit services by managing or contracting a fleet of SAVs or shuttles and subsequently provide an equitable level of access for choice and transit-dependent riders (Mo et al., 2021; Narayanan et al., 2020).

Data & methods

We used multiple methods and datasets for assessing operating costs and equity outcomes of shared automated vehicles and shuttles integrated into a public transit system as shown in Fig. 1. CBG level data is used throughout the study because smaller, low-income or minoritized communities are overlooked at more aggregate levels of geographic analysis (U.S. Environmental Protection Agency, 2016). Census block groups (CBGs) are divisions of census tracts generally covering a continuous area, and typically contain between 600 and 3000 people (U.S. Census Bureau, 2021). First, the transit supply score was determined using transit stops, routes, and service frequency data from the Port Authority of Allegheny County's General Transit Feed Specification. The transit supply score and transit need scores for each census block group determine transit coverage, revealing how the system is currently serving the transit-dependent population. By identifying the census block groups with the lowest transit coverage score and greater than average low-income or minority population, a set of census block groups are prioritized for service improvement. Census and EPA data provided demographic details to represent the transit-dependent, low-income, and minority populations in each census block group and determine transit needs. The study area is shown in Figs. 2 and 3. Task three in Fig. 1 uses the priority CBGs as origin points for calculating route distances to and from the nearest bus stop with adequate transit service, then used as inputs for cost analysis. Each priority census block group was assessed for cost efficiency of adding either shuttle, SAV, or bus service for these route distances. Cost analysis considers a variety of factors, like capital costs, fuel, insurance, wages, and is provided in more

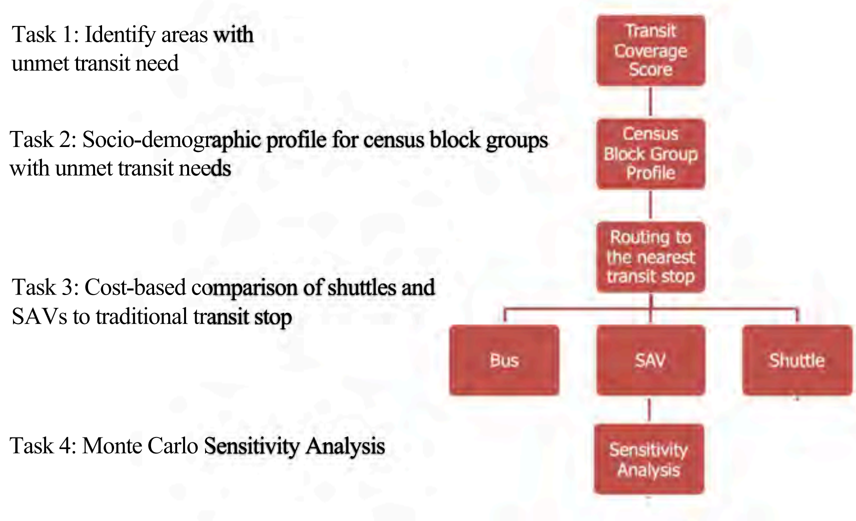

Fig. 1. Graphical Summary of the study methods.

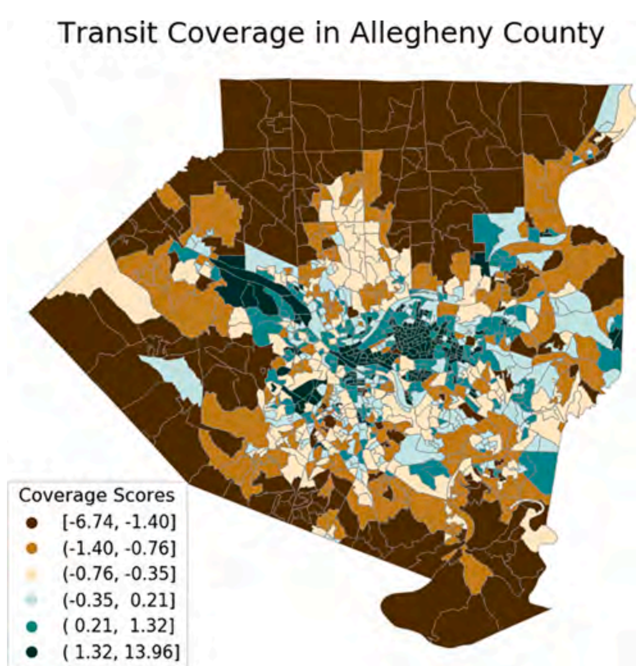

Fig. 2. Map of transit coverage based on transit-dependent rider demand and transit supply in Allegheny County, PA. Darker colors show extremes with dark blue indicating more than sufficient coverage to match demand, and dark brown is the lowest transit coverage signifying insufficient transit access for the transit-dependent population. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

