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Who benefits from AVs? Equity implications of automated vehicles policies in full-scale prototype cities

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ABSTRACT

While researchers have stressed the potential of automated vehicle (AV) technology in improving mobility and accessibility for a range of people, only a few attempts have been made to examine the impact of this new technology on different segments of the population in a realistic setting using high-fidelity simulation. To fill this gap, we analyze the equity implications of Automated Mobility-on-Demand (AMoD) in three full-scale prototype cities using SimMobility, a state-of-the-art activity- and agent-based framework. The prototype cities were developed based on two auto-dependent typologies, representing cities largely in the US/Canada, and a dense transit-oriented typology. We perform equity analyses at the individual and income-group level, in order to reveal the winners and losers from the introduction of AVs under two scenarios: (1) *AMoD Intro*, in which a low-cost AMoD service competes with mass transit, and (2) *AMoD Transit Integration*, where AMoD complements mass transit, via access/egress connectivity service to rapid transit stations. We evaluate the following outcomes: induced demand by age and income groups, mode share by income levels, individual kilometers traveled by different modes and income levels, and the spatial distribution of change in fare and accessibility. Outcomes are considered as equity-oriented if they reduce accessibility gaps, particularly among disadvantaged populations. Our results indicate that in large population-dense and transit-oriented cities, the most equity-oriented outcomes can be achieved, due to extensive mass transit usage, which depresses car usage and restricts induced demand for AMoD. Such cities provide greater opportunities for low-income groups. Specifically, the *AMoD Transit Integration* scenario results in the best outcomes and implies a new market share, as disadvantaged groups, such as children and low-income individuals, were able to travel more using the integrated AMoD-transit service. Nevertheless, in car-dependent cities, where accessibility gaps are much larger, *AMoD Intro* scenario performs better compared to *AMoD Transit Integration*, as it serves the less accessible population and significantly improves their opportunities.

1. Introduction

The potential of automated vehicles (AVs) to address a variety of current urban mobility challenges, such as congestion, access,

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safety and pollution, has spurred considerable investments in pilot programs and concurrent research efforts (Fagnant and Kockelman, 2015; Shaheen and Bouzaghrane, 2019; Duarte and Ratti, 2018). Arguably, AVs could unleash unprecedented new demand for automobile travel among long-underserved and disadvantaged groups, thus increasing opportunities at potentially lower operational costs (Cohn et al., 2019; Dianin et al., 2021). Yet, there remains a dearth of empirical evidence that focuses on the effects of AV technology at the individual level in full-scale cities, especially in comparison to the insights on network efforts and environmental impacts garnered from agent-based simulation approaches. In this regard, the equity impacts of AVs remain under-addressed. Thus, we contribute toward filling this gap in this paper by revealing the winners and losers from the introduction of AVs in three full-scale prototype cities that are most relevant to the real-world cities where AV implementation is most imminent.

A recent effort proposed a classification of cities based on urban mobility factors (Oke et al., 2019). The resulting twelve typologies represent characteristic outcomes across based on a global sample of 331 cities. In subsequent studies, three prototype cities of interest were synthesized and calibrated to resemble their corresponding typology's average variables (Oke et al., 2020). Then, future mobility scenarios focusing on Automated Mobility-on-Demand (AMoD) services, in different urban and operational settings were simulated in order to analyze impacts of AMoD on trip demand patterns, vehicle kilometers traveled, congestion and energy consumption. High-fidelity simulations were conducted using the SimMobility Mid-Term (MT) simulator—an integrated framework of activity-based demand modeling systems, with dynamic traffic assignment used for modeling supply decisions (Adnan et al., 2016). On-demand operations were also implemented in detail (Nahmias-Biran et al., 2019; Basu et al., 2018; Gross et al., 2019).

In this study, we now use these prototype cities to investigate the equity impacts of AMoD implementation. Two scenarios are considered: (1) *AMoD Intro*, in which AMoD costs riders half as much as Taxi services, and (2) *AMoD Transit Integration, in which AMoD* is subsidized as a complementary service to mass transit for access/egress connectivity to rail stops. In addition, this scenario includes non-integrated AMoD services restricted to short trips only. Based on the activity-based demand modeling systems of SimMobility-MT, we calculate a "top-level" activity-based accessibility (ABA) measure, which is extremely useful for equity analysis, as future mobility strategies impacts can be analyzed at various socio-economic and demographic levels (Nahmias-Biran et al., 2020).

The remainder of this paper is organized as follows. Section 2 provides a literature review regarding equity issues in the era of automated vehicles, and its impact on different population groups. Section 3 introduces the methodology used in this study where city generation, the simulation environment, AMoD scenarios and the approach for equity analysis are discussed. Section 4 includes the results of equity analysis in three full-scale prototype cities. Finally, Section 5 presents the main conclusions and findings of this study.

2. Literature review

In the literature, the discussion about the impact of AVs on different population groups is essentially conceptual rather than empirical, with a very limited number of full-scale case studies. The conceptual discussion in the literature regarding equity issues in the era of automated vehicles covers various aspects. Several authors have stressed the potential of AVs to improve accessibility for a range of people. Some researchers report that the use of AVs could allow greater mobility for the elderly, the disabled and children (Fagnant & Kockelman, 2015; Ticoll, 2015). For people with restricted mobility, AVs could offer increased flexibility and independence (Bohm & Häger, 2015; Begg, 2014). Alessandrini et al. (2014) state that shared AVs have the potential to improve accessibility for people living in areas that are not well connected to transportation services. They argue that shared AVs could be useful in the mobility mix as they can supply good transportation service in areas of low or dispersed demand, complementing the main mass transit network. In addition, McCarthy et al. (2015) claim that the use of AVs has the potential to increase mobility options and travel horizons for large sections of the population, resulting in increased economic opportunities and social wellbeing. Finally, shared mobility could allow more people to have access to the technology and thus reduce transportation costs (Begg, 2014).

However, other authors have pointed out that these assumptions need to be carefully examined, as research on the level of social acceptance, desire and capability to use AVs among these potential users has, so far, been limited. Wagner et al. (2014) argue that elderly, disabled and non-driving persons might be the last to benefit from AVs, as the technology will have to be completely safe and fully automated before these users can take advantage of it in the short term. Anderson et al. (2014) discuss the complexity in the interaction of a "senior" driver with complicated new technology. Researchers raised the questions of whether segments of the population with accessibility restrictions would be able to afford the use of AVs and whether the introduction of AVs could affect equity (Appleyard & Riggs, 2018; Sperling, 2018). Frisoni et al. (2016) claim that with the initial introduction of AVs, it is anticipated that the wealthy will be able to afford this technology before lower socio-economic segments of the population. Thus, social inequity could be generated by the introduction of AVs, separating those who can afford to use them from those who cannot (Milakis et al., 2018; Thomopoulos & Givoni, 2015). Enoch (2013) notes that certain groups of the population, including the elderly, mobility-impaired, young, poor and ethnic minorities, are usually the last group to benefit from the introduction of a new technology, often for financial reasons. Bierstedt et al. (2014) point out that since the cost of AV will be initially high, their use might be restricted to wealthy users. Chen & Kockelman (2016) mention that the tension between making transportation equitable and generating revenue will continue to grow as transportation demand is increasingly handled by private companies. Thus, higher revenue-to-cost ratios would favor those with a high value of travel time and may lead to inequitable distribution of infrastructure such as charging stations (Chen & Kockelman, 2016; Litman, 2017; Lee & Nickkar, 2018). Therefore, a system of government-mandated incentives supporting a public policy in mobility services is required (Cohen & Shirazi, 2016; Niles, 2019). Furthermore, the future role of public transportation authorities could change dramatically from owning and managing transportation assets, to low-cost transportation providers (Arbib & Seba, 2017).

