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Bat-hen Nahmias-Biran[1,2] · Jimi B. Oke[2,3] · Nishant Kumar[4] · Carlos Lima Azevedo[5] · Moshe Ben-Akiva[2]

Abstract

Autonomous vehicle (AV) technologies are under constant improvement with pilot programs now underway in several urban areas worldwide. Modeling and field-testing efforts are demonstrating that shared mobility coupled with AV technology for automated mobility on-demand (AMoD) service may significantly impact levels of service and environmental outcomes in future cities. Given these rapidly emerging developments, there is an urgent need for methods to adequately quantify the economic impacts of new vehicle technologies and future urban mobility policy. In this paper, we show how broader user-centric impacts can be captured by the activity-based accessibility (ABA) measure, which takes advantage of the rich data and outcomes of utility-maximization activity-based models and its interaction with mesoscale agent-based traffic simulation frameworks. Using the Sim-Mobility simulator, we evaluate shared AMoD strategies applied to a Singapore micro-model 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 AMoD city-wide in the absence of other on-demand services, were tested and evaluated. Our results provide insights into the income and accessibility effects on the population under the implementation of shared and automated mobility policies. The outcomes indicate that the city-wide deployment of AMoD results in greater accessibility and network performance. Moreover, the accessibility of low-income individuals is improved relative to that of mid- and high-income individuals. The restriction of AMoD to the CBD along with the operation of other on-demand services, however, provides a certain level of disbenefit to segments of the population in two exceptional cases. The first is to high-income individuals who live in a suburban zone and rely heavily on on-demand services; the second is to mid-income residents that have excellent public transportation coverage with close proximity to the CBD. We further establish the efficacy of the ABA measure, as these findings motivate the need for measuring socioeconomic impacts at the individual level. The work presented here serves as a foundation for policy evaluation in real-world urban models for future mobility paradigms.

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Introduction

Smart shared mobility is poised to dominate the urban transportation landscape in the coming decades as cities continue to innovate in a bid to solve pressing problems at the nexus of sustainability and efficiency. The emergence of activity-based models, coupled with the massive gains in available computing power, has made it possible to simulate urban mobility to a very high level of detail (Rasouli and Timmermans 2014). In the past decade and a half, carsharing and ride-sharing have become valid transit modes in major urban centers. Various algorithms have been developed, and continue to be improved, to manage fleets and match drivers to their would-be customers. Autonomous vehicle (AV) technology is also constantly improving, and over 80 cities are now actively hosting pilot schemes (Bloomberg Group 2018). Researchers have been demonstrating the mobility and environmental impacts of shared mobility coupled with AV technology—automated mobility-on-demand (AMoD)—at the microscopic, mesoscopic, and macroscopic levels (Pernestå and Kristoffersson 2019). With these new developments, there is a growing need to adequately quantify the economic impacts of vehicle technology and urban mobility policy. In this paper, we show how user-centric impacts can be captured by the activity-based accessibility (ABA) measure, which has been shown to be more effective compared to traditional accessibility measures for evaluating the overall performance of an urban mobility network, with regard to individual impacts (Dong et al. 2006). The ABA measure leverages on the high-fidelity outcomes of the integrated microscopic demand and mesoscale agent-based traffic simulation frameworks for detailed policy welfare evaluation. Our results provide insights into the income and location effects on the population in the implementation of shared and automated mobility policies.

Activity-Based Models (ABMs), the state of the art in travel demand models today, can capture the entire picture of an individual's activities and are able to account for trade-offs among various activities and travel alternatives in one's daily activity pattern. Thus, they provide a better understanding of travel behavior, compared to traditional modeling (Kitamura 1988; Ben-Akiva and Bowman 1998; Timmermans et al. 2002; Shiftan 2008). To date, a large number of activity-based travel demand models exist that provide highly detailed spatial and temporal measures of person-level accessibility (Bhat et al. 2013; Adnan et al. 2016; Fransen et al. 2018; Rasouli and Timmermans 2014). Rasouli and Timmermans (2014) identified three different approaches: (1) constraints-based models, (2) utility-maximizing models, and more recently and (3) computational process models. Utility-maximizing models and often computational process models utilize econometric models—mainly discrete choice models—in order to model household and individual's travel. In such a framework, a "top" accessibility measure, the ABA, capturing the overall utility from all the travel alternatives over the various dimensions can be obtained. It is the "log-sum" (the log of the denominator of this logit choice probability) which gives the expected utility of one choice from a set of alternatives and is used to link different choices, as in nested logit models. The sum of all logsums until the very top of the hierarchy structure yields the ABA. This measure accommodates individuals' probabilities of participating in a variety of activities, combination of activities through trip-chaining, entire day activity patterns, and the scheduling of activities (Dong et al. 2006; de Jong et al. 2007). The ABA

can also be used in project evaluation as it expresses the consumer benefits. It has been shown to be more effective compared to traditional accessibility measures for evaluating the overall performance of an urban mobility network with regard to individual impacts (Ben-Akiva and Lerman 1979). Although the theory on using the change in logsum as a measure for the change in consumer surplus was published in the late seventies and early eighties (Williams 1977; de Jong et al. 2007), the application of this theory has been quite limited in practice. (For a thorough review, see Nahmias-Biran and Shiftan 2016.) Given the advantages of ABM, the ABA can be extremely valuable for examining smart mobility policies. However, there is no extant work to date that uses ABA to evaluate the socioeconomic impact of shared and automated mobility strategies. This paper is, therefore, a significant contribution to filling this gap.

Thus far, scholarly efforts have been mainly focused on the technological aspects of vehicle automation and on the implications for driver and traffic flow characteristics. These efforts have ranged from the operation of vehicle automation systems and their associated technologies to the investigation of human factor aspects, such as behavioral adaptation, driver workload, and situation awareness. (For an extensive review see Milakis et al. 2017). Yet, many aspects of travel choice and traffic impacts remain unexamined (Zhao and Kockelman 2018). One important aspect is the large-scale impact of autonomous and shared vehicles on individual accessibilities. Only a few attempts have been made to investigate this impact, as highlighted in the remainder of this section. Childress et al. (2015) used the Puget Sound, activity-based transport model, to study the impact of autonomous vehicles on the Seattle, WA, region. Four different scenarios, which envision the progression of AVs transitioning from high-income early adopters to total market penetration, were tested: (1) 30% capacity increase on freeways and major arterials, which reflects AVs' efficient usage of existing facilities; (2) on top of Scenario 1, travel time perceived as 65% of actual travel time for high value of time household trips, which reflects that AV users will perceive the time spent in AVs less negatively than time spent driving in regular vehicles; (3) on top of Scenario 2, all cars assumed to be self-driving, and none shared; (4) all cars assumed to be automated, and all costs of car usage were passed on to the user as it is assumed that AVs have become so common, and shared AVs systems so effective, that personal AV ownership is no longer necessary. The researchers found that if self-driving cars are priced per mile, vehicle miles traveled (VMT) and vehicle hours traveled could be greatly reduced, by as much as 20% and 30%, respectively, with single-occupancy vehicle shares declining 40% and transit shares almost doubling. Conversely, model assumptions in the first three scenarios indicated a potential for much higher VMT and delay, with more passengers conveyed in single-occupancy vehicles, generally worse or equivalent network performance, but higher accessibility for the whole area including downtown Seattle, WA, were observed. This study, however, neglected travel demand by new user groups and changes in regional VMT and in trip lengths.