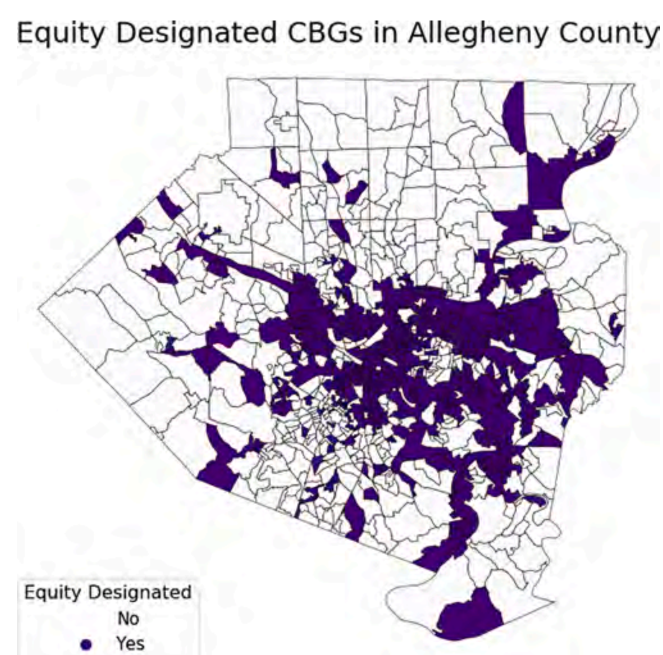

Fig. 3. Map of low-income or minority population by census block group.

detail in section 2.3. Finally, levelized cost per vehicle kilometer traveled and levelized cost per passenger-kilometer traveled for are derived for all three modes. Levelized costs for operating SAVs as shuttles in Allegheny County, PA are estimated across multiple scenarios to provide insight into the cost efficiency of different transit planning futures. Due to the uncertainty of shared autonomous mobility, sensitivity analysis is performed over a range of AV operating costs and uncovers the most important parameters influencing shared automated mobility operational feasibility.

Transit coverage analysis

To effectively identify areas with unmet transit access needs in the case study county, a transit coverage score must be calculated. The transit coverage score is a measurement found in the Transit Capacity and Quality of Service Method (Kittelson & Associates, Inc. et al., 2013). This method was used because it allowed for analysis with our census block groups that properly capture smaller, low-income, or minoritized communities that are overlooked at more aggregate levels of geographic analysis (U.S. Environmental Protection Agency, 2016). The measures of interest for this analysis included: transit-dependent population, transit stops, the number of routes, the frequency of service for each stop per weekday, and a final transit coverage score.

First, the transit-dependent population was derived from data provided in the 2016 American Community Survey (U.S. Census Bureau, 2016). Age and vehicle ownership data were aggregated to obtain the transit-dependent population by CBG. The driving eligible population was aggregated for every census block group in Allegheny County. The legal driving age in the U.S. is, on average, 15 years old, and literature shows that driving ends around 70 years old (Foley et al., 2002), which was used as a conservative input to estimate the driving eligible population in each census block group. Vehicle ownership data from the American Community Survey includes zero-vehicle households which represent the transit-dependent population in this study. Although the transit-dependent population consists of many types of riders: zero-vehicle households, those who are unable to drive due to physical limitations, and specific age groups, the zero-vehicles households are a sufficient proxy to estimate the population. The transit-dependent population density per CBG was determined by dividing the population by the net land area in Allegheny County CBG shapefiles, then normalized to ensure a direct comparison between transit-dependent population and the transit supply found in the next step.

The determinants for transit service, outlined by Jiao et al. (Jiao and Dillivan, 2013) and the TCQSM (Kittelson & Associates, Inc. et al., 2013) are (1) number of transit stops in each block group, (2) average frequency of weekday service in each block group, and (3) number of routes serving each block group (Fayyaz et al., 2017; Jiao and Dillivan, 2013). Since riders do not consider CBG borders to access a transit stop, stops near a CBG boundary are included in transit service analysis. This was accounted for by adding a 0.4 km or quarter-mile buffer around each CBG to give a count of transit stops that can potentially serve the population (Fayyaz et al., 2017; Jiao and Dillivan, 2013). The transit stop aggregate value was converted to a transit stop density per net area then normalized. The transit routes within a 0.40-km buffer of each census block group were counted for each CBG. Routes passing through a CBG without a transit stop were assigned a value of zero since service is not accessible. Like the transit stop counts, the route count output was converted to a route density by dividing by the net area for each CBG and normalized. Transit service frequency was determined using general transit specification feed (GTSF) processed data from Carnegie Mellon University's Mobility Data Analytics Center (Qian, 2018) which provided the bus frequency by the hour for each road segment in Allegheny County. The resulting value was divided by the net area then normalized. If this information is not available at the high resolution used in this study, GTSF data is sufficient for calculating the average number of buses per hour in a CBG, as used by Jiao et al. (Jiao and Dillivan, 2013). These three transit supply values–transit stops, routes, and frequency–were aggregated into a transit supply score for each CBG. The transit supply was calculated as

