ACCESS BENEFITS OF SHARED AUTONOMOUS VEHICLE FLEETS: FOCUS ON VULNERABLE POPULATIONS

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ABSTRACT

This research monetizes the access benefits of making shared autonomous vehicles (SAVs) available to residents of Texas' Dallas-Fort Worth metroplex. Residents' willingness to pay for SAV access under different fare and mode were estimated and compared across the region's 5,386 traffic zones, with emphasis on those housing the regions' most vulnerable or access-limited travelers. Assuming a $0.50-per-trip-mile SAV fare, the average per-person-trip benefit is estimated to be $0.17 for home-based work (HBW) trips and $0.20 per home-based non-work (HBNW) trips. As a point of comparison, the loss of conventional or human-driven vehicles (HVs), without access to privately owned AVs, is estimated to result in -$5 (HBNW) to -$10 (HBW) access losses per person-trip, due to the strong base preference that currently exists for privately owned HVs.

Vulnerable populations and their neighborhoods are identified based on the share of persons living below the poverty level, incomes per capita, share of persons aged 65 years or older, those with disabilities, those owning no vehicle, and share of persons from a racial minority group. Results suggest that the access benefits of SAVs will be higher in locations/neighborhoods housing more vulnerable populations, excepting neighborhoods with many above age 65. These benefits and the willingness to pay differences (across locations) falls as SAV fares rise. As is true with man innovations, careful attention to disadvantaged groups and thoughtful policy (via smart contracting and SAV-user subsidies by public agencies, for example) can better ensure valuable access improvements for those with limited mobility and resources.

KEYWORDS

Accessibility; Shared Autonomous Vehicles; Vulnerable Travelers; Willingness to Pay; Dallas-Fort Worth Metroplex

BACKGROUND

The advent of highly automated or "autonomous" vehicles (AVs) portends many access changes, especially for those unable to drive. Accessibility can be defined in different ways, but travel impedance and destination proximity are key themes (Wu & Levinson, 2020). In general, accessibility is the ability to reach opportunities (e.g., jobs, schools, and health care facilities) within a reasonable amount of travel time and/or cost. Transportation-based accessibility can be applied via analysis of vehicle ownership (Ryan & Han, 1999), road network vulnerability (Taylor et al., 2006), and public transit (Moniruzzaman & Páez, 2012).

Access to jobs, retail, services, parking, and other land uses is important in property valuation and location choices (Srour et al., 2002; Stanilov, 2003). Access inequalities readily emerge, as people sort themselves in space, with many vulnerable populations having low access to healthcare and green spaces (Gilliland et al., 2019; Rahman & Zhang, 2018).

Shared AVs are fleets of self-driving taxis, for demand-responsive door to door service, now serving travelers in Las Vegas and the Phoenix area, and soon destined for Miami and Austin (Forbes (Sam Abuelsamid), 2021). Such services may substantially enhance many residents' accessibility to services, including the young and the aged, those unable to drive, and the currently public-transit dependent. AVs lower the burden of travel or value of travel time (VOTT) for those previously driving. These lowered travel costs improve access perceptions for everyone – as long as the resulting congestion does not lower overall travel times (de Almeida Correia et al., 2019; Huang et al., 2020; Zhong et al., 2020). Such door-to-door service may eventually be integrated with or replace public transit (PT) systems (Wen et al., 2018), (Imhof et al., 2020). Self-driving features can eliminate the need to park close to one's destination (Millard-Ball, 2019), though empty AV use is only likely to be permitted in use of SAV fleets, and capped (at 15% of fleet miles, for example), to avoid excessive congestion. Ridesharing (with strangers, as done in buses, elevators, and airplanes) helps lower travel costs (Agatz et al., 2011), and SAVs are expected to lower private-vehicle ownership levels, as well as parking provision (Blumenberg et al., 2021; Fiedler et al., 2018; Xu et al., 2015).

Level 4 AVs (Lent et al., 2019) have been predicted to comprise 24% to 87% of the US light-duty vehicle fleet by 2045 (Bansal & Kockelman, 2015). Americans' willingness to pay to add AV features ranges from $650 to $1,800 depending on the level of automation (Asgari & Jin, 2019), and 10% to 20% of US (light-duty) vehicle-miles traveled (VMT) may be made by SAVs in 2045 (Quarles et al., 2021). Travel cost and time, wait time, any walk distances, and vehicle comfort will affect traveler choices, which will vary across demographics and unobserved preference attributes (Krueger et al., 2016).

While accessibility is often quantified in terms of number of opportunities reachable within a certain distance or time band (Hansen, 1959), utility-based measures are more meaningful because they better reflect individual preferences and can be converted into a willingness to pay, enabling more useful comparability across persons and neighborhoods (Jang & Lee, 2020). Using the results of random-utility-based choice models, differences in expected utility (between cases and settings, or for the same traveler living in two different neighborhoods, for example) can be normalized by estimates of the marginal utility of money. Monetized accessibility can then be interpreted as a person's willingness-to-pay to achieve the access benefits of the higher-utility setting, all else constant.

This paper estimates utility-based access measures to quantify the expected or average benefits of making SAVs available to residents of Texas' Dallas-Ft Worth Metroplex. The focus is on vulnerable persons and locations, with results summarized across various aggregations (e.g., urban vs suburban vs rural settings).

METHODS

This section describes assumptions and equations used to simulate and analyze the influence of SAV access by applying utility-based measures to quantify access benefits. The travel cost of different modes (HV, PT, and SAV) will be estimated with realistic assumptions based on distance and travel time. Using this travel cost information, access benefits due to SAV access are evaluated to estimate the impact of different SAV fares on accessibility.

Data Description

The North Central Texas Council of Governments (NCTCOG) provided the demographics including population and employment, and travel skim data of 5,386 traffic survey zones (TSZs) for model year 2020 in Dallas-Fort Worth (DFW), TX. The travel skim data provides travel time estimates (in minutes) between all origin-destination TSZ pairs for AM peak (6:30-9:00), PM peak (3:30-6:30), and off-peak (the rest).