Despite the extensive discussion, only a few studies have attempted to examine the impact of this new technology on different segments of the population in a realistic setting using large-scale simulation. Childress et al. (2015) use the Seattle, Washington, region's activity-based travel model to test a range of travel behavior impacts from AV technology development. Results from four scenarios show that improvements in roadway capacity and in the quality of the driving trip may lead to large increases in vehicle miles traveled, while a shift to per-mile usage charges may counteract that trend. They also find that low-income communities experienced nearly the same increase in accessibility as higher income groups with the implementation of AVs. Wang et al. (2019) use route-level accessibility measures and publicly available data to quantify the impact of Mobility as a Service (MaaS)—defined here as conventional and potentially automated vehicles—on job accessibility and transit service equity in the Puget Sound region, USA. Results suggest that using MaaS to service short trips either connecting to/from transit or single modal trips can substantially elevate the existing level of job accessibility regionwide. However, Wang et al. (2019) use a simple locational metric to capture job accessibility rather person-level accessibility. Cohn et al. (2019) use a regional travel demand model to quantify how transportation outcomes may differ for disadvantaged populations in the Washington, D.C., area under a variety of future scenarios. Transportation performance measures examined include job accessibility, trip duration, trip distance, mode share, and vehicle miles traveled. The model evaluates changes in these indicators for disadvantaged and non-disadvantaged communities under scenarios where AVs are primarily single-occupancy or high-occupancy. Cohn et al. (2019) also assess the impacts of agency responses to AVs: maintaining the status quo, removing low-performing routes, and applying AV technology to transit vehicles. They found that the high-occupancy AV and enhanced transit scenarios provide an equity benefit by mitigating existing gaps in outcomes among demographic groups.

Nahmias-Biran et al. (2020) demonstrate how shared mobility coupled with AV technology for AMoD service impacts can be captured by the ABA measure, which takes advantage of the rich data and outcomes of an activity-based model and a mesoscale agent-based traffic simulation framework. They evaluate shared AMoD strategies applied to a Singapore micromodel city testbed. A near-future strategy of exclusive availability of AMoD service in the central business district (CBD) and a further-horizon strategy of the full operation of AVs island-wide in the absence of other on-demand services were tested and evaluated. The policy of replacing all on-demand services with AMoD results in the best outcomes in terms of accessibility and network performance. Nevertheless, the restriction policy also results in desirable accessibility outcomes in two exceptional cases: the first is in time savings in a suburban zone that relies heavily on non-automated on-demand services for non-CBD destinations; the second is in monetary savings for the residents of a zone that has excellent public transit coverage with close proximity to the CBD. As these findings motivate the need for measuring socioeconomic impacts at the individual level, we expand this study on three full-scale prototype cities, exploring different AMoD scenarios and focusing on the person-level impacts while examining equity.

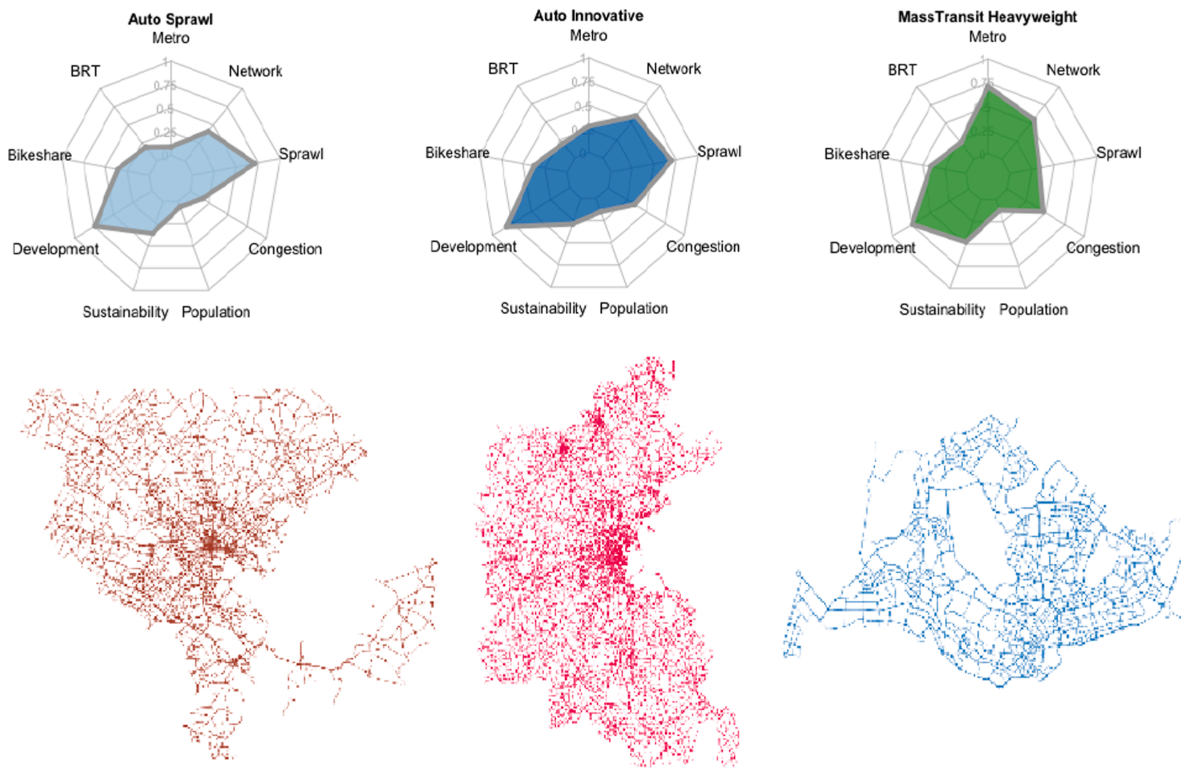

Fig. 1. The three typologies used for simulation and equity analysis: *Auto Sprawl*, *Auto Innovative* and *MassTransit Heavyweight.* Factor profiles (spider plots) are shown in the top row, while the respective archetype city networks used in the simulation are shown below. The "Network" label represents "Network Density."

3. Data and methods

We advance a framework for evaluating the outcomes of AV implementations among population groups and individuals in distinct urban typologies. We describe our data and methods as follows: (1) prototype cities; (2) simulations using the SimMobility-MT framework; (3) activity-based accessibility computation (4) AMoD scenario design and implementation; and (5) equity analysis at the individual and segment levels.

3.1. Prototype cities

In an earlier study, Oke et al. (2019) classified 331 cities on a global scale, based on urban form, socioeconomic factors and behavior. Nine underlying urban mobility factors were obtained from the variables spanning these dimensions, namely: Bus Rapid Transit (BRT) propensity, Bikeshare propensity, Congestion, Development, Metro (rail transit) propensity, Population, Network density, Sprawl and Sustainability. The factor profiles of the three typologies used in this paper are shown in Fig. 1. The "Sustainability" factor, for instance, is defined largely by equity and efficiency-related variables, such as: high bicycle usage, urbanization and safety; and low traffic, unemployment and travel time index. Further details and characterizations of these factors are given in Oke et al. (2019). The corresponding factor scores of each of the cities in the dataset were used to obtain an optimal clustering, resulting in 12 typologies.

Based on these typologies, corresponding prototype cities can be developed to represent their characteristics (Oke et al., 2020). These cities can then be used to evaluate the impacts of various mobility policies via high-fidelity simulation. The results of such studies can be considered relevant to the cities in that typology. For the purpose of this study, three full-scale prototype cities were selected and simulated using the SimMobility-MT platform as illustrated in Fig. 1:

- *Auto Sprawl*: This group of cities (largely in the U.S./Canada) relies heavily on private transport modes (86%). They have a very low share of mass transit modes (3.5%), and a low population density (1000/sq. km).
- *Auto Innovative*: This group of cities (largely in the U.S./Canada) relies heavily on private transport modes (79%). They have a low share of mass transit modes (11%), and high GDP per capita (61000 USD).
- *MassTransit Heavyweight*: This group of cities have a high share of mass transit (37%), and active modes (30.6%). They also have high population density (3900/sq. km).