$$S_i = \frac{\sum t_i}{a_i} + \frac{\sum r_i}{a_i} + f_i \tag{1}$$

where S_i is the supply score for any CBG i, t_i is the total number of transit stops, a_i was the net area, r_i was the total number of routes, and f_i was the frequency of service or average bus per hour. The supply inputs were not weighted because any configuration of transit supply can satisfy the specific needs of a CBG. Finally, the transit coverage scores for each census block group i (C_i) based on the transit-dependent population, P, was

$$C_I = S_i - P \tag{2}$$

(Jiao and Dillivan, 2013; Kittelson & Associates, Inc. et al., 2013). There are various approaches for measuring transit level of service; however, a standard coverage threshold was not found in previous studies. The CBGs within the bottom five percent of all transit coverage scores were considered low transit coverage block groups. This threshold systematically captures the most extreme cases of low transit coverage and, accordingly, transit-dependent populations with the lowest transit supply in Allegheny County.

Transit equity analysis

Sociodemographic profiles of CBGs provide pertinent information for analyzing transit equity. EJSCREEN, the EPA's environmental justice screening tool, provides sociodemographic data by CBG (U.S. Environmental Protection Agency, 2014). The groups of interest included in EJSCREEN data are low-income and minority households. Minority households are defined by the EPA as the percent or number of minority individuals that are non-white, including multiracial individuals, in a census block group (U.S. Department of Transportation, 1964). Households are designated as low-income when the household income is less than or equal to twice the federal poverty level (U.S. Environmental Protection Agency, 2014). Data aggregated by ethnicity and income were appended to spatial data to identify CBGs with greater than average low-income or minority populations. If the minority population within a block group was greater than the county average of 23.1%, it was denoted as an equity designated CBG. When the low-income population in a CBG was greater than the county average, it was denoted as an equity designated CBG. The final step in equity analysis was assigning priority to the CBGs that had both an equity designation and low transit coverage. The priority CBGs were used for calculating operational costs for the three mobility solutions.

Direct cost analysis of autonomous mobility solutions

Estimating operating costs required framing the problem to allow for equal comparison across modes of interest in the study. Calculating the levelized cost of driving (LCOD) is based on the calculations developed by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (Nealer et al., 2018). LCOD highlights the effects of advances in vehicle technology which supports the aims of this study.

Three transit modes were considered for the cost analysis to improve transit coverage

1. Bus: The base-case mode adds a transit stop in a priority CBG centroid which is served by at least one conventional diesel bus connecting a priority CBG to an established transit stop. The study assumes a 40-foot bus with an average bus capacity of 40 passengers.
2. Shared Autonomous Vehicles (SAVs): The first alternative mode operates as at least one autonomous vehicle traveling from the priority CBG to the nearest existing transit stop. Sedans and minivans are the standard vehicles used in AV testing, so this study used four-passenger gasoline SAVs to serve each priority CBG.
3. Electric Autonomous Shuttles: The second alternative mode uses electric, autonomous shuttles to serve priority CBGs with service to the nearest existing transit stop. Capital and operating costs were used to compute separate estimates of direct costs for the implementation of a 12-passenger electric autonomous shuttle.

All three modes were evaluated for the exact same service. For each priority census block group the route distance between the centroid and nearest transit stop was determined using Open Source Routing Machine's (Open Source Routing Machine, 2019) Table service. The frequency of service was determined using the average frequency of census block groups adjacent to priority census block groups. Each transit mode was evaluated for cost efficiency using levelized cost per vehicle kilometer traveled ($/VKT) and levelized cost per passenger-kilometer traveled ($/PKT).

