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Equity and Transportation System Implications of Shared Autonomous Vehicle Deployment

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Problem Statement

Low-income communities and minority communities have experienced inferior access to transportation choices when compared to their white and more affluent counterparts. Many of these same populations have also experienced greater exposure to many of the negative externalities from transportation systems, such as congestion and air pollution [1], [2]. These inequalities seed serious structural inequities in our society, from missed doctor's appointments [3] to the exclusion of these individuals from higher paying jobs [4] to differential health outcomes [5].

In the US, many individuals in lower income populations rely on public transit as their main mode of transportation. Close to 40 percent of one-parent families receiving public assistance do not own a car and rely on public transportation for day-to-day travel [6]. Most public transit systems run on a fixed route system, in which vehicles run along an established path at preset times. In densely populated neighborhoods, a fixed route system may work well, since walking distance to bus and train stops may be acceptable. But in medium or low-density areas where residents may have to travel longer distances to and from transit stops, the lack of accessibility creates tremendous challenges for human mobility and leads to usage of unsustainable transportation modes. In addition, nearly one in five people—more than 61 million Americans—have a disability [7]. Of those, some six million have a travel-restrictive medical condition—one that limits their day-to-day mobility [7]. This includes individuals with hearing, vision, and ambulatory difficulties that require the use of a wheelchair. By 2040, it is projected that there will be roughly 80 million seniors living in the U.S., which represents about a 70% increase in the number of elderlies from today's numbers [8]. In an effort to reduce the mobility gap, the Americans with Disabilities Act (ADA) began requiring transit agencies that provide fixed-route services to also provide "complementary paratransit." However, even these paratransit services face challenges in providing timely, efficient, and cost-effective service and these issues are likely to worsen as demand for these services increase [9].

More recently, transportation network companies (TNCs) (e.g., Uber and Lyft) have revolutionized mobility in many urban areas by detaching car access from car ownership, and in theory reducing many mobility gaps that arise from people not having access to a personal vehicle. Despite its high-tech luster, ride-hailing services do not serve all neighborhoods and travelers equally. Ge et al. concluded that minority TNC riders experience statistically significantly longer waiting times, on average. Studies also reveal some drivers for both UberX and Lyft discriminate based on the perceived race of the traveler, leading to more frequent ride cancellations [10].

AVs have the potential to be one of the biggest revolutions in transportation since the introduction of the personal car. The deployment of AVs is fast-approaching—Google's Waymo, for example, has already deployed fully-autonomous taxis in some cities, and many other technology firms have begun pilot operations [11]. AVs hold serious promise for promoting social equity by increasing mobility for minority, low-income, and elderly populations as well as people with travel restrictive medical conditions. However, shared AVs, as with any emerging technology, could also exacerbate existing social inequalities. The potential distribution of impacts across populations and equity considerations are absent from most AV modeling efforts. It is important to see how configurations of autonomous mobility services could make trade-off between an inexpensive service with high waiting times and a service with high availability.

Without proper policy, autonomous services could become a mode of transport for the wealthier part of the population if we only focus on the operational efficiency, putting us on a track for greater social imbalance [12].

To ensure that the path towards vehicle automation to simultaneously reduce transportation inequity and leads us towards a smarter and more sustainable transportation system, this study uses agent -based simulation to evaluate how pricing and fleet size policies on shared AV systems effects system performance (e.g., congestion and operations) as well as sub-population level outcomes (e.g., travel cost for different groups).

Case Study Area

This paper focuses on assessing the transportation system and sub-population level impacts of different pricing and fleet sizing policies for shared AV services in Seattle. While the conclusions of this research are meant to be generalizable, we focus our study on Seattle, Washington because it's a diverse city with known inequalities among income, race, and other factors. Areas outside of the city limits of Seattle are not in scope of this study.