We compare a few important characteristic variables among these typologies, including example cities in Table 1. While each prototype city was calibrated to match average demand and supply patterns across its corresponding prototype, real-world full-scale networks were used for simulation. In each case, the network and corresponding land-use patterns were chosen from the city closest to the centroid of the typology, which we refer to as the "archetype city." Thus, Baltimore, Boston and Singapore are the archetype cities for *Auto Sprawl*, *Auto Innovative* and *MassTransit Heavyweight*, respectively. Their road networks are also shown in Fig. 1.

3.2. Simulation framework: SimMobility-MT

The SimMobility-MT simulator integrates an agent-based, fully econometric, and activity-based demand model with a dynamic traffic assignment model (Lu et al., 2015). It simulates daily travel at the individual (microscopic) level. The traffic dynamics are simulated using a mesoscopic simulator. An input to the SimMobility-MT simulator is the synthetic population and land-use of the three prototype cities. The synthetic population is validated using the control variables at the individual (such as age, gender, and employment status) and household (such as income and car ownership) levels (Oke et al., 2020). Subsequently, SimMobility-MT demand models were calibrated to fit the typology average variables. Following this, the transit supply system was developed and calibrated. Details on these steps are provided in Oke et al. (2020)). Within the SimMobility-MT simulator at the *PreDay* level (agent planning stage), each individual makes a mode choice which is modeled using the random utility framework. Different AMoD services are introduced, alongside traditional modes (car, etc.) and mobility-on-demand (MoD) modes, which consist of taxi and ride-hailing services. There are five mode choice and mode-destination choice models for each travel purpose: Shop, Education, Other, and Work to (i) a usual or (ii) an unusual workplace. Each of the models includes dozens of variables and therefore can only be briefly described.

Table 1
Comparing three typologies used for simulation and equity analysis (average values of characteristics are shown).

Characteristics	*Auto Sprawl*	*Auto Innovative*	*MassTransit Heavyweight*
Car mode share (%)	86	79	32
Mass Transit mode share (%)	3.5	11	37
Bike mode share (%)	0.5	0.9	7.6
Walk mode share (%)	2.8	3.6	23
Population (million)	1.7	5.3	8.9
Population Density (1000/sq. km)	1.48	1.62	5.46
Per Capita GDP (in 1000 USD)	50	60.1	53.4
CO_2 Emissions per capita (metric tonnes p/a)	16.5	13.7	9.6
Examples	Baltimore, Tampa, Raleigh	Washington DC, Atlanta, Boston	Berlin, Madrid, Seoul

Full descriptions of the models are available in Viegas de Lima et al. (2018) and Oke et al. (2020a). The systematic utility of each mode is computed as a weighted sum of the following parameters: *total travel time*, which consists of in-vehicle travel time, waiting time, and walking time; *travel cost*, which consists of road tolls, ticket prices, service prices, and so forth; *number of transfers in public transport, dummy variables for the CBD, vehicle ownership, age* and *gender*. We make assumptions on the generalized travel cost of based on literature, since relevant data are not available for the AMoD mode (see section 3.4: "AMoD Scenario Design and Implementation"). This allows the synthetic population of agents to choose from all modes of interest for the trips associated with all planned activities. We refer the reader to Li and Nahmias-Biran (2017) for further details concerning the underlying behavioral models.

In the *PreDay* system, the ABA is computed Nahmias-Biran et al. (2020). This measure is particularly relevant when equity analysis is performed, as it enables the analyses of accessibilities at the individual level. The outcome of *PreDay* is the Daily Activity Schedule (DAS) of each individual, which is an input to the *WithinDay* and *Supply* simulators. In *WithinDay* and *Supply*, the DAS of all individuals are simulated, i.e. agent's plans become actions. *WithinDay* handles route choice and plan modifications. *Supply* performs vehicle movements and fleet operations. SimMobility-MT components along with ABA computation process are illustrated in Fig. 2. A description of the comprehensive MoD and AMoD framework within SimMobility is provided in Nahmias-Biran et al. (2019).

3.3. Activity-based accessibility (ABA) computation

In our hierarchical *PreDay* activity-based modeling framework, accessibility measures capture the impacts travel decisions modeled in lower levels of the choice hierarchy (Ben-Akiva and Bowman, 1998; Dong et al., 2006; de Jong, et al., 2007). At the top level, the logsum gives the expected maximum utility from a choice set of alternatives. The ABA is computed from the top-level logsum accessibility A_n by the following equations:

$$A_n = E(U_{an}) = \frac{1}{\mu}\ln\sum_{a\in C_n} exp(\mu V_{an}) \tag{1}$$

Scaling and leveling this logsum yields the Activity-Based Accessibility (ABA):

$$ABA_n = \alpha_{nx}\left(A_n - A_n^0\right) \tag{2}$$

Scaling is performed to convert the logsum to temporal or monetary units. The leveling is done by benchmarking the accessibility relative to the hypothetical case where only the walk mode is available (representing the lowest possible accessibility):

$$\alpha_{nx} = \left(\frac{A_n^{(\Delta x)} - A_n}{\Delta x}\right)^{-1} \tag{3}$$

Since $\Delta x = +1$, we can express the ABA as:

$$ABA_n = \frac{A_n - A_n^0}{A_n^{(\Delta x)} - A_n} \tag{4}$$

Thus, the ABA is computed directly as a benefit, which is an improvement compared to previous studies, in which it is formulated as a disbenefit. We summarize the notation below:

- n individual

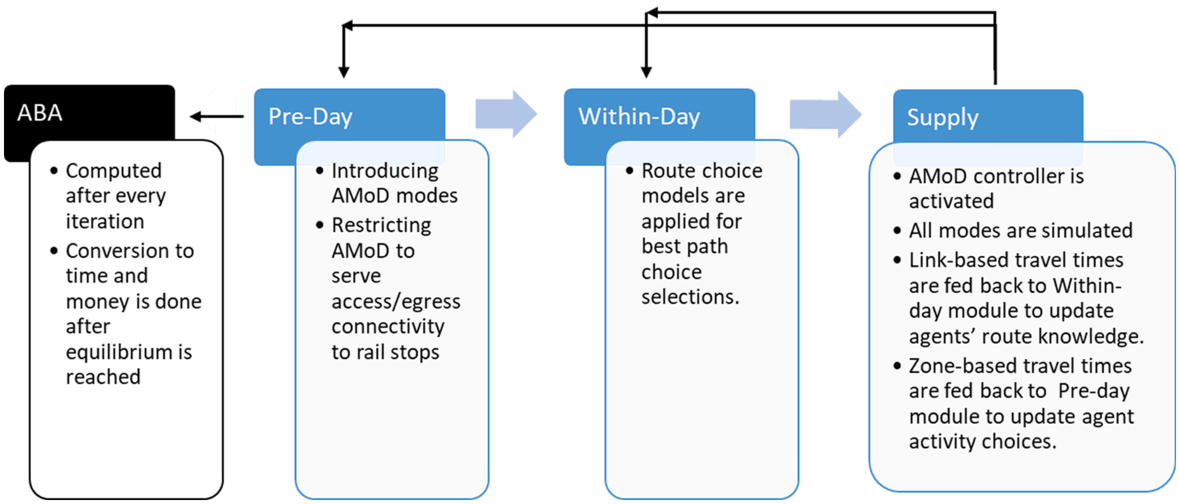

Fig. 2. SimMobility-MT components and ABA computation process.