Cost Per Vehicle Kilometer Traveled Calculation. The following equation calculates the levelized costs for each mode

$$Levelized\ Cost\ per\ Vehicle\ Kilometer\ Traveled = \frac{\sum Cc + \sum Co}{d} + c_e \tag{4}$$

where c_c is the total annualized capital cost to acquire the shuttle, SAV, or bus. The summation for c_c accounts for the cost of the shuttle and charger for the shuttle mode scenario. Annualized costs were calculated using a 6% discount rate from the state of Pennsylvania Department of Transportation bond rate (Port Authority of Allegheny County, 2016), and an estimated ten years of use based on the average ten years of use for transit vehicles (Hughes-Cromwick et al., 2017). Capital purchase costs of electric autonomous shuttles (Local Motors, 2018), gasoline SAVs (Chen et al., 2016), and conventional diesel buses (Colorado Department of Transportation, 2018) were annualized. The cost of wireless electric chargers for autonomous shuttle charging was also annualized (Nicholas, 2019; Sierra Club, 2016). Operating costs or c_o, comprises of the annual operator wages, fringe benefits, insurance, and annualized maintenance costs. Operator hourly pay for the conventional diesel bus was determined by the annual salary and revenue hours for operators reported by the PAAC (Port Authority of Allegheny County, 2016). Operator hourly pay is reduced by 60% for electric autonomous shuttles and SAVs to account for the potential operational cost savings (Wadud, 2017). Fringe benefits represent the employee benefits package of health, retirement, and other benefits offered to Port Authority of Allegheny County employees which are roughly 33% of their annual salary (Port Authority of Allegheny County, 2016). Insurance costs per mile for electric autonomous shuttles and SAVs were drawn from APTA's breakdown of operation expenses by function (Hughes-Cromwick et al., 2017). Liability and casualty costs are 2% of operating expenses and the 2016 financial performance report from PAAC detailed operating expenses, which was used to derive the insurance cost per kilometer for shuttles (similar to demand response costs) and buses (Port Authority of Allegheny County, 2016). This value was used to determine the insurance cost per kilometer for electric autonomous shuttles, as they would be categorized as a form of shared ride transit service. The American Automobile Association (AAA) reported insurance costs of \$0.20/km for vehicles that were used for SAVs. Maintenance costs for electric autonomous shuttles came from a report by the Sierra Club (Sierra Club, 2016) and the SAV maintenance cost per kilometer was estimated in a study by Fagnant and Kockelman (Chen et al., 2016). The route annual revenue kilometers were captured in d, and c_e was the energy cost per kilometer for each mode of transportation. Parameter values are shown in Table 1 and Table 2. Energy costs to propel the various vehicles were based on 2019 data from the Energy Information Administration (EIA) (U.S. Energy Information Administration, 2019). Gasoline fuel efficiency of 14.87 km per liter (km/L) and a national average of \$0.59 per liter for SAVs was used. The EIA reported average diesel costs at \$0.56/liter in 2019, so the median diesel price per kilometer was derived from a 1.69 km/L fuel efficiency for diesel buses (U.S. Department of Energy, 2018). Table 2 details these point estimates for capital costs, energy costs, and operator pay.

Cost Per Passenger-Kilometer. Next, the cost per passenger kilometer traveled was calculated for each mode using

$$\textit{Levelized Cost per Passenger} - \textit{Kilometer Traveled} = \frac{C_0 + c_c + d(C_e)}{p} \quad (5)$$

where p represents annual passenger-kilometers as detailed in Table 1 and Table 2.

This study used three analyses for levelized cost analysis to offer a variety of ways to analyze the results and provide insight about operating shared autonomous mobility integrated with an existing public transit system. First, baseline levelized costs were determined using U.S. transit system average values to determine \$/VKT and \$/PKT. Since shuttles, SAVs, and buses in this study are being used solely for first- and last-mile service, national averages of demand response transit in the U.S were used as parameter values (American Public Transit Association et al., 2017) for the baseline analysis. Second, CBG-level analysis considers the ridership demand of an individual CBG and provides a higher resolution of levelized costs to uncover the most cost-effective routes. Lastly, Monte Carlo simulation considers the uncertainty of each parameter in the model to estimate levelized \$/VKT and \$/PKT across a range of feasible scenarios.

Monte Carlo simulation presents a probabilistic representation of operating cost outputs under the uncertainty of costs associated with shuttles and SAVs, and with the choices in the mode scenarios. The simulation model used the parametrized inputs in Table 1 and Table 2, with ranges of values shown in Table 3. Probability distributions capture the optimistic and pessimistic ranges of levelized cost parameters. Using a triangular distribution of capital and energy costs accounts for optimistic cost savings or pessimistic increases in costs in the future. The annual distance was based on the range of annual distances found in CBG level analysis and parameterized as shown in Table 3 to have best- and worst-case scenarios. Annual passenger-km was similarly derived from CBG-level analysis. Lower annual passenger-km, annual distance, and operating hours are included in the pessimistic scenario because it would increase costs per kilometer and per passenger-kilometer. Conversely, a greater annual distance, annual passenger-km, capital costs, and energy costs drive down operating costs, resulting in a best-case scenario for analysis. Base values for annual distance, annual passenger-km, and operator hours are derived from the mode of the priority CBGs. Base values for capital and energy costs come from the point estimates detailed in Table 1 and Table 2. Sensitivity analysis was performed using Sobol's sequence in the SALib Python package (Herman and Usher, 2017) to estimate the main and total effects for each parameter.