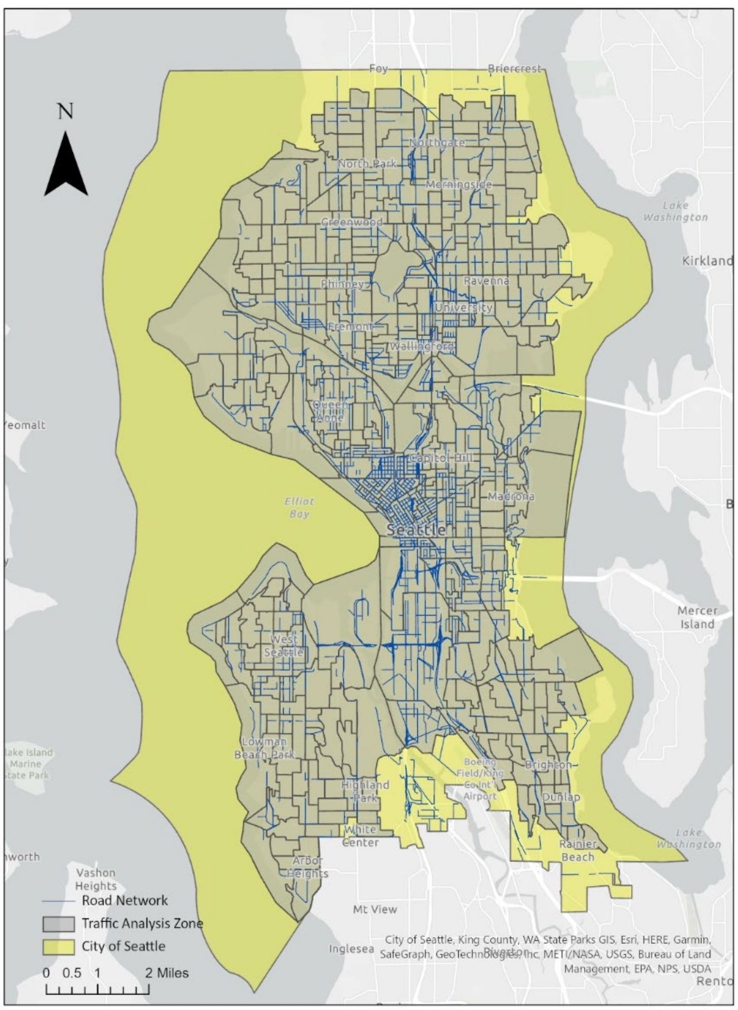

Figure 1. Study Region

Data

We extracted the road network data from OpenStreetMap and public transit network and schedules from General Transit Feed Specification (GTFS). Converting GTFS to transit schedules and mapping transit stops and transit routes to the road network are accomplished by pt2matsim tool [13]. Transit modes (bus and tram in this study) will reflect congestion effects if they share the same road with private vehicles, otherwise dedicated artificial links are created and transit vehicle will travel in fixed schedule. After cleaning and simplifying the network, 27k nodes and 57k links are extracted as the multi-modal network.

Agent-based transportation simulation requires disaggregated detailed traveler's information. A tour is required in simulation preparation to represent a chain of trips of a traveler throughout the day. Here we adopted the mobility population by cleaning and geo-constraining data from SoundCast activity-based travel model (Puget Sound Regional Council (PSRC), 2014). The household, person and trip tables from PSRC are based on extensive travel survey as well as American Census Survey (ACS) and other data source to synthesize a robust population and travel patterns of Seattle [14]. To model the heterogeneity of subpopulations, we split the synthesized population into multiple categories based on their associated household income level, age, employment status and car ownership. The value of travel time (VOTT) which reflects the wealth difference is used as a critical indicator to model the different behavioral patterns within subpopulations.

Overall, the synthetic population (home based in Seattle city) in 2014 was 625k with 30% households being low-income (lower than $50k). In this study, we focus on several categories of subpopulation. The reference group is set as an employed adult (age 18-64) with car ownership and $100k - $150k household income. The elderly and/or low-income and/or unemployed groups are treated as vulnerable subpopulation and compared with reference groups. From Table 1. below one can see can clear difference between vulnerable groups and reference groups where low-income/unemployed/elderly tends to use less private owned vehicle and low-income adults has fewer trips per day but longer travel distance.