Liu et al. (2017) provide a large-scale microsimulation of transportation patterns after applying a system of shared autonomous vehicles (SAVs) in the six-county region of Austin, Texas. Leveraging on former studies (Chen et al. 2015; Fagnant and Kockelman 2016), and using the agent-based MATSim toolkit, the SAV mode requests were simulated through a stochastic process for four possible fare levels: $0.50, $0.75, $1, and $1.25 per trip-mile. These fares resulted in modal splits of 50.9, 12.9, 10.5, and 9.2% of the region's person-trips, respectively. Mode choice results show longer-distance travelers preferring SAVs to private, human-driven vehicles (HVs). For travelers whose households do not own an HV, SAVs (rather than transit, walking and biking) appear preferable for trips under 10 miles, which is the majority of those travelers' trip-making. Simulations of SAV fleet

operations suggest that higher fare rates allow for greater vehicle replacement (ranging from 5.6 to 7.7 HVs per SAV, assuming that the average SAV serves 17–20 person-trips per day); when fares rise, travel demands shift away from longer trip distances. Empty vehicle miles traveled by the fleet of SAVs ranged from 7.8 to 14.2%, across the scenarios in this study. However, changes in road capacities or additional travel demand generated by new user groups are neglected.

Meyer et al. (2017) explored large scale impacts of AVs using a simplified travel time-based accessibility measure for Switzerland. Their work addressed some limitations of previous studies by considering different levels of road capacity and including additional travel due to new customer groups and empty rides. Three scenarios were analyzed: (a) a transition phase, in which vehicles could drive autonomously on motorways, but had to be driven manually otherwise; (b) a case which assumes private vehicle ownership as today, but with fully autonomous vehicles; and (c) a third scenario, in which a fleet of shared autonomous vehicles supersedes public transportation and private car ownership. They found that the increase in accessibility is strongest in the transition scenario, but also the other two scenarios show a considerable impact. The strongest positive impact on accessibility was observed for well-connected exurban and rural municipalities, as an increase in capacity on those roads reduces travel times and therefore increases the accessibility of such places. Weaker or even negative impacts were observed for the larger cities, in which the relative increase in demand to and from the cities exceeds the relative increase in road capacity. Azevedo et al. (2016), Basu et al. (2018), and Nahmias-Biran et al. (2019) explored the use of integrated demand (daily activity schedule-based demand) and supply (mesoscopic network) models for the evaluation of traveler and network impacts of AMoD. Scenarios for the city of Singapore and an urban toy-model were generated for the case of the restricted area- and city-wide deployments of AMoD. Changes in travel patterns including trip making, departure times, mode choices, VMTs along with multimodal travel and waiting times were computed to evaluate the accessibility changes for the considered scenarios. In agreement with the aforementioned studies, the results indicated that the accessibility benefits were sustained only when AMoD served in a complementary role to mass transit.

The above examples and the wider range of model-based studies reviewed in Milakis et al. (2017) and Pernestå and Kristoffersson (2019) show that the current state of the art still relies on single dimension AV accessibility measures, lacking the integration of multiple traveler choice dimensions and more amenable user-centric economic measures. In this paper, we go further by developing a framework for assessing the large-scale impacts of shared and automated mobility policies via the ABA measure.

Data and methods

For the purpose of showcasing the application of ABA measures for the evaluation of impacts of AV in a utility-maximizing ABM setting, we use the SimMobility Mid-Term (SimMobility-MT) simulator (Lu et al. 2015). The SimMobility-MT modeling framework is an integration of daily-activity-schedule-based demand modeling system, which is where the ABA measure is computed, with dynamic traffic assignment used for modeling supply decisions (Li 2015). There are three components in the SimMobility-MT framework that interact with each other leading to feedback mechanisms for agent decisions:

1. *Pre-day* models daily-activity travel patterns at the individual level for a synthetic population;
2. *Within-day* simulates departure time choice and route choice decisions incorporating en-route decisions such as re-scheduling;
3. *Supply* provides network attributes and supply-based models for both private and public transportation modes.

While different modeling features can be found in other ABM frameworks, SimMobility MT relies on a multi-level architecture with several feedback loops linking the different travel decisions, allowing us to showcase the benefits of our proposed ABA method for the evaluation of AV deployments. For a review of existing generic ABM frameworks, the reader is referred to Rasouli and Timmermans (2014) and Viegas de Lima et al. (2018).

The rest of this section is organized as follows. First, we explain in greater detail the simulation framework used in this paper, SimMobility-MT. In the following "Simulation framework" and "The activity-based accessibility measure in the SimMobility simulator" sections, we then describe the activity-based accessibility measure and its computation process in the context of random utility-based ABMs such as SimMobility-MT. In "Study area" section, an overview of the study area is presented. Finally ("Experimental design" section), an explanation of the experimental design approach used in implementing the scenarios considered.

Simulation framework

In this section, we describe each module of SimMobility-MT, which enables the evaluation of different ride-sharing strategies. A synthetic population and land use characteristics are an input for the Mid-Term simulator, and more specifically, the *Pre-day* models (Adnan et al. 2016). At the *Pre-day* level, AMoD services are introduced to allow individuals from the synthetic population to choose AMoD modes. In addition to the existing modes, which are single occupancy car (Car), pooling with one extra passenger (Carpooling 2), sharing with two extra passengers (Carpooling 3), public bus (Bus), Mass Rapid Transit (MRT), traditional taxis (Taxi), motorcycle (Motorcycle), and walking (Walk). The following AMoD modes were added: (1) AMoD as a single ride, (2) AMoD as a shared ride, (3) AMoD as a first/last connector to Mass Rapid Transit (MRT) stations, (4) AMoD as a first/last connector to MRT stations as a shared ride. These modes are included in the joint mode and destination choice models as part of an individual's choice set. To reflect individuals' preference towards AMoD we assume that the new service is a driverless point-to-point taxi service, i.e. the taxi utility function was modified, similar to the modification made for MoD service, but with further travel cost reduction (For the detailed specification, see "Experimental design" section).