The travel cost (in cents) of HV, PT and SAV for traveling from origin i to destination j are estimated by modifying Liu et al's model (Liu et al., 2017), as shown in Eq. (1) to Eq. (3). This model assumes the value of travel time for HV users is twice as large than that of PT users and SAV users. Two different demographic groups are assumed, one has a higher value of travel time of $15/hr. and the other has a lower value of travel time of $7.5/hr. The weighted value of travel time for an origin i is estimated by assuming that persons below the poverty estimate have the lower value of travel time, and the other group has the higher value of travel time. The travel cost of HVs and SAVs are relying on both travel time and travel distance, while the cost of PT is only affected by the travel time. HV has a fixed parking cost, and PT and SAV have a fixed ticket fare of $2 and $1, respectively. The parking cost of an HV differs by the type of destination. If the destination is an urban area, the parking cost is assumed as $3, if it is suburban, $1.5, and if it is rural, $0.50 is assumed. For PT and SAV, out-of-travel time is assumed to reflect the time needed to walk and wait to start the travel.

$$C_{HV,ij} = Parking + 60D + VOTT \cdot IVTT \tag{1}$$

$$C_{PT,ij} = 200 + (VOTT/2)IVTT_{PT} + 2VOTT(OVTT_{Walk} + OVTT_{PTwait}) \tag{2}$$

$$C_{SAV,ij} = 100 + Fare \cdot Distance + (VOTT/2)\ IVTT + 2VOTT(OVTT_{SAVwait}) \tag{3}$$

where

$Parking$= Parking cost by destination ($3 for Urban, $1.5 for Suburban, and $0.50 for Rural destination *j*)

D= travel distance from origin *i* to destination *j* (mi.)

$VOTT$= weighted value of travel time of origin *i* by population group
$15/hr. and $7.5/hr. for population above and below poverty level, respectively

$IVTT$= in-vehicle travel time from origin *i* to destination *j* (hr.)

$IVTT_{PT}$= $1.5IVTT$

$OVTT_{Walk}$ & $OVTT_{PTwait}$= out-of-vehicle travel time from *i* to *j*,
uniformly distributed between 0 and 15 minutes

$Fare$= $0.50, $0.75, $1.00, and $1.25 per mile assumed

$OVTT_{SAVwait}$= out-of-vehicle travel time from *i* to *j*,
randomly determined between 0 to 10 minutes by following Gamma distribution
with shape parameter k=2, scale parameter θ=1

In Liu et al's model (Liu et al., 2017), SAVs are assumed to pick the closest available travel request within a predefined service radius. In the case of SAVs arriving earlier than the traveler's prior activity ends, it waits until the traveler finishes the activity by idling on the road. When both the SAV and the traveler are ready, they move together to the traveler's destination. After arrival at the destination, the SAV becomes available for the next travel request.

Model Development

The log sum method used by Kalmanje & Kockelman (Kalmanje & Kockelman, 2009) is used to evaluate the accessibility improvements with SAV access. Accessibility improvements are defined to be the change in consumer surplus or compensating variation (CV), which is measured by log sum differences of the traveler's systematic utilities. This log sum method of welfare estimation is known to be better than the rule of half method, since rule of half assumes a linear relationship between consumer demand and generalized travel costs (Kockelman & Lemp, 2011).

The multinomial logit models for mode / departure-time choices are obtained from (Gupta, 2004) as shown in Table 1. For the trip purposes, only home-based work (HBW) and home-based non-work (HBNW) trips are considered in this paper. Using the model specifications from Table 1, a measure of generalized travel cost across all mode and departure time combinations is estimated by Eq. (4).

Table 1. Joint Model of Mode and Departure Time Choice

Parameters	HBW	HBNW
Level of Service		
Time (min)	-0.0548	-0.0755
Cost (₵)	-0.0098	-0.0158
Constants		
HV AM Peak	0.3347	0.0844
HV PM Peak	0.2397	0.1872
HV Off-peak	-1.3938	-0.1143
PT AM Peak	-5.3211	-3.6438
PT PM Peak	-5.2257	-4.0821
PT Off-peak	-	-5.0853
SAV AM Peak	-2.3515	-0.5004
SAV PM Peak	-1.7653	-0.3273
SAV Off-peak	-3.5061	-0.6731

Source: (Gupta, 2004)

$$LOGSUM_{ijp} = ln\left(\sum_{m,t \in S_{ij}} exp(\beta_{tp} TT_{ij} + \beta_{cp} C_{m,ij} + \beta_{mtp})\right) \quad (4)$$

where S_{ij} denotes the choice set of all mode, departure-time combination set, TT_{ij} refers to the travel time (minutes), and $C_{m,ij}$ represents the travel cost (cents) obtained from Eq. (1) to Eq. (3) from origin *i* to destination *j* using mode *m*, β_{tp} is the time coefficient by trip purpose *p*, β_{cp} is the cost coefficient by trip purpose *p*, β_{mtp} is the constant with respect to mode *m*, departure time *t*, and trip purpose *p*. The 'no-vehicle owned' population may not have utility benefits from HVs, so the HV utility should be discounted by the vehicle ownership. The no-vehicle owned population by TSZs are obtained from the social vulnerability index provided by Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry/ Geospatial Research (CDC/ATSDR, 2018).