- a activity schedule
- U_{an} random utility for activity schedule a and individual n
- V_{an} systematic component of utility for activity schedule a and individual n
- μ the scale parameter
- C_n choice set for individual n
- α_{nx} scaling and leveling parameter
- A_n accessibility measure: expected maximum utility from all individual n's activity alternatives (logsum)
- A_n^0 accessibility measure in benchmark scenario (only walk mode available)
- x model variable (travel time or travel cost)
- Δx change in model variable: 1 min (temporal scaling) or 1 USD (monetary scaling)
- $A_n^{(\Delta x)}$ accessibility measure computed when travel time or cost is perturbed by Δx

Further details of the incorporation of the ABA computation within *PreDay* are given in Nahmias-Biran et al. (2020).

3.4. AMoD scenario design and implementation

In addition to the *Base Case*, we designed and tested two AMoD scenarios in the *Auto Sprawl*, *Auto Innovative* and *MassTransit Heavyweight* prototype cities. We simulate the prototype cities multiple times so that the agents in the simulation are aware of travel times by various routes and modes in order to make informed decisions, in a process called "day-to-day learning". Further, in each AMoD implementation, for every demand case, optimal fleet sizes are computed prior to the final simulation configurations. MoD (Taxi and ride-hailing) fares used in the prototype cities are specified in Table 2. These fares were obtained from 2018 estimates from the archetype cities of the respective typologies (Oke et al., 2020).

The following scenarios were simulated and assessed:

1. *Base Case*

The Base Case simulation for each of the prototype cities represents the existing conditions and services offered in each city. For example, they each include taxis, ride-hailing (MoD) and various levels of public transit. The Car mode is most expensive in *MassTransit Heavyweight*, compared to the other cities. Conversely, on-demand and transit are cheapest in this prototype city (see Table 1).

2. *AMoD Intro*

In this scenario, we simulate what would happen if a low-cost AMoD service were offered in these prototype cities. In the context of this simulation, the key differentiation between AMoD and the human-driven mobility on-demand (MoD) service (e.g., Uber, Lyft) is the fare. The nominal assumption is that the AMoD service will cost riders half as much as the Taxi service (see Table 2). This assumption is based on high maturation of automated vehicle technology, low cost of future automated vehicle equipment, and a developed and supportive regulatory framework (Pavone 2015; Chen et al., 2016; Liu et al., 2017 (for Austin); Oh et al., 2020 (for Singapore); Horl et al., 2019 (for Paris); Horl et al., 2021 (for Zurich)). This scenario also includes a shared ride (pooling) AMoD option for the consumer to enable further reduction in fares and in energy consumption. The model assumes that consumer preference for AMoD is similar to that for MoD.

3. *AMoD transit Integration*

This scenario describes a situation where AMoD largely functions as a complementary service to mass transit. Thus, AMoD is subsidized by 20% for shared access/egress connectivity to rail stops in *Auto Sprawl* and *Auto Innovative* within a 7.5-mile radius, and in *MassTransit Heavyweight* within a 3-mile radius. Furthermore, non-integrated AMoD is restricted to only local trips.

3.5. Equity analysis

Equity is a measure of the distribution of outputs (or inputs) across the population in a fair manner (Levinson, 2010). A large number of studies show that accessibility is the most strategic and appropriate measure for evaluating the distribution of benefits from a transportation project, since it corresponds directly with the perceptions of transportation users (Nahmias-Biran and Shiftan, 2016). Yet, the concept of fairness does not have a standard definition, and the integration of equity in scenario evaluation involves great

Table 2
Mobility on-demand (MoD) fare breakdown in prototype cities.

MoD mode	Fare component	*Auto Sprawl*	*Auto Innovative*	*MassTransit Heavyweight*
Taxi	Base fare (USD)	1.8	2.6	2.6
	Distance charge (per km)	1.38	1.75	0.4
	Waiting time charge (USD per excess minute*)	0.4	0.47	0.22
Ride-hailing	Minimum fare (USD)	6.85	6.85	
	Service charge (USD)	2.35	1.85	
	Base fare (USD)	1.1	2.1	1.37
	Distance charge (USD/km)	1.38	1.35	0.28
	Travel time charge (USD/min)	0.12	0.21	0.09

*Note: for the taxi fare, an "excess minute" is defined as the additional trip time beyond the estimate for a given trip, computed using a fixed speed of 40 km/h.

complexity, it is usually neglected despite its great importance (Rietveld, 2003). Complexity arises from several factors such as: multiple types of equity; various ways to categorize people for equity analysis (according to socio-economic status, income level, education, etc.); numerous impacts to consider; and various methods of measuring these impacts (Nahmias–Biran et al., 2014; Nahmias–Biran et al., 2017; Nahmias–Biran et al., 2016; Nahmias–Biran & Shiftan., 2019). In this study, we perform equity analysis at both socio-demographic and individual levels. We analyze the distribution of resources as a result of *AMoD Intro* and *AMoD Transit Integration* scenarios in the chosen prototype cities in terms of: (1) induced demand by age; (2) induced demand by income categories; (3) mode choices by income; (4) change in kilometers traveled by income levels; and (5) spatial distribution of fare change with respect to income levels.

4. Results and discussion

We compare the scenarios across the cities to examine the impacts of AMoD on individuals and different socioeconomic groups in the prototype cities representing the following urban typologies: *Auto Sprawl*, *Auto Innovative* and *MassTransit Heavyweight*.

4.1. Induced demand

We define induced demand as the proportion of new trips generated as a result of the introduction of a new mobility service or mode relative to the baseline in a given community or population. In this case, the new service is AMoD. Fig. 3 shows the induced demand as a result of *AMoD Intro* and *AMoD Transit Integration* implementation in the prototype cities by age category: child (0–19 years old), adult (20–64 years old) and elderly (over 64 years old). The percentage of demand growth was calculated relative to the respective age group's share of the population. In general, the highest induced demand was observed in *Auto Sprawl*, while in *MassTransit Heavyweight*, the induced demand was minimal. The *AMoD Transit Integration* scenario led to a higher increase in demand, especially in *Auto Sprawl*. Under *AMoD Intro*, the higher induced demand was observed among adults, which was 20 times more than that of other age groups. Elderly individuals accounted for 8% of the induced demand, as they took advantage of the low-cost, door-to-door service. Interestingly, in the *AMoD Transit Integration* scenario, a significant increase in demand was due to children who used AMoD for short trips as a connector to mass transit. However, the elderly who previously used the MoD option (Uber-like services and Taxis) did not all shift to AMoD. This can be explained by the fact that the new *AMoD Transit Integration* service did not bring them directly to their destinations. Hence, it was less suitable for the elderly.

Induced demand by income groups as a result of the introduction of *AMoD Intro* and *AMoD Transit Integration* policies is shown in Fig. 4 for the three prototype cities. The percentage of demand growth by income was calculated relative to the relevant group's portion in the population. In *Auto Sprawl* under the *AMoD Intro* scenario, the least affected groups were the two lowest income levels (1–1000 USD and 1001–1499 USD). The other income groups exhibited a similar effect of around 16% induced demand. Under the *AMoD Transit Integration* scenario in *Auto Sprawl*, the lowest induced demand was observed in the highest income group. In fact, in that group, the additional demand is two to three times lower compared to all other income groups. This can be explained by the fact that the integrated AMoD service is used more by low-income groups.

In *Auto Innovative*, generally we observe under *AMoD Intro* that lower incomes indicated greater induced demand. This was the trend under the *AMoD Transit Integration* scenario, as well. In *MassTransit Heavyweight*, the induced demand was insignificant in both cases.