In *Pre-day*, the individual makes a chain of decisions following the random utility approach (Li 2015). From the decision whether to participate in an activity, through to the exact number of tours and stops, mode and destination choice models, time of day choice and intermediate stops choices (see Fig. 1). The *Pre*-day architecture allows for the simulation of not only the above mentioned mode features but also of other AMoD implementation strategies, such as its restricted operation in certain urban areas, such as a Central Business District (CBD), making it available to all individuals only if the origin and destination are within the operational area. The implications of such a restriction is that individuals traveling by Carpooling 2 and 3, Taxi or MoD will have to be dropped off at CBD
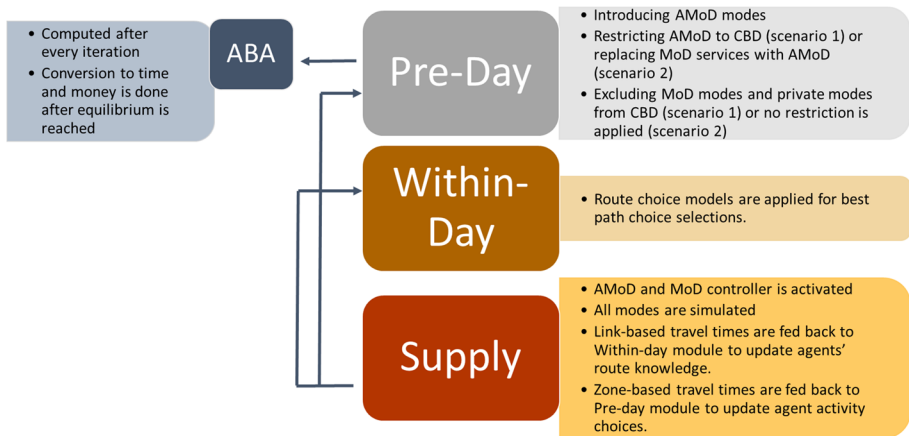
Fig. 1 Shared mobility framework in the SimMobility Mid-Term simulator

entrance and will require to switch to PT or AMoD to reach their destination. Individuals traveling by Car or Motorcycle will have to park their vehicle outside the CBD and switch to PT or AMoD. If parking is not available, they would not choose these modes. Another option is to use the MRT as the main mode while AMoD is used as an access/egress mode under the condition that the MRT station is located inside the CBD. When all mobility-on-demand services are operated by an automated fleet city-wide, for example, AMoD is thus available for any origin and destination while other MoD modes are removed from the choice set. The outcome of *Pre-day* models is the Daily Activity Schedule (DAS), which is generated from a Monte Carlo simulation based on the estimated parameters of the hierarchical discrete choice models, and the ABA measure which will be discussed in detail in "The activity-based accessibility measure in the SimMobility simulator" section.

The DAS is an input to the *Within-day* models which is where the exact route is determined. Public and private transport route choice models are applied for best path choice selections (Lu et al. 2015). At the *Supply* level, the DAS of all individuals are simulated and AMoD or MoD trips are handled by the Smart Mobility Service (SMS) controller. In the SMS controller framework, the passenger sends a request to an AMoD/MoD service, specifying the intended pick-up and drop-off locations. The requests directed to an AMoD/MoD service are periodically processed by the respective controller, thus creating a schedule for each vehicle subscribed to that service. A schedule is a sequence of vehicle/driver instructions, of which there are three types:

(1) *PICKUP* pick up a passenger from the location where the request was generated.
(2) *DROPOFF* drop off a passenger at the desired location as determined by *Pre-day* models.
(3) *CRUISE* drive to a random location in the network until the next schedule is received.

Each schedule is then sent to a matching available vehicle/driver for execution. The algorithm of the AMoD/MoD controller performs the assignment of each incoming request to an available vehicle periodically as in Basu et al. (2018). In summary, the match is feasible if adding the pick-up and the drop-off of the new passenger to the schedule of the vehicle/driver satisfies the waiting time of up to 15 min for all passengers already included

in the schedule, as well as of the new passenger. In addition, the delay for the passengers sharing the vehicle will not be more than 15 min. Supply link travel times are then fed-back into the *Within-day* models to replace the historical travel time and update the agents' route choice. As a day-to-day learning mechanism, these travel times are also aggregated to zonal travel times and fed back to the *Pre-day* level, replacing the historical one, to update the agent's daily activity plan. The ABA measures are re-computed after each day-to-day iteration is completed. For the graphical description of the shared mobility framework in SimMobility-MT please see Fig. 2.

These ABA's are then scaled and translated into both time and monetary terms to allow comparison among individuals. In the following subsection, we explain in detail how the ABA measure is computed and scaled within the SimMobility framework.

The activity-based accessibility measure in the SimMobility simulator

Disaggregate utility-based accessibility measures originating from random utility theory are included within the *Pre-day* activity-based modeling framework. The accessibility measure A_n is defined for an individual n as the expected value of the maximum utility across possible activity schedules, given the choice of alternatives (Ben-Akiva and Bowman 1998):

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

where V_{an} is the systematic component of utility U_{an} for individual n choosing alternative activity schedule a from choice set C_n.

In our hierarchical modeling system, accessibility measures are essential for capturing the sensitivity of activity and travel decisions modeled in lower levels of the choice hierarchy. In formal nested modeling hierarchies, such as the one for the *Pre-day* model, the upward integrity comes from the composite measure of expected utility across the lower level alternatives, or the so-called "logsum". The logsum, the log of the denominator of this logit choice probability, gives the expected utility from a choice (from a given set of alternatives) and can be used to link different choices. (See de Jong et al. (2007) for a thorough review of the logsum definition and its usage).

The *Pre-day* model adopts a simple accessibility measure structure where disaggregate logsum measures from tour mode or mode and destination choice models are fed the Exact Number of Tours model. This model predicts the number of tours performed by each individual according to four activity types: *Work*, *Education*, *Shop* and *Other*. From that level of decision, logsums are fed to the choice models in the day pattern level—the *Day Pattern Tours* model and the *Day Pattern Stops* model, which predict the availability of making a tour/stop according to the four activity types.