The systematic utility of choosing a certain destination *j* from a particular origin *i* for trip purpose *p* is determined not only by the generalized travel cost, but also by the attractiveness that destination *j* can provide. In (Gupta, 2004), total employment (EMP_j), population (POP_j), and size ($SIZE_j$) of the destination *j* are suggested as the attractiveness that affects the traveler's destination choice from origin *i*. Eq. (5) represents the systematic utility of choosing destination *j*, suggested by (Gupta, 2004), with model specifications shown in Table 2.

$$V_{ijp} = \beta_{logsum,p} LOGSUM_{ijp} + \beta_{emp,p} ln(EMP_j) + \beta_{pop,p} ln(POP_j) + \beta_{size,p} ln(SIZE_j) \quad (5)$$

Table 2. Destination Choice Model

Parameters	HBW	HBNW
Impedance		
Log sum of generalized costs	0.3618	0.5714

Zonal Attractiveness		
log(total employment)	0.4836	0.2284
log(population)	0.0053	0.0690
log(size)	0.0248	0.1468

Source: (Gupta, 2004)

The expected maximum utility of the travel from origin *i* for trip purpose *p* with all modes *m* and departure times *t* can be derived using Eq. (6). It is the log sum of the exponential equations of the utilities for traveling to destinations $j \in D$ from origin *i*, where *D* is the set of all destinations. Therefore, the changes in consumer welfare or consumer surplus (ΔCS) can be computed by the difference of this log sum between the two scenarios as shown in Eq. (7). In Eq. (7), V_{ip}^{1} and V_{ip}^{0} denotes the systematic utility of the scenario of interest and the base case, respectively. The log sum difference is divided by the marginal utility of money (α_p) for trip purpose *p* to monetize the difference. According to (Kalmanje & Kockelman, 2009), $\alpha_p = \beta_{logsum,p}\beta_{cp}$ can be derived from the destination choice model by taking the derivative of the systematic utility in Eq. (5) with respect to the travel cost, $C_{m,ij}$. This paper proposes the monetized difference of consumer surplus (ΔCS_{ip}) derived from Eq. (7) as a measure to quantify accessibility.

$$E\big(Max(V_{ip})\big) = ln\big(\textstyle\sum_{j \in D} exp(V_{ijp})\big) \tag{6}$$

$$\Delta CS_{ip} = \frac{1}{\alpha_p}\Big(E\big(Max(V_{ip}^{1}\big) - E\big(Max(V_{ip}^{0}\big)\Big) \tag{7}$$

MODEL ANALYSES RESULTS

The utility-based accessibility measures are evaluated with various SAV fares ($0.50, $0.75, $1.00, and $1.25 per mile) and different trip purposes (HBW and HBNW). Two scenarios are assumed, ‘SAV Access’ and ‘HV Ban After Access’. The ‘SAV Access’ scenario compares the accessibility measures of having SAVs in the mode choice option ($m \in \{HV, PT, SAV\}$) versus the base case ($m \in \{HV, PT\}$) where no SAVs are assumed. The ‘HV Ban After SAV Access’ scenario evaluates the accessibility differences of a future where HVs are banned after SAV access ($m \in \{PT, SAV\}$) versus the base case ($m \in \{HV, PT, SAV\}$) assuming SAVs coexist with existing HVs and PTs.

SAV Access

The accessibility measures by comparing ‘with SAV’ versus ‘without SAV’ are estimated. NCTCOG categorized the 5,386 TSZs as ‘Central Business District’, ‘Outer Business District’, ‘Urban Residential’, ‘Suburban Residential’, and ‘Rural’ areas. This paper simplified this categorization by defining the first three categories as ‘Urban’ (*n*=3,116) area and followed the categorization of ‘Suburban’ (*n*=1,204) and ‘Rural’ (*n*=1,066) areas as NCTCOG defined them.

In Table 3, SAV access results in access benefits for HBW trip purpose since all regions in DFW will have positive changes in consumer surplus. With a low SAV fare ($0.50/mi), the access benefits did not show much difference by region. With higher SAV fares, the accessibility decreases since SAVs become less attractive. For HBW trip purpose, Table 3 shows 11.8% lower average accessibility improvements ($0.15/person trip/zone) with SAV fare $1.25/mi compared to $0.50/mi case ($0.17/person trip/zone). When compared by the regional category, urban regions show a greater decrease in access benefits followed by suburban and rural regions with the increase of SAV fares. It is presumed that urban areas may have other travel mode to use when the SAV fare is high (e.g., public transit), so that SAV becomes less attractive for urban residents with higher SAV fares. Also, rural areas with longer travel time may still enjoy the advantages of SAVs even with higher SAV fares, since SAV users are assumed to have a lower value of travel time than HV users.

HBNW trip purpose follows a similar tendency with respect to the SAV fare, but with greater access benefits than HBW. Table 3 suggests under SAV $0.50/mi assumption, overall access benefits for HBNW purpose are 117% higher than that of HBW purpose, and overall HBNW access benefits are 126% higher than that of HBW with SAV fare $1.25/mi assumption. HBW trips are more regular than HBNW trips by having home at one end of the trip and work at the other, so that the traveler may be more used to the route, destination, and infrastructures (parking facilities, traffic signals, etc.) of the trip than in the case of HBNW trip. Therefore, SAVs can be advantageous when traveling to a non-work and possibly unfamiliar location for a HBNW trip. For instance, SAV travelers may not have to take care of parking, even though they are traveling to an unfamiliar location without having experience of where the parking lot is located. SAVs will pick-up and drop-off the travelers autonomously without having severe parking limitations.

The difference in HBNW trip compared to HBW is that in HBNW trips, urban regions have the highest access benefits followed by suburban and rural regions for all SAV fare scenarios. This result suggests that a non-work trip originating from urban regions will be the most beneficial combination to operate SAVs.