Table 1. Subpopulation Summary

	Percentage of population	Average trip rate (per day)	Average trip distance (miles)	Mode share (%)
Low-income, 18-64, employed	11.1%	3.10	3.56	28% walk, 4% bike, 57% car, 11% transit
Low-income elderly	4.9%	3.53	3.03	30% walk, 1% bike, 56% car, 13% transit
Unemployed, 18-64	11.2%	3.65	3.11	29% walk, 5% bike, 55% car, 11% transit
Reference group	14.5%	3.62	3.13	23% walk, 2% bike, 67% car, 8% transit

Methodology

SAV configuration and MATSim simulation

We implemented SAV vehicles in the simulation as demand-responsive transportation (DRT) service by using MATSim's DRT module. These vehicles have a maximum capacity of 4 passengers, and the automation was reflected by the change of road capacity in a mixed traffic condition (In this case the SAV consists only 3% of the vehicles, which makes the capacity change ignorable). Ridesharing will be executed when ride requests are in the proximity of the vehicle and the agents have similar destinations, implemented in DVRP algorithm [15]. The SAV vehicles are randomly distributed across the simulation area. Idle vehicles will return to one of these starting locations as they are regarded as depots and all vehicles returned to their predefined, random locations after each day operation. The maximum waiting time is set to 20 minutes. the request will be rejected if waiting time exceeds the limit, although travelers have the ability to replan their activity by mutate departure time, mode choice, etc.

Choice dimensions and scoring function

In our simulations, the mode options include car, transit, bike, walk and SAV. Daily itineraries or agents' plans contain up to five different activity types: "home", "work", "shop", "school" and "others", which can be linked via several possible trip-chain combinations.

Regarding the mode split procedure, note that user equilibrium is not reasonable enough to depict the mode choice of traveler and goes far from the observed results. This process is influenced by a large number of factors, many of which are difficult to quantify and measure. To account for these factors in practice, the multinomial logit (MNL) model is applied as follows,

$$\Pr(m) = \frac{\exp(\theta S_m^w)}{\sum_{m \in M} \exp(\theta S_m^w)}, w \in W$$

where for each OD pair $w \in W$, $\Pr(m)$ is the probability of choosing mode m and θ is nonnegative empirical parameters associated with the degree of passenger's perception of travel cost and set to 1 in our model. S_m^w represents the scores (utility) of users choosing mode m between OD pair w.

In addition to mode choices, agents can modify the departure time and duration of each activity in their plans set to reflect aspects like the optimal duration for the activity type, and site opening and closing times. These out-of-home activity attributes are described in Table 2.

Table 2. Activity Type Time Specification

Activity Type	Opening time	Closing time	Optimal duration
Home	undefined	undefined	12:00:00
Work	undefined	undefined	08:00:00
School	07:00:00	21:00:00	08:00:00
Shop	07:30:00	21:00:00	01:00:00
Others	undefined	undefined	undefined

In MATSim, the travel plan may be modified given constraints of one day time and real-time road conditions. Part of travelers will change their daily activities based on the utilities of individuals. Besides monetary costs and travel time, early departure, late arrival, or cancelling an activity will also affect activity utility. Agents' daily activities are modeled in MATSim through an iterative learning mechanism based on a quantitative score illustrated in the section below. The score of a plan is similar to the mode utility in the mode choice model but incorporates the additional utility (score) of activities [19]. The basic function of calculating the plan score is as follows,

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)}$$

where N is the number of activities in the plan, $S_{\mathrm{act,q}}$ refers to the score of activity q and $S_{\mathrm{trav,mode(q)}}$ represents the score of trips after activity q via $mode(q)$. The last activity is combined with the first one to have the same number of activities and trips. More specifically, the activity score is broken down as follows to capture the activity duration performance and late arrival penalty.

$$S_{act,q} = S_{dur,q} + S_{late\ arr,q}$$

$$S_{dur,q} = \beta_{dur} t_{typ,q} \ln\left(t_{dur,q}/t_{0,q}\right)$$

$$S_{late\ arr,q} = \begin{cases} \beta_{late\ arr}(t_{start,q} - t_{late\ arr,q}), \text{if } t_{start,q} > t_{late\ arr,q} \\ 0, \text{otherwise} \end{cases}$$

where $t_{\mathrm{typ,q}}$ (in hours) is the typical duration of activity q, $t_{\mathrm{dur,q}}$ is the actual duration of activity q, $t_{0,\mathrm{q}}$ is the duration when the utility of activity q starts to be positive. $t_{0,\mathrm{q}}$ is set to $t_{\mathrm{typ,q}}$exp $(-10/t_{\mathrm{typ,q}})$, $t_{\mathrm{start,q}}$ is the actual start time of activity q, $t_{\mathrm{latest\ arr,q}}$ is the latest start time of activity q without penalty. Without further information regarding travelers' preference for early departure/late arrival, we set these activity scoring parameters as default in MATSim.