The *Exact Number of Tours* model results are provided to the *Intermediate Stop Generation* model to constrain the availability of each activity purpose. The *Day Pattern* level generates a list of tours as well as intermediate stop availabilities for each individual in the synthetic population. From this level, the logsums are passed to the *Day Pattern* binary model which predicts whether a person will travel. The accessibility measures, or logsums, introduced in the *Pre-day* model are shown in Fig. 2 with dashed arrows. The ABA—a measure of accessibility obtained at the top of the hierarchy from the day pattern binary model—captures the relative attractiveness of various activity types, the number of tours
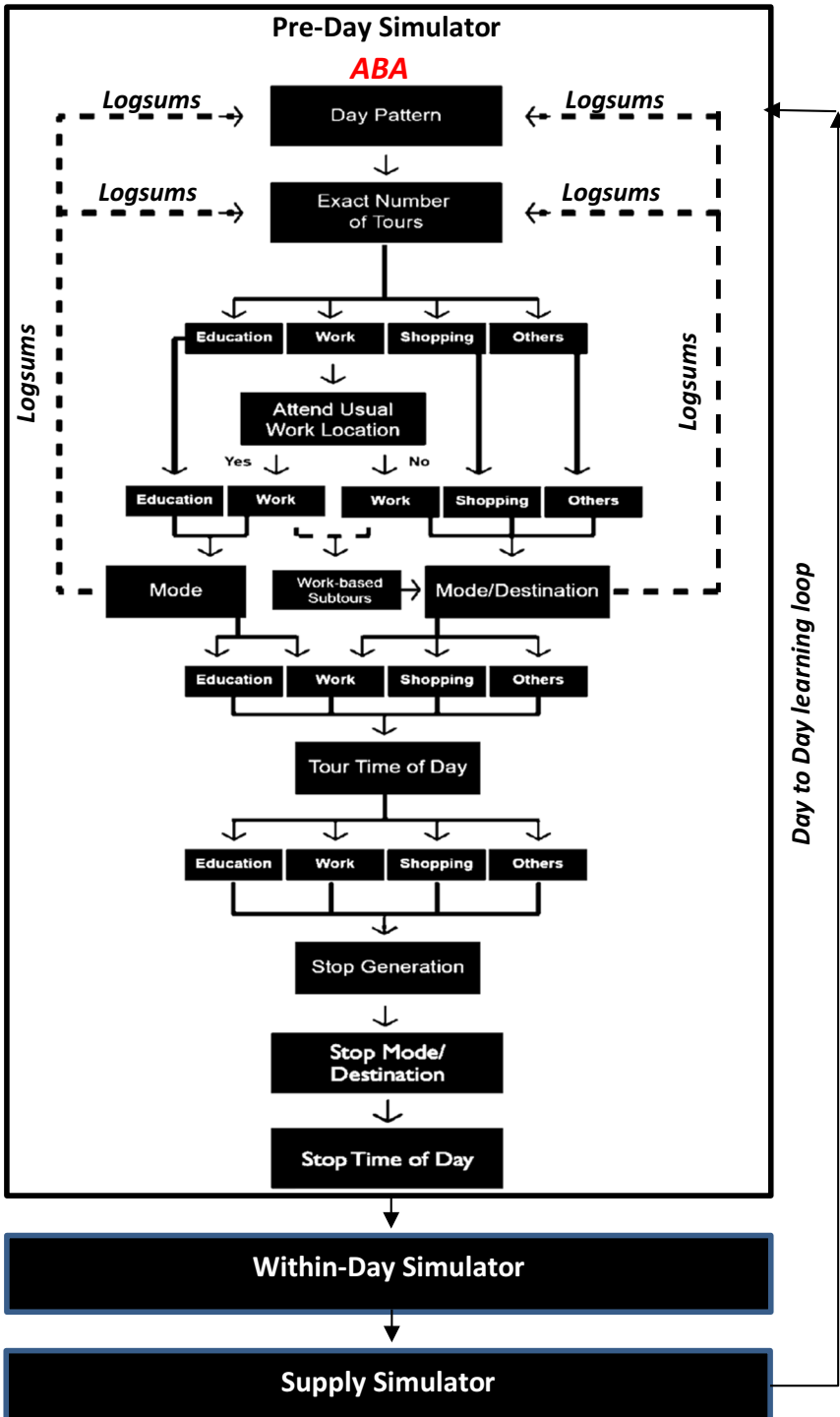
Fig. 2 The activity-based accessibility (ABA) measure computation procedure in SimMobility-MT

and stops to perform, and mode and destination alternatives for individual n. Note that while SimMobility-MT models were estimated in a bottom-up fashion, the implementation here described relies on a top-down approach. It relies on an iterative simulation process between the first step of logsum computation and a joint choice simulation and logsum update step.

For the ABA measure to be considered useful for project evaluation and comparison across individuals, it must satisfy both the scale and level conditions (Dong et al. 2006). To level or normalize the accessibility, it must be benchmarked to an extreme value that retains heterogeneity across individuals. To achieve this, we compute A_n^0, the day pattern binary logsum for individual n in the hypothetical case where the total travel time and cost are taken to be zero. The ABA is then given as the difference between A_n and A_n^0, and scaled to convert it to units of time or cost.[1] The multiplying scaling factor α_{nx} approximates the inverse of the marginal utility with respect to the variable of choice (time or cost) for individual n is defined by model variable x, e.g. travel time or cost, uniformly across income levels, and given by:

$$\alpha_{nx} = \left(\frac{A_n^{(\Delta x)} - A_n}{\Delta x} \right)^{-1} \tag{2}$$

The term $A_n^{(\Delta x)} - A_n$ represents the change in accessibility when the value of a particular model variable x is perturbed (i.e. increased) for all trips and for all activity schedules. For this experiment, we take Δx as 1 min (for time conversion) and as SG\$1 (or 0.735 US Dollars for monetary conversion).

The ABA is then given as the scaled and normalized (leveled) individual accessibilities, thus:

$$ABA_n = \alpha_{nx}\left(A_n - A_n^0\right). \tag{3}$$

Study area

This case study was tested using a prototypical "Virtual City" (VC), which consists of a moderately sized network and population, generated by sampling households, buildings, jobs and activity locations from Singapore, along with their characteristics. The VC network was chosen for demonstration purposes, the method presented in this paper can easily be applied to a full-scale system, at some computation cost. Virtual City was calibrated to represent the land use patterns, travel behavior, and activity patterns observed in Singapore (Adnan et al. 2016) on a typical day. Selected attributes for validation are shown in Fig. 3: person's main tour activity share (in terms of number of tours), Fig. 4: person's mode share (in terms of number of trips), and Fig. 5: net household monthly income distribution (in SGD). The starting points for the VC *Pre-day* model parameters were obtained from the model calibrated for Singapore, based on data from the Household Interview Travel Survey (HITS) 2012 (Li 2015; Azevedo et al. 2016). A Monte Carlo simulation of the estimated ABM generated the DAS for the full population,

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[1] If done with respect to cost, then the ABA is proportional to the [change in] consumer surplus and can be used directly in project evaluation. However, computing the consumer surplus directly from the logsum is more straightforward (de Jong et al. 2007).

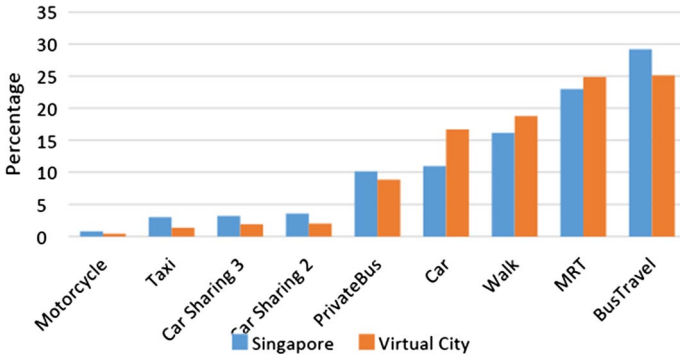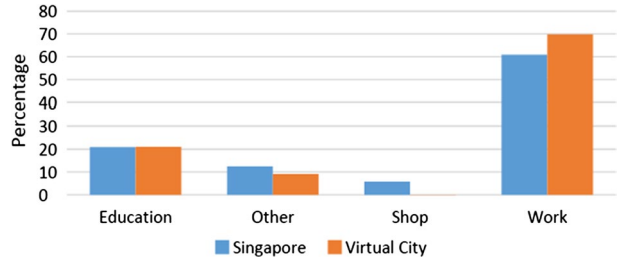**Fig. 3** Main tour activity share comparisons between Singapore and Virtual City

Fig. 4 Mode share comparisons between Singapore and Virtual City
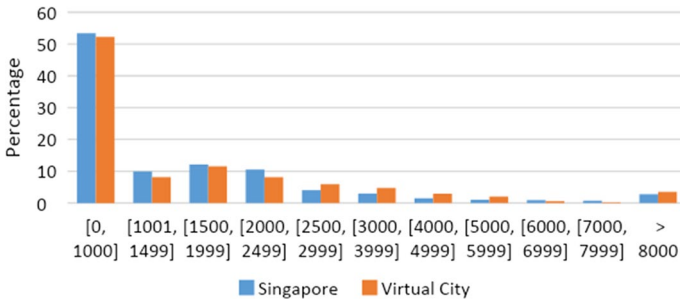
Fig. 5 Income distribution (in SGD) comparisons between Singapore and Virtual City

which consists of the output of pre-day model. Then, in the *Within-day* and *Supply* components, a full-scale mesoscopic simulation was performed, and actual network capacities were used.