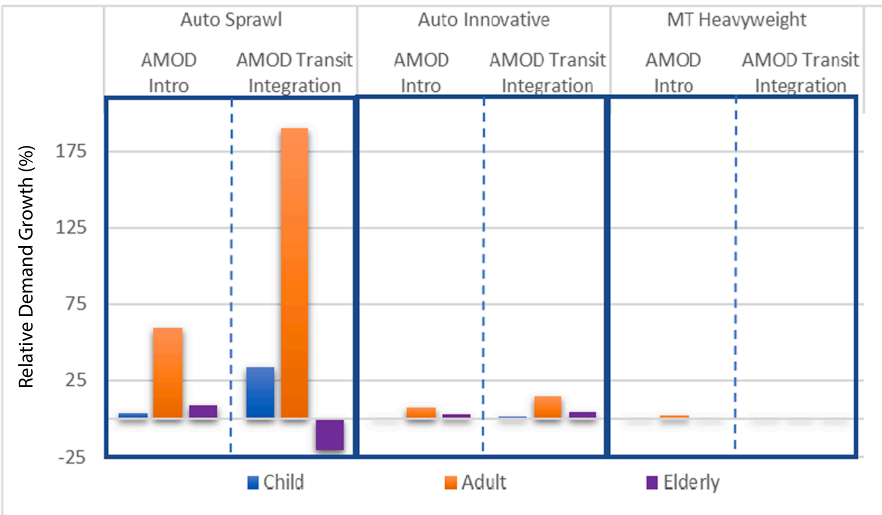

Fig. 3. Induced demand by age groups in prototype cities for (a) *AMoD Intro*, and (b) *AMoD Transit Integration* scenarios in the. The y-axis indicates induced demand relative to the corresponding age group's demand in the *Base Case.*

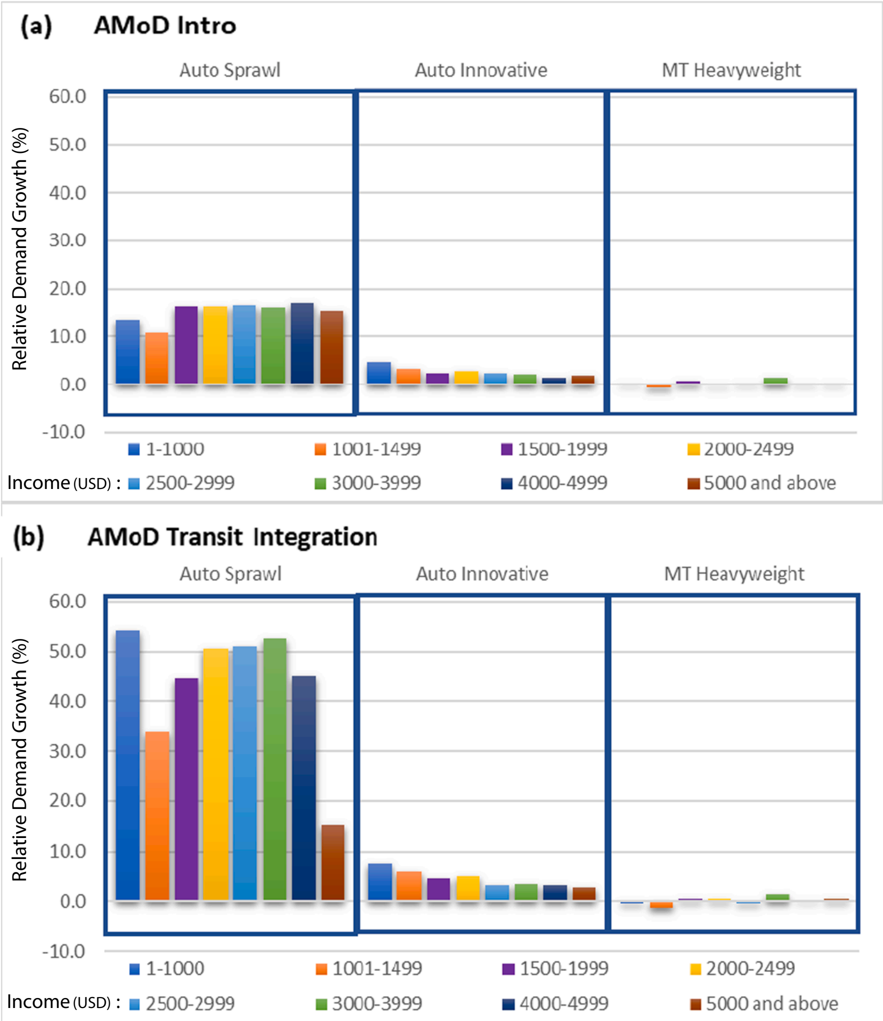

Fig. 4. Induced demand by income group for (a) *AMoD Intro*, and (b) *AMoD Transit Integration* scenarios in the prototype cities. The y-axis indicates induced demand relative to the corresponding income group's demand in the *Base Case*.

4.2. Mode share and passenger kilometers traveled

We provide a visual summary of the mode share distribution by income level in the *Auto Sprawl*, *Auto Innovative* and *MassTransit Heavyweight* prototype cities across all 3 scenarios in Fig. 5. In the *Base Case*, the car is the dominant mode among mid and high-income individuals in all three cities. However, after implementing the new AMoD policies, low-income individuals were more responsive to AMoD compared to the mid and high-income groups. Fig. 6 shows the passenger kilometers traveled (PKT) by income levels in prototype cities for (a) trips by all modes except on-demand modes (MoD and AMoD), and (b) on-demand modes only. PKT is defined here as the total distance traveled by all individuals over the course of a 24-hr day. On examining PKT by car, mass transit and active modes, we find that low-income individuals traveled less compared to mid- and high-income individuals for the three cities under all scenarios. The biggest gap in PKT between low- and mid-to-high-income individuals was observed in *Auto Sprawl* where individuals traveled the most. However, examining PKT by on-demand modes in *MassTransit Heavyweight* revealed that low-income individuals traveled more in both AMoD, as this typology favors mass transit usage, which is used more frequently by low-income individuals. Under the *AMoD Transit Integration* scenario in *Auto Sprawl*, the PKT for low-income individuals increased for mid-to-high-income individuals by factors up to 1.75 and 2.3, relative to *Base Case* and *AMoD Intro*, respectively. In fact, the new integrated service encouraged both low and mid-to-high-income individuals to use mass transit more (Fig. 5).

This can be attributed to the increased connectivity to rail transit stations, which are further apart in *Auto Sprawl*.

4.3. Travel cost impacts

In Fig. 7 we present a spatial distribution of change in the daily travel costs at the zonal level as a result of policy implementation in