Calibration Process

We validated the simulations based on other open-sourced data including 2014 Household Travel survey conducted by City of Seattle & PSRC and hourly link traffic counts from Seattle Open Data Program published by city departments. Real-world traffic observations are given by DOT with hourly counts of 30 links of freeway selected. By incorporating CaDyTS (Calibration of dynamic traffic simulations), MATSim is able to calibrate the daily plans to match closer to observed link counts. The mode share is also compared with 2014 Household Travel survey.

Results and Recommendations

To understand the impact of introducing a new SAV mode on multi-modal transportation systems, three aspects of SAV impacted were analyzed, considering the congestion effects, SAV operations/performance and the variety of subpopulation's benefits.

System level performance

Figure 2 and Figure 3 show the traffic volume and volume change of some representative links in

Seattle. With the introduction of SAV, we can conclude that there's an increase in congestion, due to the increase in distance driven on the roads caused by modal shifts and SAV operations. By calculating the link travel time, however, the increase of time is 1.3% on average and 1.9% at 90% quantile. However, the maximum delay compared to base case is about 6.9 times of travel times for certain links. The red lines in Figure 3 shows the link count change over 60% compared with base scenario in the morning peak hour, where most congestion effects occur in downtown and surrounding areas.

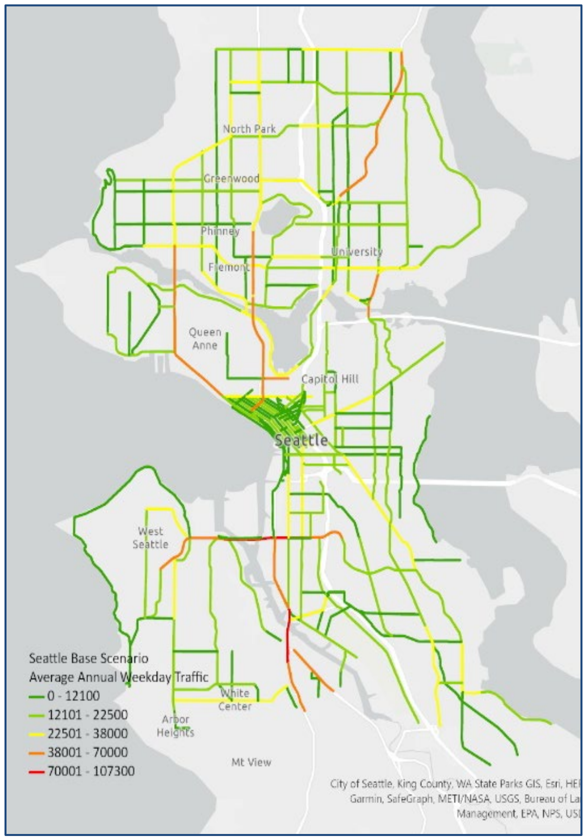

Figure 2. Average Annual Weekday Traffic Volume

Figure 3. Percentage of Traffic Volume Change (7-8 am) with SAV Fleet size of 5000

Subpopulation-level evaluation

It’s critical to understand how SAVs would mode choice for different subpopulations. Since the travel time wasn’t change to much for other modes of transportation, here we consider all the trips that each subpopulation groups switch from other mode to q SAV and compare their disutility improvement due to SAV service (see Table 3). By calculating the relative ratio of each subpopulations using SAV, it clearly shows that SAV service would be more appealing to higher-income level groups, with more than 70% of the SAV users come from the reference groups (employed high-income adults). This is due to the benefits of reducing the value of in-vehicle travel time, which provides more value savings for the high-income group since their value of time are substantially higher than low-income groups. These observations occur both in \$0.5/mile and \$1/mile pricing schemes, and higher SAV price will impose heavier effects on vulnerable groups and hinder their accessibility to SAV.