The total population in Virtual City is 351,000 (~7% that of Singapore) with an average tour rate of 1.14 per individual per day. The road network consists of 95 nodes (intersections), 286 segments (road sections with homogeneous geometry), 254 links (groups of one or more segments between nodes) and 24 Traffic Analysis Zones (TAZs) overall. There are 12 bus lines, each having a constant service headway that ranges from 3 to 9 min, spanning the region with 86 bus stops. Virtual City also has 4 Mass Rapid Transit (MRT) lines with a total of 20 subway stations.
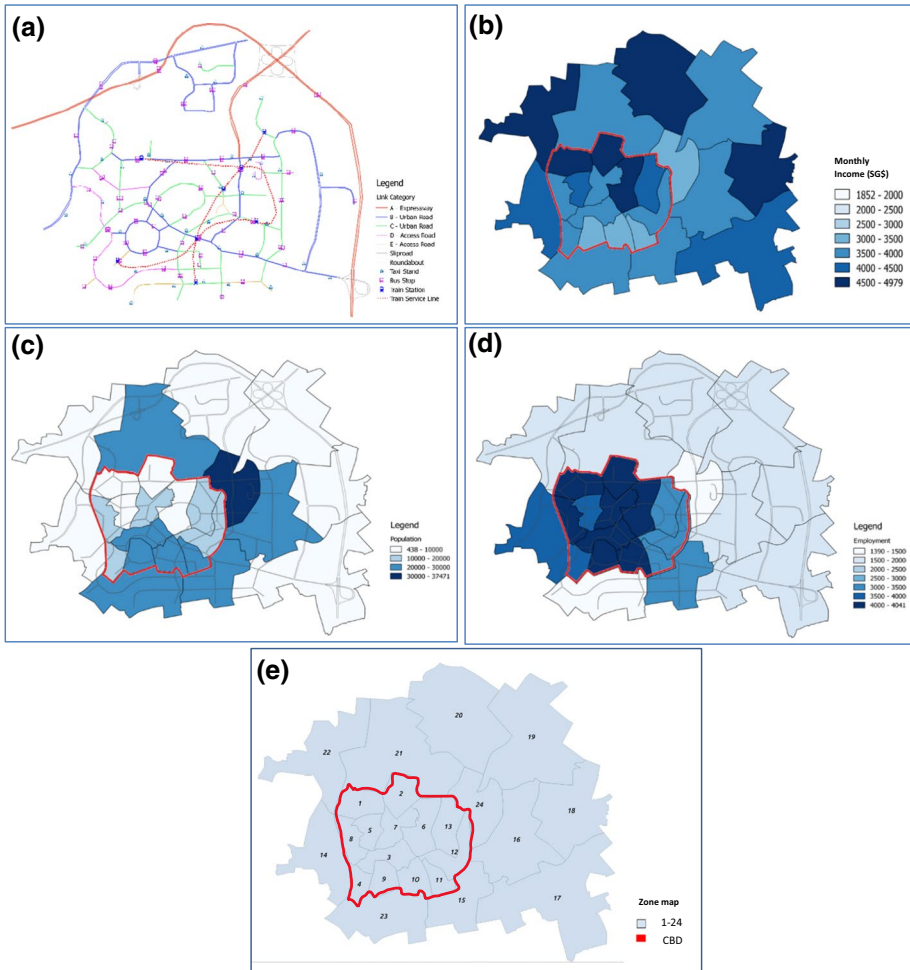
Fig. 6 Maps of Virtual City: supply network (**a**), monthly income (**b**), population (**c**), and employment distributions at the Traffic Analysis Zone (TAZ) level, as well as (**e**) TAZ map

In Fig. 6, the supply network and TAZ-resolution maps of population, employment and income are presented. The central business district (CBD), marked by the red ring, is characterized by excellent public transportation coverage and high number of employment opportunities. The outermost zones are more isolated with low PT coverage. Most of VC residents live in the zones immediately surrounding the CBD as shown in Fig. 6.

Experimental design

We implement the ABA measure in the SimMobility MT simulation environment in which we demonstrate the accessibility outcomes of the AMoD restriction and rideshare dominance scenarios. Thus, three scenarios were designed and tested, as described below.

Base Case scenario

In the Base Case, we consider all ten available modes in Singapore in 2017, namely: single occupancy private vehicle (Car), private vehicle with one extra passenger (Car Sharing 2), private vehicle with two extra passengers (Car Sharing 3), Public Bus, Private Bus, Mass Rapid Transit (MRT), traditional taxis (Taxi), motorcycle (Motorcycle), walking (Walk), Mobility on Demand service (Uber-like service) as a non-shared ride (MoD Single), and Mobility on Demand service as a shared ride (MoD Shared). In order to generate the demand for MoD modes, given the absence of appropriate data in HITS 2012, we assumed that individual preferences towards MoD are similar to those for Taxi, with some modifications. Regarding the level of service, the first set of assumptions is that a single MoD ride will be 28% cheaper as compared to taxi, and that a shared ride will be 30% cheaper than a single ride (Lee 2017). Second, based on Uber statistics for Singapore, we calibrated our models so that 25% of all MoD trips are shared trips and that 25% of all MoD trips end at MRT stations. We also implemented a distance based additional in-vehicle travel time for the passengers who share the vehicle with other passengers (based on the Uber app information). Furthermore, we have added the expected additional waiting time for the share rider. All assumptions regarding MoD are valid where such a service is available (i.e. in scenarios 1 but not in scenarios 2).

Scenario 1

In this scenario, a possible near future for Singapore is simulated such that AVs are exclusively operated in the CBD of Singapore. The available AMoD modes are: AMoD as a non-shared, driverless ride (AMoD Single), and AMoD as a shared driverless ride (AMoD Shared). Motorized private modes (Car, Carpooling 2 and 3, Taxi, Motorcycle and MoD) are forbidden from entering the CBD area. However, Bus and MRT are available in the CBD. In order to generate the demand for AMoD modes, given the absence of appropriate data, we assumed that individual preferences towards AMoD are similar to those for MoD, with travel cost modifications. We assumed the travel cost for AMoD Single is 33% of that of MoD Single (Litman 2017). As this scenario encourages the use of AMoD, we would like to determine the extent to which this service will be used and the consequences of such a policy on individual accessibility and service efficiency. Furthermore, it is important to note that public transit is still available in the CBD under this scenario. Hence, we can also determine how different income levels and other population segments are affected by this policy.