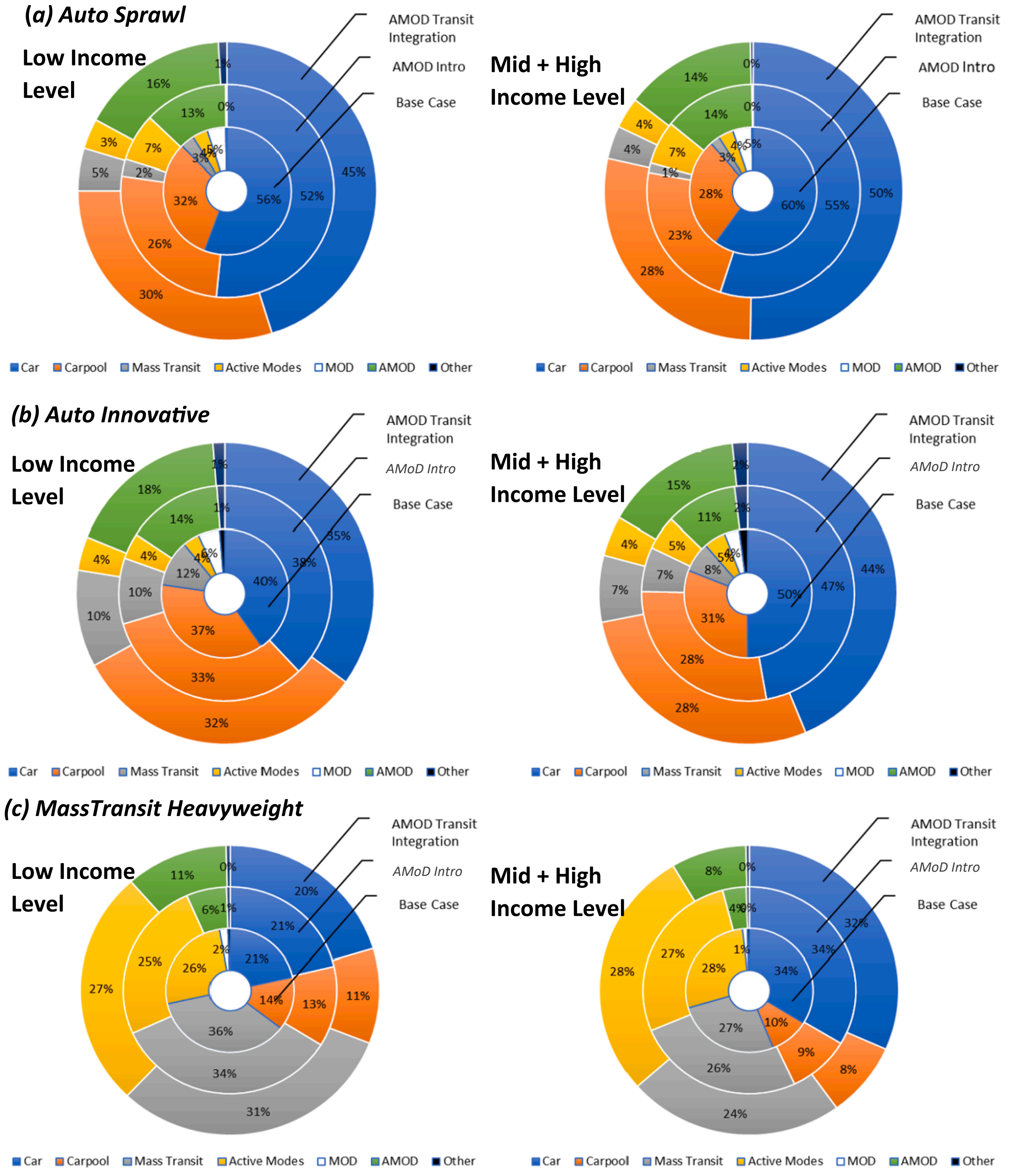

Fig. 5. Mode share by income levels in the (a) *Auto Sprawl*, (b) *Auto Innovative* and (c) *MassTransit Heavyweight* prototype cities.

the three cities. On the right, the change in travel costs under *AMoD Transit Integration* relative to *Base Case*, is presented. On the left, the change in fare under *AMoD Intro*, relative to *Base Case*, is shown.

In *Auto Sprawl*, map (1) clearly shows that under the *AMoD Intro* scenario, city periphery residents paid more—0.3 USD per trip on average—for transport services. The core city residents, on the other hand, paid 1.16 USD less per trip on average. This is due to city typology, which is characterized by long trip distances and, hence, higher transport expenses. It is important to mention that the income distribution map was created to examine the link between income and residence location. However, no clear connection was found in any of the cities. Under the *AMoD Transit Integration* scenario, individuals benefitted from a 0.9 USD discount on average for short trips in the CBD, as they used the new transit-integrated AMoD service, which was cheaper, relative to their mode of transport in

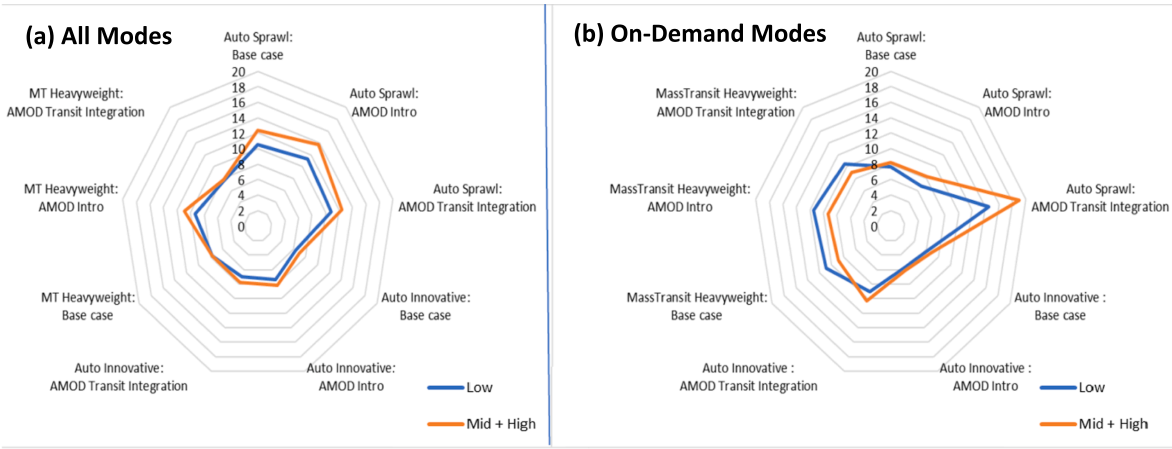

Fig. 6. Passenger kilometers traveled for (a) all modes, and (b) on-demand modes, disaggregated by income level.

the *Base Case*. Outside the CBD, individuals travel far and pay 0.6 USD more on average for a better service.

For *Auto Innovative*, it can be seen from map (1) that core city residents paid 0.4 USD more on average per trip as they used fewer cars and carpooled less. Both these modes are cheaper compared to AMoD. In addition, AMoD is more expensive (0.8 USD for single AMoD or 0.6 USD for shared AMoD per km) in *Auto Innovative* than in *Auto Sprawl* (which costs 1.1 USD for single AMoD and 0.8 USD for shared AMoD per km). In the periphery, residents paid 0.7 USD less on average per trip. However, under *AMoD Transit Integration* (see Fig. 2), no clear trend was observed.

In *MassTransit Heavyweight*, neither AMoD scenario resulted in any significant impacts. The savings and expenses were very small (0.05 USD for *AMoD Intro* and 0.1 USD for *AMoD Transit Integration*). This is because AMoD per-km fare is very similar to the mass transit fare in *MassTransit Heavyweight.*

4.4. Activity-based accessibility outcomes

In Fig. 8 we present a spatial distribution of change in accessibility at the zonal level, calculated using the ABA measure using monetary scaling (see Section 3.3), as a result of policy implementation in the three cities. On the right, the change in accessibility under *AMoD Transit Integration* relative to *Base Case*, is presented in USD units. On the left, the change in accessibility under *AMoD Intro*, relative to *Base Case*, is shown.

Both the *AMoD Intro* and *AMoD Transit Integration* scenarios led to increased accessibility in much of *Auto Sprawl*. However, *AMoD Intro* was slightly more beneficial on average. Residents at the outskirts of the city gained more accessibility compared to those in the city center. Conversely, in *Auto Innovative*, individuals experienced reduced accessibility in the city center under both policies. This is because the new AMoD service introduced significant congestion in the city center. Under the *AMoD Intro* scenario the trend was very clear: residents on the outskirts gained accessibility, while residents in the center lost accessibility. This outcome was less pronounced under the *AMoD Transit Integration* scenario, as some of the remote zones gained accessibility. Overall, it appears that *AMoD Transit Integration* reduced the accessibility of individuals compared to *AMoD Intro*. Again, the congestion introduced by the new modes was responsible for the trend in accessibility reduction. In *MassTransit Heavyweight*, both scenarios produced very similar trends. Individuals lost accessibility in various parts of the city. However, the *AMoD Transit Integration* scenario appeared worse in terms of accessibility gain, due to a higher number of AMoD trips which were used as a transit feeder.