Table 3. Accessibility Measures with SAV Access ($/person trip/zone)

SAV Fare	HBW				HBNW			
	Urban	Suburban	Rural	Overall	Urban	Suburban	Rural	Overall
$0.50/mi	0.17 (0.02)	0.17 (0.02)	0.17 (0.02)	**0.17** **(0.02)**	0. 21 (0.03)	0.20 (0.03)	0.19 (0.02)	**0.20** **(0.03)**
$0.75/mi	0.16 (0.02)	0.16 (0.02)	0.17 (0.02)	**0.16** **(0.02)**	0. 20 (0.03)	0.19 (0.03)	0.19 (0.01)	**0.20** **(0.02)**
$1.00/mi	0.15 (0.03)	0.15 (0.02)	0.16 (0.02)	**0.15** **(0.02)**	0. 20 (0.02)	0.19 (0.02)	0.19 (0.02)	**0.19** **(0.02)**
$1.25/mi	0.14 (0.03)	0.14 (0.02)	0.16 (0.03)	**0.15** **(0.03)**	0. 19 (0.03)	0.18 (0.02)	0.18 (0.02)	**0.19** **(0.02)**

Note: Average (St.Dev.)

HV Ban After SAV Access

This paper follows the possible SAV access scenario by first introducing SAVs to the market ('SAV Access' scenario); then, SAVs fully replace the existing HVs thereafter ('HV Ban After SAV Access' scenario). Thus, in this section, the scenario of interest restricts HV use ($m \in \{PT, SAV\}$), while the base case assumes HVs coexist with SAVs and PTs ($m \in \{HV, PT, SAV\}$).

Restricting HVs after SAV access results in loss of accessibility for HBW trip purpose since all regions in DFW will have negative changes in consumer surplus. Table 4 shows that the higher the SAV fare is, the higher the negative impact is in all regions, because SAVs become less attractive. Moreover, greater uncertainty in accessibility is expected with higher SAV fares, where the standard deviation increases with higher SAV fares.

When compared by the regional category, urban regions show a greater decrease in average accessibility than suburban or rural areas in high SAV fares. As urban regions had smaller accessibility improvements from the SAV access than other regions, especially with higher SAV fares, restricting HVs in urban regions would be detrimental. Therefore, HV use will be still preferred in terms of enhancing overall accessibility even after SAVs are introduced.

When compared by trip purpose, Table 4 shows that HBNW trips had less negative impact than HBW trips. SAV access scenario showed that HBNW had higher accessibility improvements with SAVs than HBW, so HBNW was less affected by removing HVs from the market. As was the case in HBW purpose, having higher SAV fare results in greater negative impact in accessibility in HBNW.

Table 4. Accessibility Measures with HV Ban After SAV Access ($/person trip/zone)

SAV Fare	HBW				HBNW			
	Urban	Suburban	Rural	Overall	Urban	Suburban	Rural	Overall
$0.50/mi	-9.98 (0.48)	-10.09 (0.47)	-9.93 (0.43)	**-10.00** **(0.47)**	-4.92 (0.23)	-5.02 (0.22)	-5.10 (0.15)	**-4.98** **(0.23)**
$0.75/mi	-10.24 (0.52)	-10.33 (0.50)	-10.09 (0.48)	**-10.23** **(0.52)**	-5.01 (0.22)	-5.09 (0.21)	-5.14 (0.14)	**-5.05** **(0.21)**
$1.00/mi	-10.46 (0.57)	-10.54 (0.54)	-10.22 (0.54)	**-10.43** **(0.57)**	-5.08 (0.23)	-5.14 (0.21)	-5.16 (0.15)	**-5.11** **(0.21)**
$1.25/mi	-10.66 (0.62)	-10.72 (0.58)	-10.34 (0.59)	**-10.61** **(0.62)**	-5.13 (0.23)	-5.19 (0.22)	-5.18 (0.15)	**-5.16** **(0.22)**

Note: Average (St.Dev.)

ACCESSIBILITY FOR VULNERABLE POPULATION

SAVs have the potential to enhance the mobility and accessibility of vulnerable populations. Elderly, disabled, and those without a driver's license may benefit from the efficient self-driving door-to-door service (Wang et al., 2020). Ridesharing can lower the price for rides and provide more affordable travel options to travelers (Shen et al., 2018). The self-driving feature allows SAVs to reduce parking costs, thereby providing reasonable travel cost to and from the urban cores (Millard-Ball, 2019). Riders will be able to participate in other activities while riding in the SAV, enabling them to use their time in a more efficient way (Steck et al., 2018). When the riders agree with sharing their information to others, autonomous vehicles can contact emergency services or drive to the nearest health care facilities directly in emergency situations (Gluck et al., 2020).

In this sense, the welfare impacts of SAVs for the vulnerable population in the Dallas-Fort Worth region are analyzed in detail. The types of vulnerabilities used in this paper are 'below poverty estimate', 'income per capita', 'aged 65 or older', 'disabled', 'no vehicles owned', and 'minority population who are not white or non-Hispanic, obtained from the social vulnerability index (CDC/ATSDR, 2018). Percentage of persons below the poverty estimate and income per capita by zone represents the vulnerability from lack of economic capacity. Past studies suggests that opportunities including access to employment, healthy food and healthcare are not equally shared by low-income populations (Dillahunt & Veinot, 2018). The percentage of persons aged 65 or older and persons with a disability corresponds to the lack of ability to travel freely. The percentage of persons with no vehicles owned shows the lack of mobility. Finally, the percentage of minority group (defined as all except white or non-Hispanic) stands for the racial or ethnic groups who are underserved in American society.