Table 1
Point estimate inputs for calculating \$/VKT and \$/PKT for baseline cost analysis and CBG-level cost analysis.

Parameters	Baseline Analysis (Average U.S. Transit System)	CBG level Analysis (mean)
Annual Distance (km)	71,500	68,872
Annual Passenger-KM	51,000	200,763
Operator Vehicle Hours	1,700	2,871

Table 2
Point estimate inputs for calculating \$/VKT and \$/PKT by transit mode. All values are \$2019 and used for transit standard cost analysis and CBG-level cost analysis.

Parameters	Mode of Transit			
	Shuttle	SAV	Bus	Reference
Operator Wages (\$/hour)	10.20	10.20	25.51	(Port Authority of Allegheny County, 2016; Wadud, 2017)
Fringe Benefits (\$/hour)	3.36	3.36	8.41	(Port Authority of Allegheny County, 2016; Wadud, 2017)
Insurance (\$/km)	0.10	0.20	0.18	(Port Authority of Allegheny County, 2016; American Auto Association, 2017; American Public Transit Association, 2020)
Maintenance Cost (\$/km)	0.39	0.32	0.89	(Fagnant and Kockelman, 2015; Sierra Club, 2016)
Energy Cost (\$/km)	0.04	0.08	0.33	
Acquisition (Capital) Costs (\$)	238,095	70,000	300,000	(Chen et al., 2016; Colorado Department of Transportation, 2018; Local Motors, 2018)
Annualized Acquisition Cost (\$/year)	32,349	10,130	43,417	(Hughes-Cromwick et al., 2017; Port Authority of Allegheny County, 2016)
Annualized Charger Acquisition Cost	24,796	–	–	(Nicholas, 2019; Sierra Club, 2016)

Table 3
Monte Carlo Simulation Parameters.

Parameters	Probability Distribution	Pessimistic	Base	Optimistic
Annual Distance	Uniform	18,000	71,000	111,000
Annual Passenger-KM	Triangular	131,000	160,000	317,000
Annual operating hours	Uniform	1,700	3,000	5,000
Electric Charger ($/year)	Triangular	40,000	14,000	9,5000
Bus Fuel Costs-Diesel ($/kilometer)	Triangular	0.35	0.33	0.3
SAV Fuel Costs-Gasoline ($/kilometer)	Triangular	0.1	0.07	0.05
Shuttle Electricity costs ($/kilometer)	Triangular	0.07	0.05	0.02
Shuttle Capital Cost ($/year)	Triangular	39,000	32,000	26,000
SAV Capital Cost ($/year)	Triangular	12,000	10,000	8,000
Bus Capital Cost ($/year)	Triangular	52,000	43,000	35,000

Results & discussion

Allegheny County

The Port Authority of Allegheny County (PAAC) is the public transit system that serves Pittsburgh, PA, and surrounding suburbs. There are 105 transit routes, that serve 6,896 transit stops plus paratransit services. There are two reasons why the PAAC was selected as the case study. First, the PAAC has proposed direct service for underserved, lower density areas namely coverage routes (Port Authority of Allegheny County, 2019). To provide basic service to these areas with coverage routes is reported to be a better choice than to deviate an existing route. Second, all trips in our scenario begin and end within county boundaries which helps with framing and subsequently completing analysis for the study.

Before the scenario analysis, the typical transit service for a census block group in Allegheny County, there were approximately 124 transit dependent riders that has access to 24 stops that connecting to one roue with service every 12 min. For the 16 CBGS identified as those with the lowest transit coverage service was much lower and the transit dependent population was much higher. On average these priority CBGs had 489 transit-dependent riders and only 14 transit stops within a quarter-mile radius of the CBG boundary. These CBGs also had access to one route but service increased to every 30 min. The disparity in service transit dependent riders in the priority census block groups experience means that there is an opportunity to improve transit access, and thus equity where it would be most impactful and can further PAAC goals of coverage routes for the system.