Table 3. Subpopulation Utility Comparison

	Fleet size = 5000, Price = $0.5/mile		Fleet size = 5000, Price = $1/mile	
	Percentage of request among targeted SAV users	Travel disutility improvement	Percentage of request among targeted SAV users	Travel disutility improvement
Low-income, 18-64, employed	9.2%	20.9%	6.8%	9.9%
Low-income elderly	5.7%	22.4%	3.3%	11.4%
Unemployed, 18-64	13.6%	21.2%	15.3%	8.2%
Reference group	71.5%	29.6%	74.6%	20.7%

Discussion

This study performed multiple agent-based simulations with SAV settings to show the impacts with of different fleet size and pricing policy from different perspectives: transportation authorities, SAV companies, and subpopulation considerations. With fleet size increase from 2000 to 8000, the average/median waiting time for SAV reduces substantially and provide a more efficient operations given higher occupancy rates traveled and a higher revenue-to-cost ratios. The optimal fleet size and pricing policy still need investigation (with more fleet size experiments). The operations of SAV induce a slightly more congested road network, and the spatial distribution of waiting time and trip rates implies an uneven service for different geographical locations. The comparison of SAV use and disutility change among different subpopulation shows that the benefits of SAV varies across populations, and high-income groups would benefit more from the service. Future analysis should be conducted (e.g., subsidies for vulnerable groups, different fleet size and pricing policies, dynamic routing/rebalancing strategies) to provide a more equitable SAV operations for the transport authorities.

References

[1] Forkenbrock, D.J. and Schweitzer, L.A., 1999. Environmental justice in transportation planning. Journal of the american planning Association, 65(1), pp.96-112.
[2] Schulte, J.K., Fox, J.R., Oron, A.P., Larson, T.V., Simpson, C.D., Paulsen, M., Beaudet, N., Kaufman, J.D. and Magzamen, S., 2015. Neighborhood-scale spatial models of diesel exhaust concentration profile using 1-nitropyrene and other nitroarenes. Environmental science & technology, 49(22), pp.13422-13430.
[3] Syed, S.T., Gerber, B.S. and Sharp, L.K., 2013. Traveling towards disease: transportation barriers to health care access. Journal of community health, 38(5), pp.976-993.
[4] Thakuriah, P. and Metaxatos, P., 2000. Effect of residential location and access to transportation on employment opportunities. Transportation Research Record, 1726(1), pp.24-32.
[5] Gwynn, R.C. and Thurston, G.D., 2001. The burden of air pollution: impacts among racial minorities. Environmental health perspectives, 109(suppl 4), pp.501-506.
[6] Foster, A.C. and Hawk, W.R., 2013. Spending patterns of families receiving means-tested government assistance.
[7] United States Department of Transportation, “National Household Travel Survey,” 2017. https://nhts.ornl.gov/ (accessed Feb. 02, 2021).
[8] Administration for Community Living and Administration for Community Living, “2017 Profile of Older Americans,” U.S. Department of Health and Human Services, Washington, DC, Apr. 2018.
[9] Murray, J., 2017. A systems analysis of Access-A-Ride, New York City’s paratransit service. Journal of Transport & Health, 6, pp.177-186.
[10] Ge, Y., Knittel, C.R., MacKenzie, D. and Zoepf, S., 2016. Racial and gender discrimination in transportation network companies (No. w22776). National Bureau of Economic Research.
[11] White, J., 2021. Waymo opens driverless robo-taxi service to the public in Phoenix. Detroit. Reuters USA. Online verfügbar unter https://www. reuters. com/article/us-waymo-autonomousphoenix-idUSKBN26T2Y3, zuletzt geprüft am, 15.
[12] Hörl, S., Becker, F. and Axhausen, K.W., 2021. Simulation of price, customer behaviour and system impact for a cost-covering automated taxi system in Zurich. Transportation Research Part C: Emerging Technologies, 123, p.102974.
[13] Poletti, F., Bösch, P.M., Ciari, F. and Axhausen, K.W., 2017. Public transit route mapping for large-scale multimodal networks. ISPRS International Journal of Geo-Information, 6(9), p.268.
[14] Puget Sound Regional Council. Spring 2014 Household Survey. https://www.psrc.org/travel-surveys-spring-2014-household-survey. Accessed Jun. 2, 2021.
[15] Maciejewski, M., Bischoff, J., Hörl, S. and Nagel, K., 2017, June. Towards a testbed for dynamic vehicle routing algorithms. In International Conference on Practical Applications of Agents and Multi-Agent Systems (pp. 69-79). Springer, Cham.