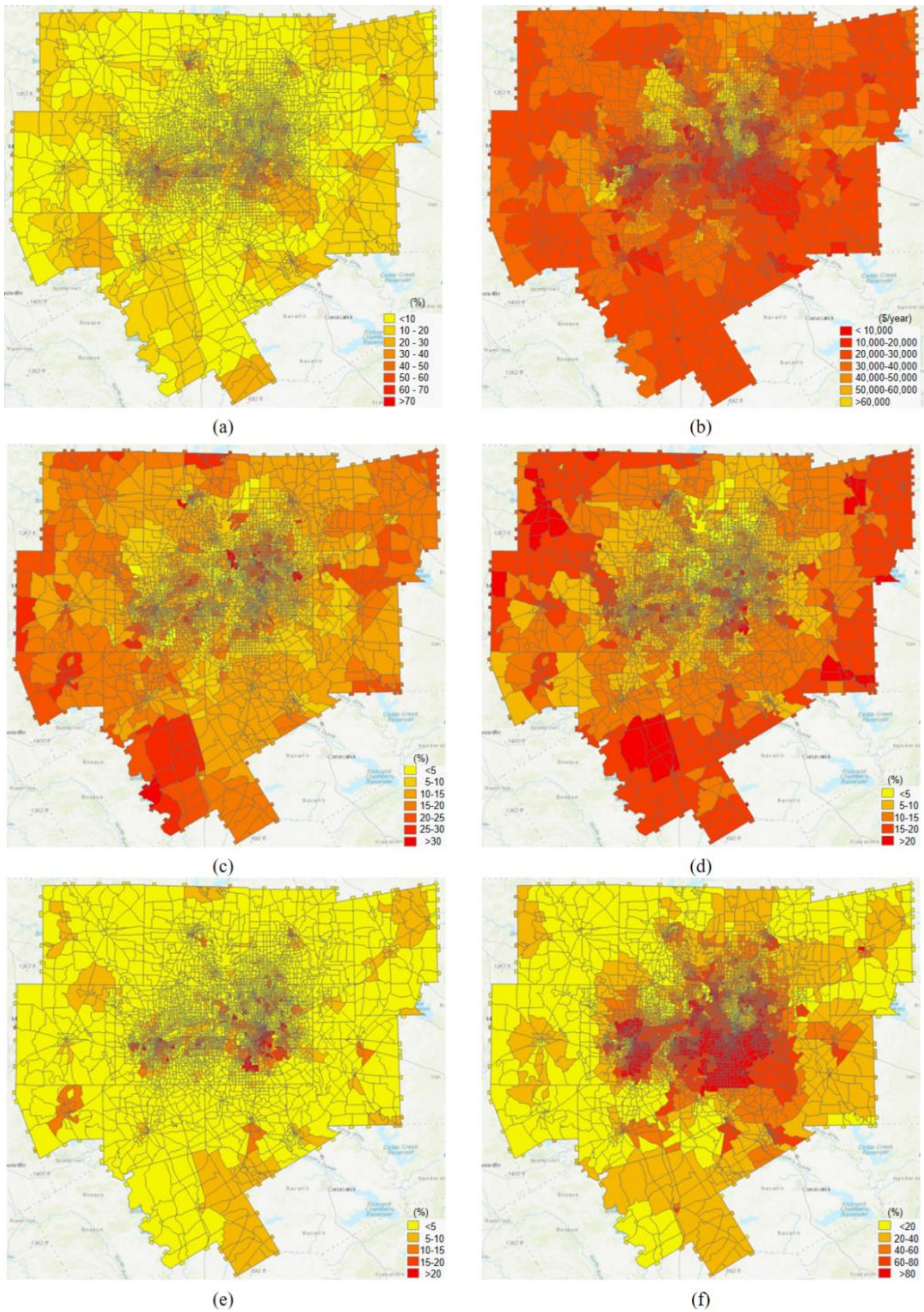

Figure 1. Distribution of Vulnerability (a: Below Poverty Population, b: Income per Capita, c: Aged 65+, d: Disabled, e: No-vehicle Owned, f: Minority)

Figure 1 shows the spatial distribution of each vulnerability type in the study area obtained from the social vulnerability index (CDC/ATSDR, 2018). The average percentage of the population below the poverty estimate is 13.97%, and a higher percentage is expected in urban centers and rural areas. Average annual income is $35,074 per capita and suburban areas had the highest income level. The average percentage of population aged over 65 is 11.88%, and rural areas at the southwestern part of DFW showed highest rate over 65. The average percentage of disabled population is 10.36%, and rural areas showed higher rates than other areas. The average percentage persons with no vehicles owned is 5.37%, and they are concentrated in urban cores. The average percentage of minority groups inhabiting an area is 51.45%, and southeastern suburban areas showed the highest rate.

Figure 2 shows the accessibility benefits by each type of vulnerability after SAVs become accessible. The best-case scenario of SAV fare ($0.50/mi) is assumed since this is the lowest SAV price, resulting in the highest accessibility. For all types of vulnerabilities except 'aged over 65', accessibility is increasing when more people are vulnerable. This result suggests that SAV HBW trips become affordable to all groups to satisfy their mobility needs, and having more access to SAVs can improve the welfare of vulnerable population. Nonetheless, the access benefits tend to fall if more population are aged over 65, but still with positive values of access benefit. Seniors tend to travel less than other groups, so SAVs' access benefits decrease with more seniors in the population. For the older population, other modes of transportation should be still considered to offset the decreasing access benefits from SAVs with older population.

HBNW trips follow the similar tendency, but with greater access benefits from SAVs. In terms of income and age, higher income groups and a higher percentage of older residents results in lower access benefits from SAVs. The high-income groups will have a higher value of travel time, and they may be reluctant to share their trips via ridesharing options. However, the poverty, disability, no vehicles owned, and minority groups showed increased access benefits when the degree of vulnerability is high. Having higher access benefits with a higher percentage of persons below the poverty estimate corresponds to the higher access benefits with lower income per capita. The disabled population and no-vehicle population groups' need of mobility can be satisfied with SAV access, resulting in higher access benefits when the percentage of these persons are high. Minority groups who are underserved in American society can also benefit with SAV access.

Figure 3 shows the worst-case SAV fare scenario with pricing of $1.25/mi, which is the highest SAV fare assumed in this paper, resulting in the lowest SAV accessibility. The values of access benefit are smaller than those of the best-case scenario, but access benefits for both HBW and HBNW trips have a similar tendency to the best-case scenario with respect to the degree of vulnerability: access benefits increase with a higher percentage of persons below poverty, disabled, no vehicles owned, or classified as minority group, and access benefit decreases with higher income and higher percentage of persons aged 65 or above.