Transit coverage & equity in allegheny county

Transit coverage combines the transit-dependent population and transit supply scores to identify CBGs with unmet need and low transit supply by CBG in Fig. 2. The importance of evaluating transit coverage scores based on the transit-dependent population is to highlight areas that might be unknown regions of missing or depleted transit access. Fig. 2 shows that many dark brown regions, which represent low transit coverage scores, are primarily beyond the Pittsburgh city boundaries. Notably, the dark brown areas also correspond with Pittsburgh suburbs where population density is lower and therefore rider demand is typically lower. Approximately 78% of the transit-dependent population overlaps with the priority CBGs accounting for over 120,000 transit-dependent riders who are also low-income or minority households. CBGs with low-transit coverage had higher percentages of low-income and minority populations when compared to the county average. Minority populations in low-transit coverage CBGs averaged 46% while the county average was only 23 percent. Fifty-five percent of low-transit coverage CBGs were also low-income, while the county average is 32 percent.

Cost analysis

Table 4 shows the levelized cost per kilometer traveled ($/VKT), levelized cost per passenger-kilometer ($/PKT) traveled, and total costs for each analysis. Although each analysis has varying results for levelized costs due to differences in calculation, both levelized costs and total annual operating costs are within the same order of magnitude. Fig. 4 illustrates the wider range of levelized costs from the Monte Carlo simulation. The range of cost per vehicle kilometer traveled ($/VKT) was very similar for electric autonomous shuttles and SAVs, while buses resulted in a wider range of costs per km. SAVs were lowest for cost per passenger-kilometer traveled ranging from $0.77/PKT to $0.90/PKT for each analysis. SAVs also had the lowest costs per vehicle kilometer traveled with $/VKT between $2.15 and $2.28 for each analysis. Costs per passenger-kilometer traveled were typically lower than the costs per vehicle kilometer traveled overall. Sensitivity analysis determined which parameters have the greatest influence on the levelized cost outputs.

Sensitivity analysis

Sensitivity analysis identifies the parameter or set of parameters that have the greatest influence on the model output. It consequently provides useful insight into which model input contributes most to the variability of the model output. Sobol's approach for global sensitivity analysis revealed the parameters that most influenced levelized cost per vehicle kilometer and levelized cost per passenger-kilometer across each mode. Table 5 shows the rank of influence for each parameter for $/VKT and $/PKT. Across all modes, it is not surprising that levelized cost per vehicle kilometer traveled is most sensitive to the number of revenue kilometers traveled annually. The sensitivity analysis ranked the second most important parameter for SAVs and buses as operator hours. Most priority CBGs have lower ridership demand, thus one shuttle or bus provides adequate service in most cases. However, a small fleet of no more than three SAVs provides service for some of the priority CBGs. As a result, fleet size was the second most influential parameter for SAVs whereas buses and shuttles were not influenced by fleet size. Other studies have noted the importance of shared AV fleet size which is supported in these results (Golbabaei et al., 2021; Mo et al., 2021; Shen et al., 2017). Table 5 also shows the total effects for each parameter in the order of influence for cost per passenger-kilometer. Annual passenger-kilometer is the most influential parameter across all three modes. Similar levelized costs per km, the fleet size is the next most influential parameter for SAVs and the least influential for buses and shuttles since fleet size did not vary for these two modes. The parameters followed the same order of influence across modes from greatest to least: annual distance, operator hours, capital costs, and energy costs. These rankings provide insight into the most important factors in planning shared automated mobility services for increasing equity and transit coverage in a public transit system. When considering $/VKT, planners can focus on the annual distance, operator hours, and fleet size. If $/PKT is a metric of interest the top three factors for consideration are annual passenger-kilometers, annual distance, and fleet size.

Levelized cost analysis for each CBG offers a higher resolution exploration of parameter sensitivity along with important social indicators like the transit-dependent population served and transit coverage improvement. The five priority CBGs detailed in Table 6 are prioritized based on the factors identified in the sensitivity analysis as well as the equity indicators of interest. Overall, CBG #3 is the most ideal census block group for additional transit service because transit

Table 4
Mean levelized costs and total costs comparison for each approach.