Scenario 2

In Scenario 2, a long-term vision for Singapore is realized, where all mobility-on-demand services are operated by an automated fleet city-wide. Specifically, MoD modes (both single and shared) and traditional taxis will no longer be available. The AMoD cost assumptions for this scenario are the same as those in Scenario 1.

We conducted 24-h of VC simulations for each scenario in SimMobility. The initial simulation was used to generate real-time parameter estimates such as travel times for different modes, which were then used as feedback for the choice models in the *Pre-day* component. This day-to-day learning feedback methodology was already described in "Simulation

Fig. 7 Tour mode share distributions for the given scenarios

framework" section and was utilized in all scenarios. The results of subsequent simulations, with special emphasis on the ABA measure results, are presented and discussed in "Results and discussion" section.

Results and discussion

Demand

Tours mode share distribution for each scenario is shown in Fig. 7. In the Base Case, MRT and Public Bus each account for up to 20% of the share, while single private car accounts for 15% of the share and additional 3.6% will share the Car with other passengers. Walk takes 20% of the share, and Private Bus about 8%. Taxis and MoD services account for 12% of the share.

In Scenario 1, where AMoD is exclusively operated in the CBD, and all private and MoD modes cannot enter the CBD, we see a large increase in PT mode share from 40% in the Base Case to 56%, which will come mainly from Car modes. A dramatic reduction in Car usage from more than 19% in Base Case to 6.4% is observed, as well as significant reduction in Walk and Private Bus mode share, which were cut by half as compared to Base Case. Although Walk and Private Bus were not restricted in Scenario 1, the attractive cost of AMoD services caused a shift from Walk and Private Bus demand to AMoD. We also observe a reduction in MoD demand from 11.7% in base case to 7% due to the CBD restriction and the competing AMoD services and its attractive travel fares. In Scenario

Table 1 Summary of terms used in activity-based accessibility (ABA) results discussion

Symbol	Description
$\Delta_{t,1}ABA$	Difference in time-based ABA between Scenario 1 and Base Case
$\Delta_{c,1}ABA$	Difference in monetary-based ABA between Scenario 1 and Base Case
$\Delta_{t,2}ABA$	Difference in time-based ABA between Scenario 2 and Base Case
$\Delta_{c,2}ABA$	Difference in monetary-based ABA between Scenario 2 and Base Case

1, AMoD modes will take 15.2% of the share. In Scenario 2, where AMoD modes will replace the traditional and Uber-like services city-wide, AMoD consists of 12.7% of the demand, while all other mode shares are similar to those in the Base Case.

Activity-based accessibility impacts

We compute individual-specific ABA values for each of the three scenarios discussed. We consider the ABA change in Scenarios 1 and 2 with respect to the Base Case, as this enables us to measure the time and monetary gains or losses for each individual under the scenario of interest. We summarize the following terms to be used in the discussion from here onward in Table 1.

In Fig. 8, we plot the 25% trimmed histograms of the relative ABA change in each of these cases. Given the heavy tails of the logsums, we trim each ABA by 25% at both tails in order to clearly show the differences in central tendency between the two scenarios relative to the Base Case. The median relative accessibility is a loss under Scenario 1, while the opposite is the case in Scenario 2. The motivation for individual-level measurements is given by the mean ABA changes, which show a gain in monetary accessibility under both scenarios (and more so in Scenario 1). Summary statistics are provided in Table 2. These results suggest that further analyses at the income and spatial levels based on individual characteristics can provide insights into the socio-economic impacts of the strategies across various segments of the population that may not be observed at the aggregate level.

In Table 3, median ABA differences in time and cost are computed for each income category, for both scenarios as compared to based case. In the $\Delta_{t,1}ABA$ column, the accessibility differences in time are all negative and increasing as the level of income increases. Except for the first income category for which the accessibility is positive in terms of time. The first income category suffers from a poor level of accessibility in terms of time at the base case. Following the principle of diminishing marginal utility, which can be applied to accessibility as a quantity of good or service (Nahmias-Biran and Shiftan 2019), these individuals will gain much more from an additional unit of accessibility compared to travelers with initial high levels of accessibility. In other words, for them, the new service is a significant improvement in time relativity to their poor accessibility at the base case, therefore the change in ABA is large and positive.

For the accessibility differences in cost, the opposite trend is observed. Accessibility differences are increasing as the level of income decreases. For $\Delta_{t,2}ABA$, the temporal accessibility differences are decreasing as the level of income increases. The ABA in time is positive for low-income people, i.e. low-income individual's accessibility is increasing as compared to Base Case, while mid- and high-income individuals lose accessibility in terms of time.
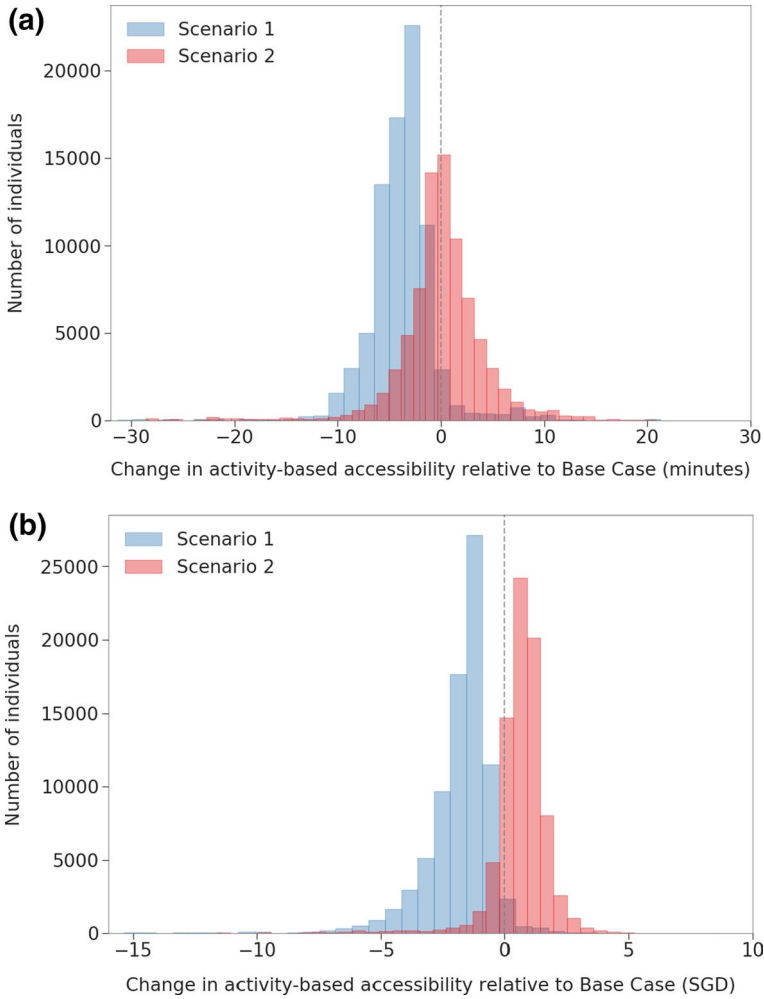
Fig. 8 Distributions of ABA change, as **a** time savings and **b** monetary savings. The 25% trimmed distributions are shown for ease of comparison between the two scenarios. Corresponding statistics are shown in Table 2