Generally, *AMoD Intro* performs better in terms of accessibility gains for underserved population segments, thereby significantly improving their opportunities. The additional accessibility was most significant in *Auto Sprawl* and least so in *MassTransit Heavyweight*. The results also suggest that the highest gap in the level of service between city center residents and those on the outskirts exists in *Auto Innovative*.

4.5. Summary

We found that in low-density auto-dependent cities (*Auto Sprawl*), the highest induced demand was observed as a result of new AMoD policy implementation. It is also where individuals traveled the most. The highest induced demand was observed among mid and high-income adults, yet 8% of the induced demand was generated by the elderly under the *AMoD Intro* scenario. However, the elderly found the *AMoD Transit Integration* service less attractive, as they preferred door-to-door service. A significant portion (34%) of induced demand in the *AMoD Transit Integration* scenario was attributed to children, who used the AMoD service for mass transit access. These results provide empirical support for a significant new market shares to be created by children and the elderly—claims that have heretofore been only speculative. Under *AMoD Intro*, the least affected groups were the two lowest income levels, yet when *AMoD Transit Integration* was offered, the least affected group was the highest income group. Furthermore, in *Auto Sprawl*, the biggest gap in kilometers traveled between low and mid and high-income individuals was observed. It is also where the largest gap between

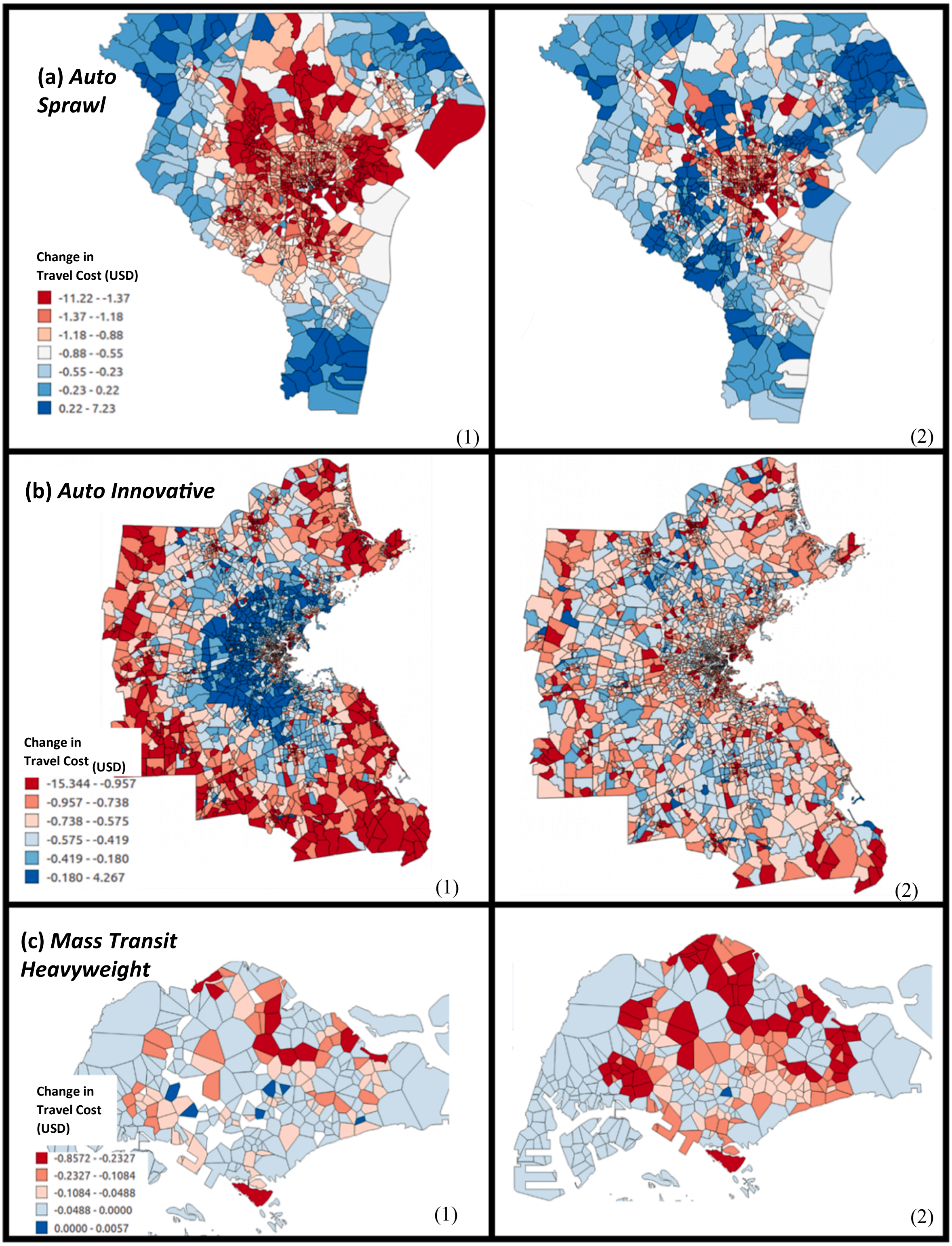

Fig. 7. Spatial distribution of change in travel costs per zone for (a) *Auto Sprawl*, (b) *Auto Innovative* and (c) *MassTransit Heavyweight*. Where: (1) is calculated as *AMoD Intro* minus *Base Case* (IN–BC), and (2) is calculated as *AMoD Transit Integration* minus *Base Case* (TI – BC).