	Levelized $/VKT			Levelized $/PKT			Total Annual Operating Costs		
	Shuttle	SAV	Bus	Shuttle	SAV	Bus	Shuttle	SAV	Bus
CBG Level Analysis	$2.79	$2.15	$4.06	$1.31	$0.90	$2.14	$158,000	$114,000	$252,000
Baseline Analysis	$2.77	$2.21	$3.85	$1.36	$1.08	$1.89	$112,000	$89,000	$155,000
Monte Carlo Simulation	$2.71	$2.28	$4.24	$0.94	$0.77	$1.49	$149,000	$122,000	$235,000

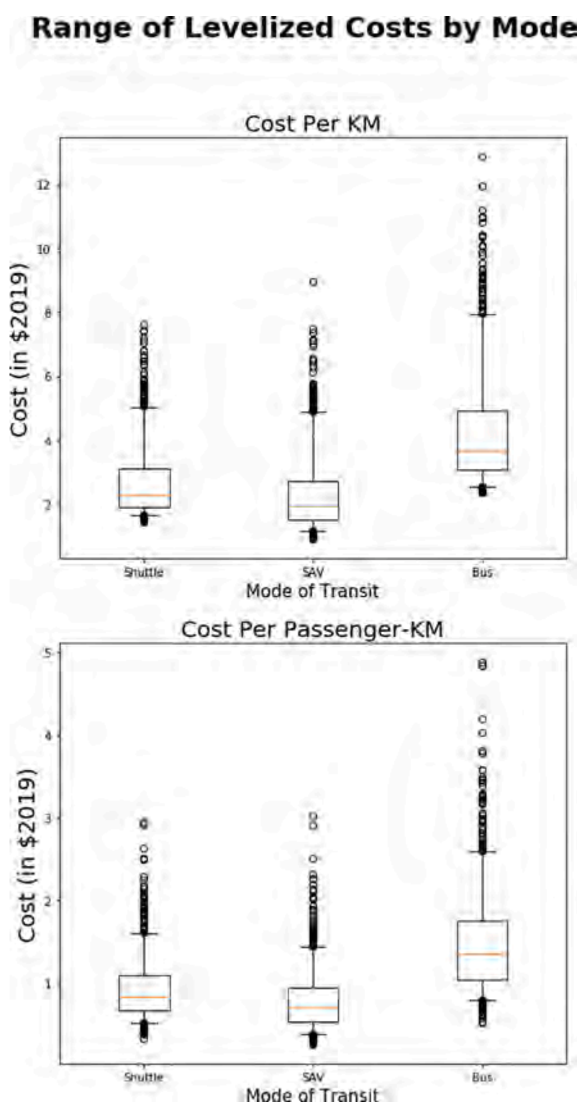

Fig. 4. Box plot showing the full range of costs from Monte Carlo Simulation for each mode of transportation. The line inside the box plot represents the median and the whisker boundaries represent the 5th and 95th percentile.

coverage improved the most. A new transit service would connect this CBG to the existing transit system, as there was only one route previously serving the area. The transit coverage score increased from −2.53 to 12.12. The positive score, 12.12, indicates that service improved for the transit-dependent population and now exceeds transit demand for this CBG. The route would operate with 79,000 km traveled annually, and 159,000 annual passenger kilometers traveled. Based on total operating costs, levelized cost per km traveled and cost per passenger kilometer traveled, one SAV is the most cost-effective service choice for the CBG.

Table 5
Monte Carlo Sensitivity Analysis Ranking. Table values represent total-order sensitivity indices in descending order to show the rank order of influence for each parameter for levelized costs.

$/VKT Parameter	Rank	SAV	Shuttle	Bus
Vehicle KM	1	0.724	0.96	0.898
Operator Hours	2	–	0.046	0.129
Fleet Size	2	0.132	–	–
Capital Cost	3	0.001385	0.0056	0.003950
Energy Costs	4	0.000099	0.00014	0.000061
Fleet Size	5	–	0.00	0.00

$/PKT Parameter	Rank	SAV	Shuttle	Bus
Passenger-KM	1	0.1445	0.15167	0.1794
Vehicle KM	2	–	0.063976	0.1311
Fleet Size	2	0.049	–	–
Operator Hours	3	0.043	0.017519	0.037912
Capital Costs	4	0.00326	0.011787	0.001323
Energy Costs	5	0.0006	0.000136	0.00009
Fleet Size	6	–	0.000	0.00000

Table 6
Transit coverage scores before and after analysis and lowest levelized costs for each priority CBG.