Table 2 Median and 25% trimmed mean of ABA change in both temporal and monetary terms for Scenarios 1 and 2 relatives to the Base Case

Relative ABA	Median	25% Trimmed mean
$\Delta_{(t, 1)}ABA$ (min)	− 3.04	− 3.73
$\Delta_{(c, 1)}ABA$ (SGD)	− 0.70	− 1.81
$\Delta_{(t, 2)}ABA$ (min)	0.53	0.11
$\Delta_{(c, 2)}ABA$ (SGD)	1.08	0.63

Table 3 Change in activity-based accessibility by income level for Scenarios 1 and 2 relatives to the Base Case

Income category	Income range (SGD)	$\Delta_{t,1}ABA$ (min)	$\Delta_{t,2}ABA$ (min)	$\Delta_{c,1}ABA$ (SGD)	$\Delta_{c,2}ABA$ (SGD)
1	[1, 1000]	13	25	0.7	1.3
2	[1001, 1499]	− 4.2	3.7	− 0.8	0.6
3	[1500, 1999]	− 3.8	2.0	− 1.0	0.7
4	[2000, 2499]	− 3.6	0.9	− 1.2	0.7
5	[2500, 2999]	− 3.4	0.4	− 1.4	0.7
6	[3000, 3999]	− 3.4	− 0.4	− 1.7	0.7
7	[4000, 4999]	− 3.3	− 0.9	− 2.1	0.6
8	[5000, 5999]	− 3.2	− 1.0	− 2.5	0.5
9	[6000, 6999]	− 3.1	− 1.1	− 2.9	0.3
10	[7000, 7999]	− 3.0	− 0.9	− 3.5	0
11	≥ 8000	− 2.8	− 1.3	− 3.3	0.1

The differences in time and cost come from Eq. 2, where time or cost parameters in the mode and destination choice models were changed as part of the scaling process
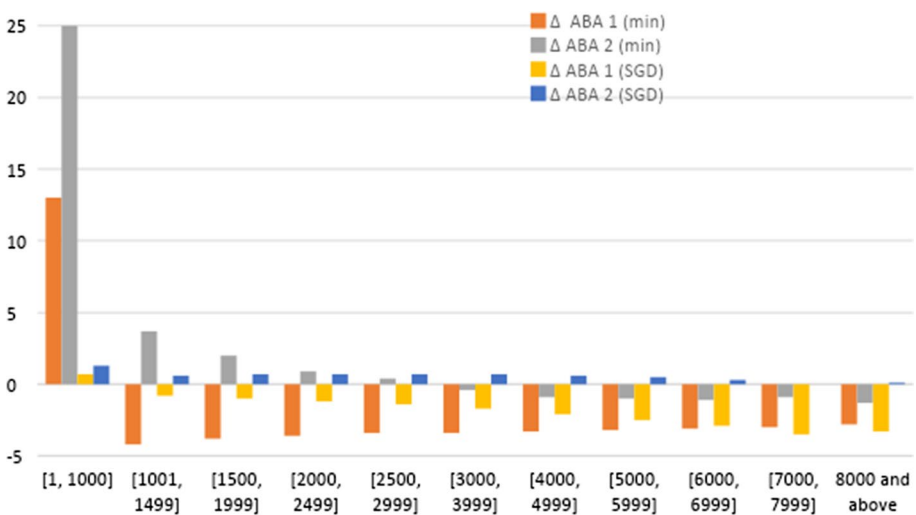

Fig. 9 Chart showing change in activity-based accessibility by income level for Scenarios 1 and 2 with respect to Base Case

In considering the accessibility differences in cost, it can be observed that there is an accessibility gain, or positive change in consumer surplus, for all income categories. Mid- and high-income individuals are gaining less accessibility as compared to low-income groups. These differences are further highlighted in Fig. 9 to contrast the variation of ABA change by income under Scenarios 1 and 2. While examining distributional effects on different income levels, it should be noted that choices of travelers are based on their willingness to pay (WTP) for travel options. The WTP of low-income people for (additional)
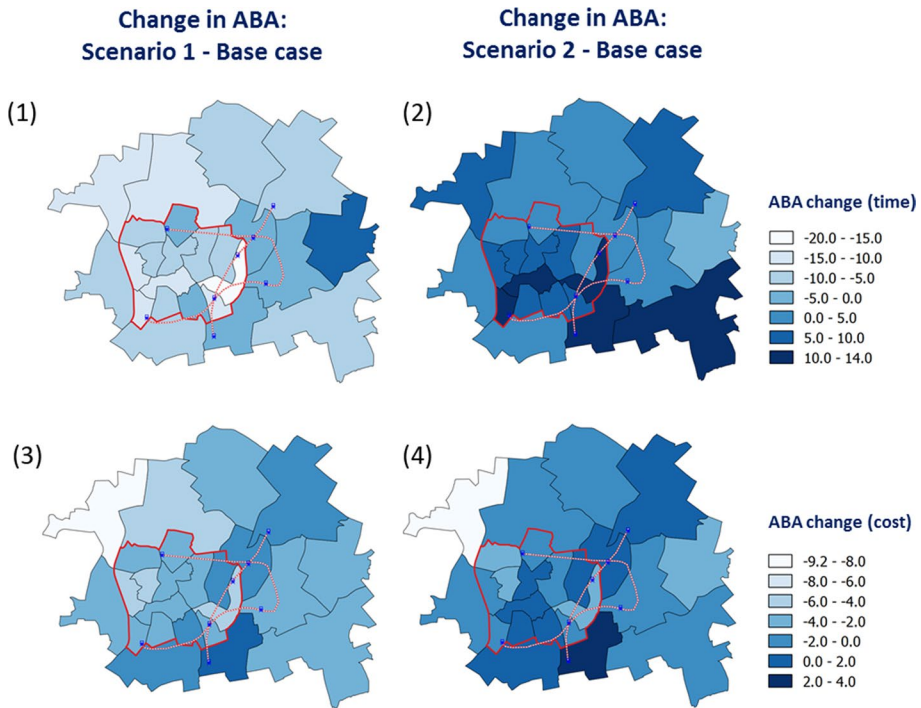
Change in ABA:
Scenario 1 - Base case

Change in ABA:
Scenario 2 - Base case

Fig. 10 Spatial distribution of relative change in activity-based accessibility by Traffic Analysis Zone, measured in minutes and in Singapore dollars (SG$)

travel is inherently low because they require a significant portion of their income for housing, food, clothes and medical services, leaving less money for travel. Introducing AMoD service with reduced travel costs might thus reduce inequalities more than estimated based on the WTP.