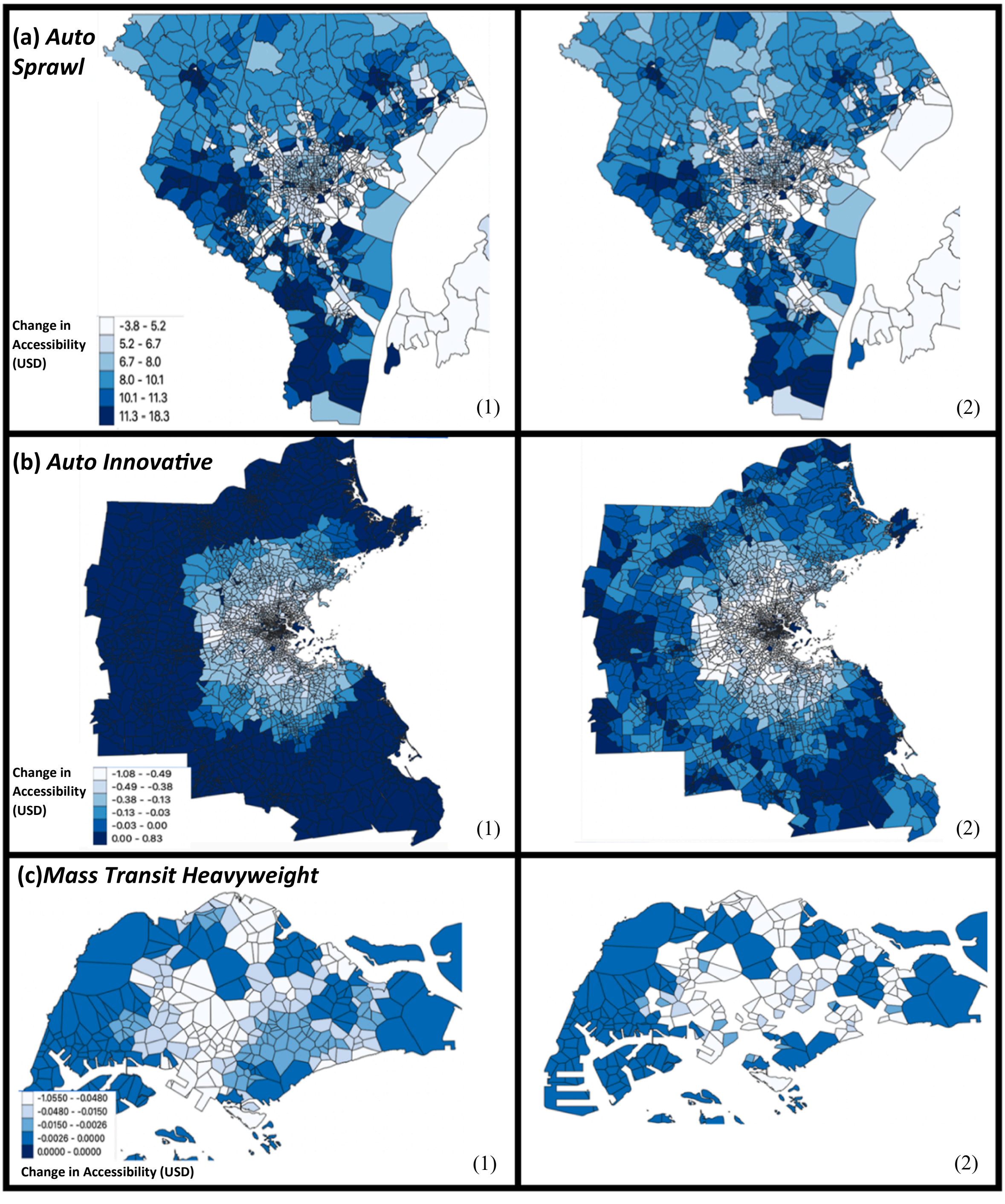

Fig. 8. Spatial distribution of change in accessibility in monetary units per zone for (a) *Auto Sprawl*, (b) *Auto Innovative* and (c) *MassTransit Heavyweight*. Where: (1) is calculated as *AMoD Intro* minus *Base Case* (IN-BC), and (2) is calculated as *AMoD Transit Integration* minus *Base Case* (TI - BC).

core and periphery residences, with respect to the change in travel cost per trip, was recorded.

In dense auto-dependent cities (typified by *Auto Innovative*), both AMoD scenarios demonstrated greater induced demand among the lower income segments of the population. Furthermore, the introduction of AMoD resulted in a similar reduction in car usage, and incremental usage of AMoD modes for both low- and mid-to-high income groups (Fig. 5). As AMoD is more expensive in *Auto Innovative* compared to *Auto Sprawl*, under *AMoD Intro*, core city residents paid more on average per trip than periphery residents, as they used fewer cars and carpooled more frequently (cheaper modes compared to AMoD). However, this was not the case under the *AMoD Transit*

Table 3
Summary of equity outcomes in three prototype cities under two automated mobility on-demand (AMoD) implementation scenarios. In *AMod Intro*, AMoD is introduced in direct competition with mass transit, while in *AMoD Transit Integration*, AMoD complements transit as it restricted for first/last mile transit station connections or for local circulation. (Note: (+) and (++) signify small and large increase respectively; similarly (-) and (–) signify small and large decrease, respectively.)

Scenario (→)	***AMoD Intro***					***AMoD Transit Integration***				
	Change in travel demand by:		**Change in:**			**Change in travel demand by:**		**Change in:**		
Urban Typology (↓)	**Age group**	**Income group**	**AMOD share by income group**	**Accessibility (ABA)**	**Travel cost**	**Age group**	**Income group**	**AMOD share by income group**	**Accessibility (ABA)**	**Travel cost**
Auto Sprawl (Low-density auto-dependent cities)	Elderly (+) Children (+)	Low-income group (+) Mid & High-income group (++)	Similar trend	Outskirt residents (++) Core residents (+)	Outskirt residents (+) Core residents (–)	Elderly (–) Children (++)	Low- & mid-income group (++) High income group (+)	Low-income group (+)	Outskirt resident (++) Core resident (–)	Outskirt resident (++) Core resident (+)
Auto Innovative (Dense auto-dependent cities)	No clear trend	Low income group (+) Mid income group (+)	Low-income group (+)	Outskirt residents (+) Core resident (-)	Outskirt residents (–) Core residents (+)	No clear trend	Low-income group (+) Mid income group (+)	Low-income group (+)	Mixed results Overall (-)	No clear trend
MassTransit Heavyweight (Very large, dense and transit-oriented cities)	No clear trend	No clear trend	Low-income group (+)	Mixed results Overall (-)	No clear trend	No clear trend	No clear trend	Low-income group (+)	Mixed results Overall (–)	No clear trend

Integration scenario, which showed no clear distinction between core city and periphery residences.

In large, population-dense and transit-oriented cities (*MassTransit Heavyweight*), the introduction of AMoD services resulted in the smallest induced demand under both the *AMoD Intro* and *AMoD Transit Integration* scenarios (~0.2%) without any clear distinction among income levels. However, the relative child usage of the integrated AMoD service was noticeable. Under both AMoD scenarios in these cities, carpool and mass transit usage slightly decreased at the expense of AMoD usage, which increased for both income levels at similar rates. Our analyses indicate that low-income individuals traveled more in all scenarios, as the *MassTransit Heavyweight* typology heavily favors mass transit, which is used more by low-income individuals. In this prototype city, neither policy resulted in any significant trend with respect to fare changes. The highlights of the outcomes under each of the scenarios considered are summarized in Table 3.

5. Conclusion

This study addresses the need to evaluate the outcomes of AV scenarios within population groups and individuals in different urban typologies. Three prototype cities were selected for examining social implications of AMoD scenarios. We used the activity-based accessibility (ABA) measure, along with changes in travel cost across age and income groups, to quantify the equity impacts of AMoD in these cities.

We found that large, population-dense and transit-oriented cities had smaller accessibility gaps compared to the other cities, as a result of AMoD implementation. This is due to their extensive mass transit availability and usage, which depress car usage and restricts the induced demand of AMoD. However, in car-dependent cities, such as *Auto Sprawl* and *Auto Innovative*, accessibility gaps were much larger, most notably between the center's residents and the more remote residents. Thus, the *AMoD Intro* scenario performed better in the *Auto* cities compared to *AMoD Transit Integration* in terms of accessibility gain, as it significantly improved the opportunities of those with initially low accessibility. This trend was more pronounced in *Auto Sprawl*, while the highest gap in accessibility between city-center residents and those on the outskirts was found in *Auto Innovative*. We note, however, that the *AMoD Transit Integration* scenario allowed disadvantaged groups, such as children and low-income individuals, to travel more via the mass transit connectivity service.

These results illustrate the importance of individual-level assessments of new AMoD policies and the variability in outcomes based on urban typology. While network performance measures, such as congestion and vehicle kilometers traveled, are usually of interest, the accessibility benefit to individuals must also be considered when comparing the potential of AMoD policies. In these case studies, we see that activity-based accessibility (ABA) is a viable approach for measuring these benefits both in terms of time and cost. The ABA is sensitive to location and income level and indicates how AMoD impacts are felt across different segments of the population. Given that equity implications will dominate in coming years as new AV technologies are introduced, this study provides a framework that can be harnessed to generate valuable typology-specific insights to policymakers in evaluating future AMoD implementation strategies for their respective cities. Finally, in a future study, we would like to examine AMoD services elasticity to prices and show how different population groups are affected by the change in service fee in urban areas of different transport structure. Furthermore, we would like to incorporate findings on the variability in people's perception towards AV technology and show the range of impact these perceptions may have on individual's choice. As suggested by Shi et al. (2021), people's perception towards AV technology are affected by many parameters such as: people's age, personal income, monthly fuel cost, daily commute time, driving alone indicator, willingness to pay for AV technology, and previous AV experience.

CRediT authorship contribution statement

Bat-hen Nahmias-Biran: Conceptualization, Data Curation, Methodology, Formal Analysis, Writing, Project Administration. **Jimi B. Oke:** Conceptualization, Data Curation, Methodology, Formal Analysis, Writing. **Nishant Kumar:** Data Curation, Methodology, Software, Formal Analysis, Writing.

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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