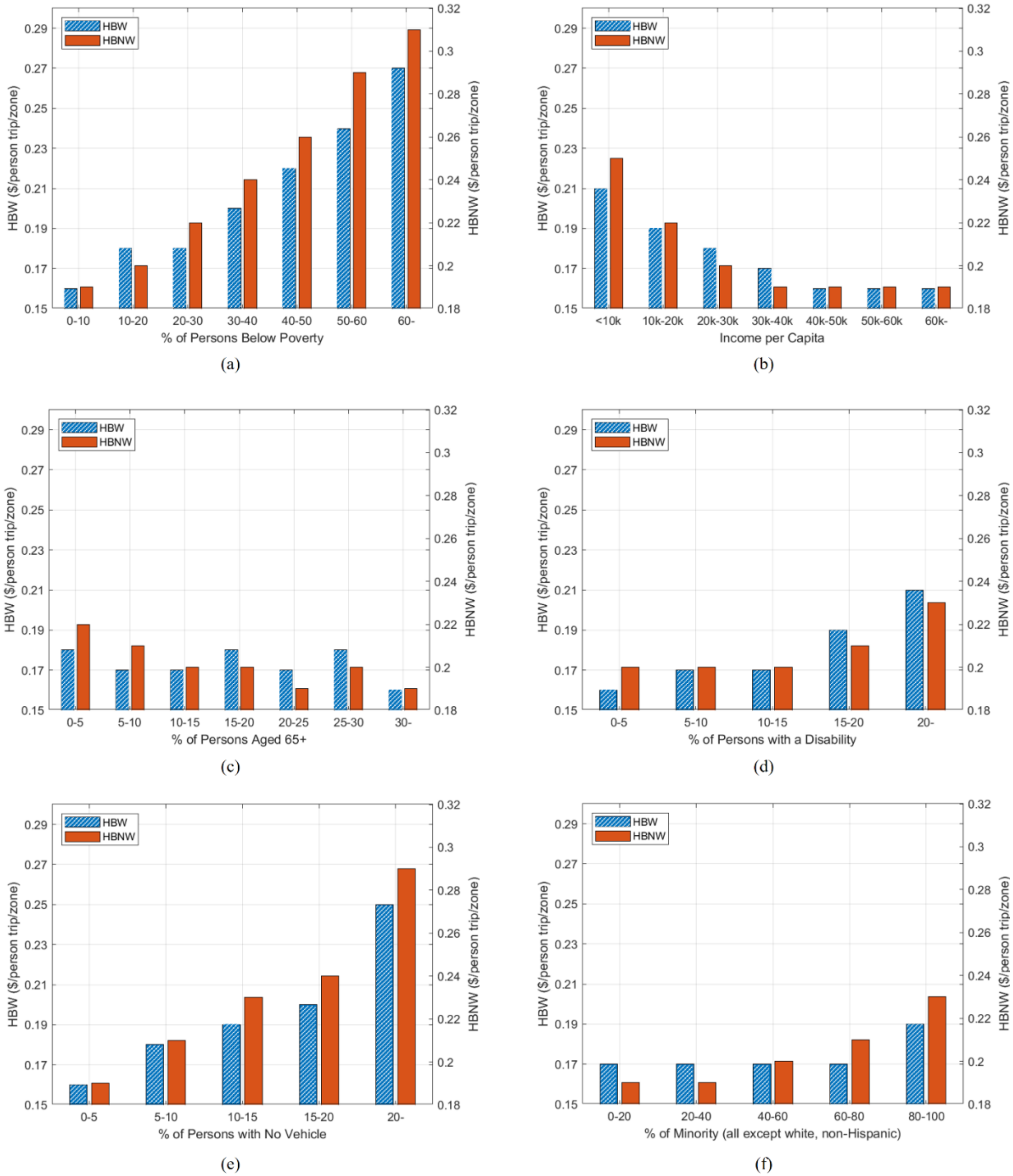

Figure 2. Accessibility Benefits (SAV Fare $0.50/mi assumed, a: Below Poverty Population, b: Income per capita, c: Aged 65+, d: Disabled, e: No-vehicle Owned, f: Minority)