Priority CBG Analyzed Census Tract ID Number	0 810003	1 900024	2 4511042	3 3001004	4 5623006
Transit Dependent Population	596	47	92	639	652
Minority Population (%)	0.45	0.29	0.04	0.74	0.8
Low-Income Population (%)	0.67	0.45	0.33	0.8	0.52
Stop Count (before)	36	0	0	55	36
Average Hourly Frequency (before)	4.36	0	0	5.15	5.62
Routes (before)	1	0	0	1	2
Transit Dependent Population Need Score	3.82	−0.52	−0.54	6.01	7.02
Transit Service (before)	0.95	−3.07	−3.07	3.48	4.39
Transit Coverage (before)	*−2.87*	*−2.55*	*−2.53*	*−2.53*	*−2.63*
Stop Count (after)	51	13	18	70	47
Average Hourly Frequency (after)	4.28	1.96	1.4	5.09	5.54
Routes (after)	16	1	2	16	16
Transit Dependent Population Need Score	3.82	−0.52	−0.54	6.01	7.02
Transit Service (after)	11.48	−2.03	−2.29	18.13	19.13
Transit Coverage (after)	*7.68*	*−1.51*	*−1.75*	*12.12*	*12.11*
Lowest $/VKT	$ 1.23	$ 3.02	$ 3.49	$1.23	$ 1.49
Lowest $/VKT mode	SAV	Shuttle	SAV	SAV	SAV
Lowest $/PKT	$ 0.85	$ 0.34	$ 0.47	$ 0.70	$ 2.09
Lowest $/PKT mode	SAV	Shuttle	SAV	SAV	SAV

Conclusion

This study aimed to determine the feasibility of improving equitable transit access using autonomous mobility as a part of a public transit system. The results of this study support previous work that states these new technologies can reduce transit costs. Overall, this study revealed service parameters that are important for improving transit coverage and equity with SAVs or shuttles operate at substantially lower costs than buses. Sensitivity analysis revealed the most important parameters for consideration in future transit planning and policy of shared autonomous mobility. Thus, SAVs and shuttles can be constrained to certain service metrics to improve transit coverage equity and to remain a cost-efficient complement to existing transit service.

The increase in transit coverage means that the needs of the transit-dependent, low-income, and minority populations could be better addressed in Allegheny County. Implementing SAVs or shuttle does not impact the existing transit system, so other transit rider groups are not affected. The increased access for the transit-dependent population could also result in ridership increases, as these locations are currently underserved.

By coupling transit coverage with equity analysis, the low-income and minority populations were identified in Allegheny County. The results of this study indicate while the overlap for transit-dependent, low-income, or minority populations was not significant for this transit system, there were CBGs that held both vulnerable populations. This approach could be applied to another transit system, to assess the degree of overlap in their populations. The policy implications of these findings are clear; this approach can be used to satisfy the requirements of Title VI from the FTA, where many transit agencies receive funding for most types of capital investments. Incorporating equity into transit coverage analysis will improve the transit planning process and more importantly, positively impact vulnerable populations that need transit access the most. More broadly this study supports the efforts towards low carbon mobility outlined in the 2030 Agenda for Sustainable Development and the seventeen Sustainable Development Goals (SDGs). While low carbon mobility is not explicitly articulated as a goal, increased public transit access and ridership supports many of the SDGs.

This works also strengthens the idea that SAVs and shuttles can equitably improve public transit access cost-effectively. The findings suggest public transit agencies could begin integrating shared automated mobility into their transit system. However, continued technology advancement, and an evaluation of other potential negative social and environmental impacts of these vehicles are needed before a full deployment is possible. There are opportunities for more robust transit coverage analysis tools and data that focus on the transit-dependent population.

Limitations

There were some limitations in this study. First, datasets and point estimates are from or adjusted to 2019. In some cases, the most up-to-date and comprehensive dataset available was for this time period. As more SAV and shuttle cost information becomes publicly available, future studies can update mean levelized costs and potentially realize more savings. Second, only direct costs were included in the analysis. Some additional costs such as cleaning, garaging, administrative costs, are not included. These are unlikely to affect the differences in costs across the three vehicle types we examined. Further, environmental impacts, rider comfort, safety, unbanked rider accessibility, etc., while important and socially beneficial, were not included as they do not directly contribute to operating costs. Third, analysis methods for transit coverage vary in transportation planning and research efforts. This paper did not seek to create a new approach and instead used existing tools for aggregating the transit-dependent population and transit coverage. Extracting the transit-dependent population also varies from one transit agency to another, which could be standardized for reproducibility across agencies and analysis. Lastly, further research could usefully explore the impacts autonomous mobility solutions will have as part of a public transit system. Not every public transit system is like PAAC, thus analysis that explores operational feasibility in other cities with different sized transit systems can provide more information about what is feasible with shared autonomous mobility. More research on the changes in perceived quality, willingness to pay, passenger trust in autonomous technology, transit-SAV scheduling, environmental impacts need to be developed for a more comprehensive understanding.

Author contributions

The study was conceived by A.W., C.T.H., H.S.M., and C.S. The data was collected and analyzed by A.W. All authors assisted in interpreting the results and drafting the manuscript. All authors approve the manuscript for submission.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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