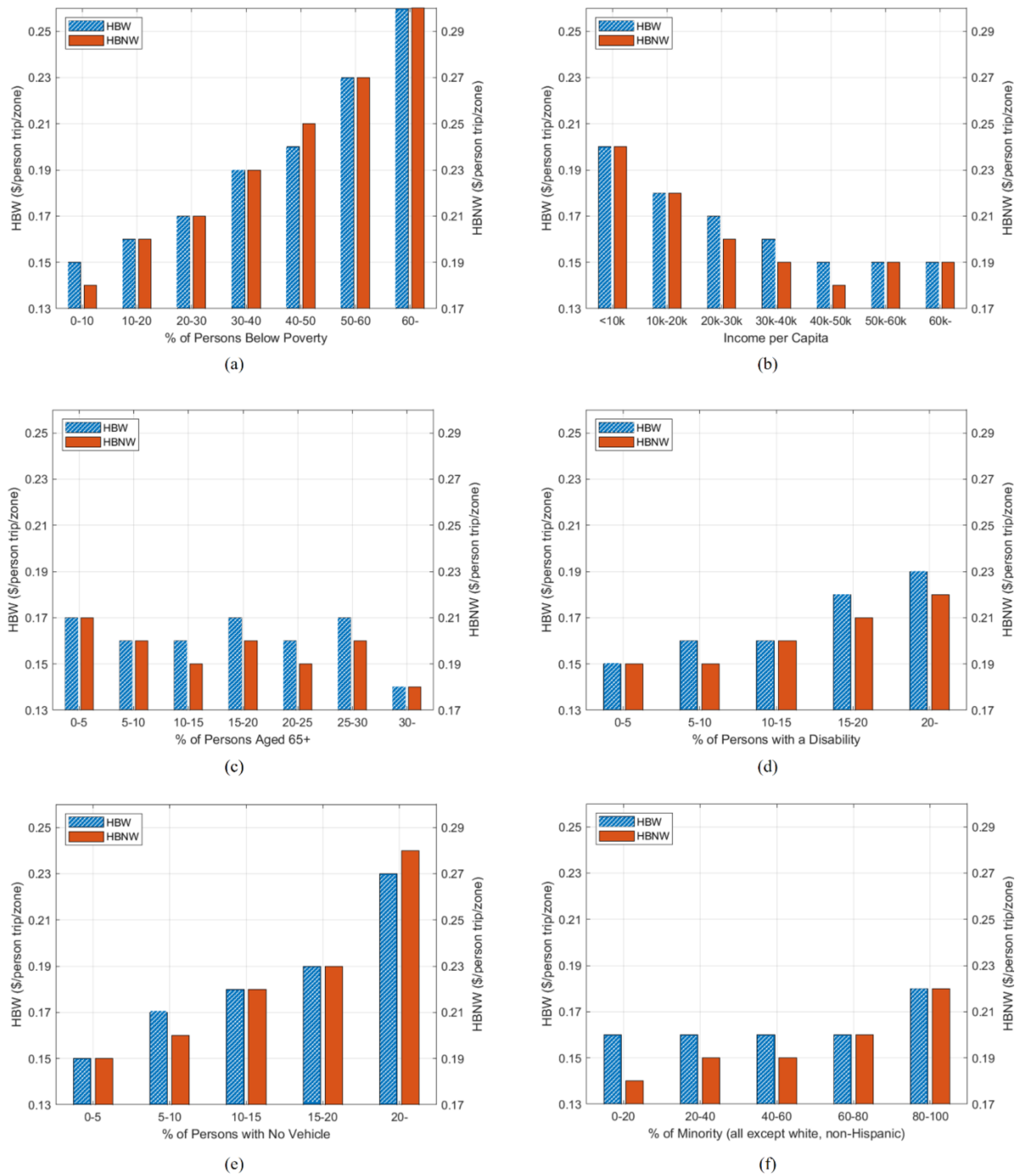

Figure 3. Accessibility Benefits (SAV Fare $1.25/mi assumed, a: Below Poverty Population, b: Income per capita, c: Aged 65+, d: Disabled, e: No-vehicle Owned, f: Minority)

EXTREMELY VULNERABLE ZONES' SAV ACCESSIBILITY

The extremely vulnerable zones have extremely worse conditions than the average estimate of the DFW region. In this paper, extremely vulnerable zones have a value above the average estimate of the percentage of persons that are below the poverty level, aged 65 or over, disabled, have no vehicle, or in minority groups, and below the average estimate of the income per capita. A total of 196 zones out of 5386 TSZs are classified as extremely vulnerable zones. Figure 4 shows the location of these 196 zones in two different SAV fare scenarios ($0.50/mi and $1.25/mi) and two different trip purposes (HBW and HBNW). Among the 196 extremely vulnerable zones, the zones that have SAV access benefits above the average are colored in patterned green, and zones with SAV access benefits below the average are colored in solid red. Thus, the conditions of extremely vulnerable zones can be improved with SAV access when the access benefits are above average, but the conditions may be even worse after SAV access when the access benefits are below average.

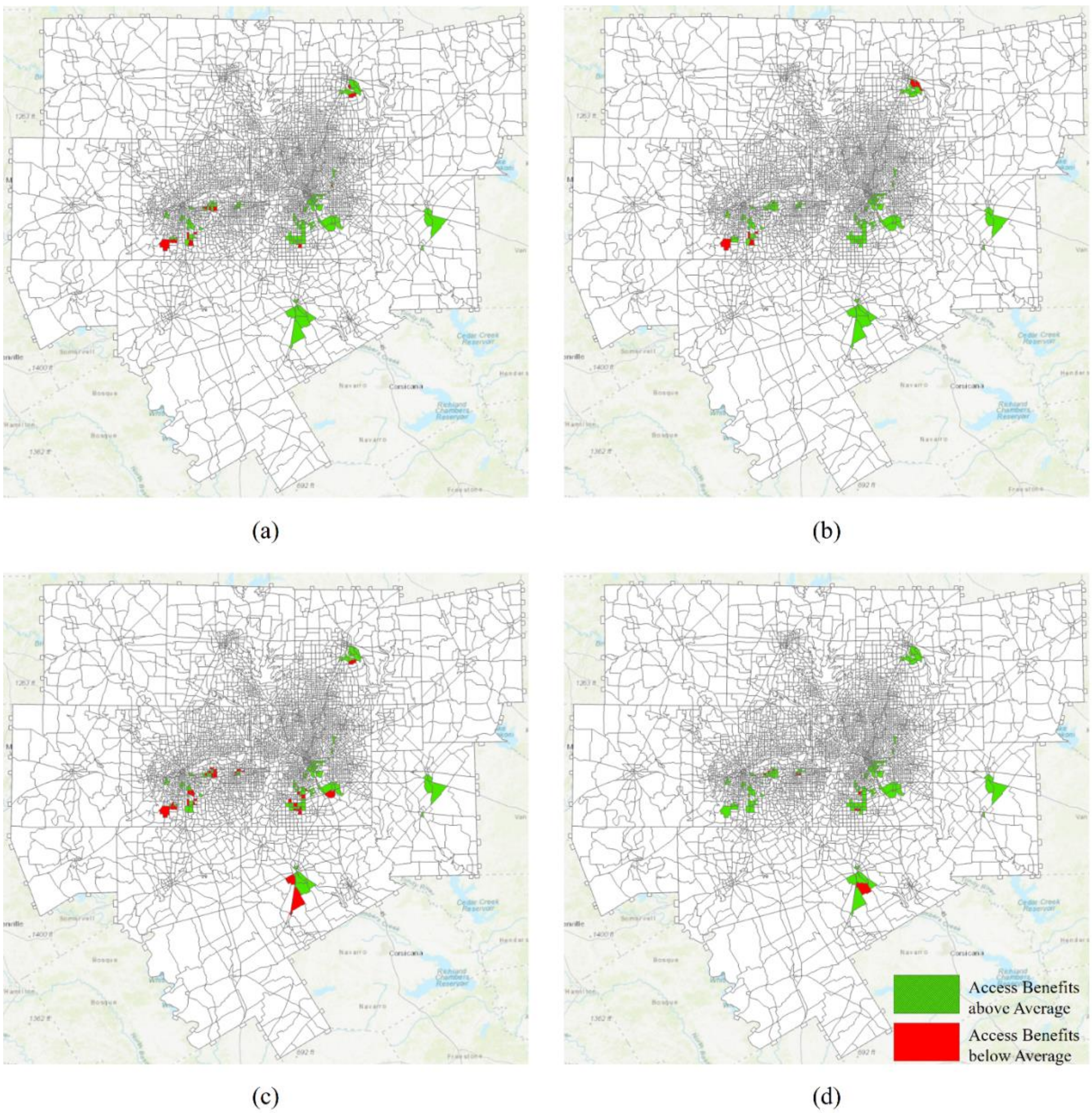

Figure 4. Location of the Most Vulnerable Zones and Access Benefits (a: HBW $0.50/mi, b: HBNW $0.50/mi, c: HBW $1.25/mi, d: HBNW $1.25/mi)

Table 5 shows the comparisons of the extremely vulnerable zones' access benefits in more detail. The

$0.50/mi scenario has more zones with access benefits above average than the $1.25/mi scenario. Comparing the extremely vulnerable zones' access benefits to the overall average access benefits, the $0.50/mi scenario generally has a slightly smaller difference in % difference than the case from $1.25/mi scenario. By comparing the trip purposes, the conditions in HBNW trip purpose were better than that of HBW trip purpose. More zones were above the overall average in HBNW trip purpose, and the % difference from the overall average was smaller, indicating more stable access benefits can be expected in HBNW purpose trips.

Table 5. Extremely Vulnerable Zones' Accessibility Benefits Compared to Overall Average

$0.50/mi	**HBW**		**HBNW**	
	Below Average	**Above Average**	**Below Average**	**Above Average**
# of Zones	14	182	7	189
% Difference	-4.1%	+23.2%	-2.0 %	+22.5%
$ Difference	-0.01	+0.04	<-0.00	+0.05
$1.25/mi	**HBW**		**HBNW**	
	Below Average	**Above Average**	**Below Average**	**Above Average**
# of Zones	33	163	10	186
% Difference	-5.4%	+24.9%	-1.9%	+20.9%
$ Difference	-0.01	+0.04	<-0.00	+0.04

In Table 5, a notable remark can be made for the $1.25/mi scenario, HBW purpose results. The % difference of these zones' average access benefits showed the greatest difference of -5.4%/+24.9% from the average. access. This is presumably because of the high SAV fare, some extremely vulnerable populations' trips cannot be satisfied properly and results more observations of below average access benefits than other scenarios. This result suggests that certain population may not benefit from SAV access as much as others, if the SAV system is not designed deliberately. A variable SAV fare by origin and destination should be considered, while local communities should consider providing alternative modes (e.g., public transit) and subsidizing SAV fares to support specific groups who may not enjoy the state-of-the-art technology due to their socioeconomic conditions.

CONCLUSIONS

SAVs have the characteristics of both HVs (via door-to-door service) and public transit (via shared rides); thus, SAVs have the potential to enhance the accessibility and mobility of residents living in an urban environment. This paper proposed a utility-based accessibility measure to monetize the access benefits of SAVs and focused on the access benefits of vulnerable populations. By fare and trip purpose scenarios, a lower SAV fare had higher access benefits than higher SAV fares due to lower travel cost, and HBNW trips had higher access benefits than HBW trips due to SAVs' advantage (e.g., no parking needed, self-driving feature) expected while traveling to a less routine destination. Another possible scenario is when HVs are banned after SAVs are fully adopted. The result suggests that HVs are still required, especially for HBW trips from urban areas with the highest SAV fare assumption.

In-depth analyses of SAV access benefits were performed on the vulnerability groups. In the best-case scenario with the lowest SAV fare, both HBW and HBNW trips showed difference in access benefits, where access benefits increased with a higher rate of persons below poverty, grouped as a minority, aged 65 or above, no vehicles owned, disabled, or income was low. On the other hand, in the worst-case scenario having the highest SAV fare, the access benefit falls and results in lower accessibility. Those who could not afford the high SAV fare had lower access benefits than those who could afford the SAV fare. However, the access benefits were still positive suggesting that SAVs can improve vulnerable populations' mobility and welfare conditions.

Among the vulnerable population, even more extremely vulnerable groups' SAV access benefits were analyzed. The results suggest that SAVs may improve the accessibility conditions at some locations, but some population may not enjoy the access benefits as others may, if the fare was high and the trip purpose was HBW, which are fundamental parts of living. In order to help the vulnerable population, subsidizing SAV fares via transit providers, food stamps, or other methods should be considered. SAV fleet is advantageous by providing cost-efficient door-to-door service and demand-responsive mobility options, so that transit agencies can shift to subsidize SAV use to support not the general public, but also extremely vulnerable population. This paper emphasizes that SAV systems should be designed deliberately with careful attention to underserved groups, so that they are not left behind in the introduction of new technologies.

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