In Fig. 10, the median change in accessibility, which was obtained from both scenarios compared to Base-Case, is shown as a spatial distribution on the Virtual City map. The time-based differences are presented in maps (1) and (2). Map (1) indicates that the accessibility change in time is negative for all zones except the one labeled Z^*. That is, when private modes are restricted from the CBD and AMoD modes fulfill transportation needs, individual accessibilities decrease both inside and outside the CBD, as more time is spent in transit. As for zone Z^*, it appears that taxis serve a large part of the demand from that remote zone. Thus, restricting taxis from entering the CBD allows better taxi service for the remote zones outside the CBD. On the other hand, in introducing AMoD under Scenario 2, the accessibility in time was improved in all areas apart from zone Z^*, which, as earlier identified, relies on MoD service and therefore now competes with other remote zones for the same service. The change in consumer surplus as captured by the median change in ABA in monetary terms are shown in maps (3) and (4). It is clear from map (3) that individuals pay up to SG$9.2 more for transportation services under Scenario 1 relative to Base Case. One exception is zone Z' in which individuals' median change in consumer surplus is SG$1.80 per day. By applying Scenario 2, map (4) shows that for some of the riders, the consumer surplus was positive (between SG$0.24 and

Table 4 Zone-based median changes in activity-based accessibility in monetary terms (SGD) and time (minutes) for Scenarios 1 and 2 with respect to Base Case

Zone code	$\Delta_{c,1}ABA$ (SGD)	$\Delta_{c,2}ABA$ (SGD)	$\Delta_{t,1}ABA$ (min)	$\Delta_{t,2}ABA$ (min)
1	− 3.80	− 2.94	− 8.92	3.12
2	− 2.56	− 1.19	− 4.88	4.89
3	− 2.08	0.70	− 12.06	11.93
4	− 3.68	− 0.94	− 11.20	14.03
5	− 4.37	− 2.28	− 9.86	9.61
6	− 3.03	− 0.49	− 7.71	5.06
7	− 2.14	0.38	− 7.96	8.30
8	− 4.12	− 1.35	− 11.79	7.85
9	− 2.13	0.35	− 9.97	7.52
10	− 0.56	1.89	− 4.87	7.28
11	− 2.87	− 0.58	− 10.24	7.11
12	− 5.22	− 2.84	− 19.93	10.88
13	− 1.69	0.24	− 6.11	4.82
14	− 3.61	− 1.51	− 8.45	1.97
(Z′) 15	1.79	3.94	− 4.00	10.48
16	− 2.99	− 0.74	− 1.32	0.18
17	− 2.69	− 0.53	− 9.07	11.02
(Z*) 18	− 3.51	− 2.65	6.79	− 3.72
19	− 0.60	1.17	− 5.46	8.11
20	− 2.34	− 0.44	− 7.12	1.16
21	− 4.13	− 1.49	− 10.63	2.35
22	− 9.19	− 8.08	− 13.86	9.36
23	− 0.97	1.19	− 9.24	4.53
24	− 1.32	0.62	− 3.50	3.28

Table 5 Comparing travel times and car trip time and distance across scenarios

Metrics	Base Case	Scenario 1	Scenario 2
Average travel time (min)	5.6	8.0	5.6
Average waiting time (min)	5.7	12.9	5.4
Average car trip distance (km)	5.7	7.3	5.3
Average car trip time (min)	5.2	6.5	5.4

SG$3.94 savings per day), mainly those that are well connected to the rail system. While for others, the consumer surplus was negative (as high as SG$9.2 spending per day). This can be explained by the fact that because AMoD offers cheaper service compared to MoD services, some individuals who previously used PT shifted to AMoD and hence their transportation cost slightly increased. (See Table 4 for a complete summary of the ABA changes by zone).

Table 6 On-demand modes level of service across all scenarios

On-demand modes	Trips requested	Trips supplied	%	Ave wait time (min)	Ave travel time (min)	Ave trip length (km)
Base Case						
MoD	20,943	16,225	77	3.0	6.0	5.5
MoD Pool	17,069	12,535	73	10.5	10.2	12.8
Rail MoD	41,192	16,870	41	3.1	4.7	4.3
Scenario 1						
MoD	8229	6384	78	21.9	8.7	7.89
MoD Pool	9339	7110	76	12.1	12.8	13.5
Rail MoD	30,654	12,144	40	24.0	6.6	4.32
AMoD	44,832	41,898	93	23.6	4.2	2.87
AMoD Pool	22,059	20,765	94	11.0	7.6	7.34
Rail AMoD	29,704	11,856	40	27.7	3.8	3.36
Rail AMoD Pool	20,186	7989	40	12.1	9.1	7.20
Scenario 2						
AMoD	56,077	53,715	96	5.13	6.3	5.35
AMoD Pool	17,552	16,685	95	10.7	10.0	12.5
Rail AMoD	30,048	12,037	40	6.5	5.4	4.33

Table 7 On-demand controller performance across scenarios

	Base Case	Scenario 1	Scenario 2
Driver subscriptions	5000	5000	5000
Ride requests	45,772	108,381	82,670
Driver assignments	40,253	88,203	74,911
Passenger pick-ups	45,727	108,248	82,582
Passenger drop-offs	45,669	108,120	82,432
Ride request: driver assignment ratio	88%	81%	91%
Ride request: drop-off ratio	99.8%	99.8%	99.7%

Table 8 Impact of fleet size on AMoD and MoD waiting and trip times in Scenarios 1 and 2

	Scenario 1				Scenario 2			
Fleet size	5000		7500		5000		7500	
Ave time (min)	Wait	In-vehicle	Wait	In-vehicle	Wait	In-vehicle	Wait	In-vehicle
MoD	21.9	8.7	10.8	10.5				
MoD Pool	12.1	12.8	14.9	15.2				
Rail MoD	24.0	6.6	13.5	8.1				
AMoD	23.6	4.2	12.8	4.9	5.1	6.3	3.9	6.3
AMoD Pool	11.0	7.6	13.8	8.9	10.7	10.1	11.4	10.4
Rail AMoD	27.7	3.8	15.5	8.1	6.5	5.4	4.8	5.4
Rail AMoD Pool	12.1	9.1	16.1	11.5				

Level of service and network performance analyses

Overall, we observe that Scenario 2 outperforms Scenario 1 on the bases of average travel and waiting times across all modes (Table 5). This is due to the region restriction policy excluding all private car trips from the CBD in Scenario 1, thus resulting in a 28% and 25% increase in the average car trip distance and average car trip time, respectively, with regard to the Base Case.

Given our interest in shared mobility services, we further analyze the on-demand trip statistics. In the Base Case, 79,204 on-demand trips are initially requested, but only 45,630 are supplied. Hence only 57% of the trips were served. We note that over half of the Rail MoD trips are converted to Walk trips in the *Within-day* module of Sim-Mobility as these are very short trips (less than 1 km travel). In Scenario 1, 165,003 on-demand trips are initially requested, while 108,146 of them are ultimately satisfied. The service rate improves in this scenario to 66%. This improvement might be due in part to the restriction of AMoD operations to a smaller area (the CBD). Finally, in Scenario 2, where the on-demand service is fully automated and available across the entire network, 82,437 trips are completed from the 103,677 initially demanded. The level of service in this scenario (percentage of served trips) is 80%, which is the best-performing across all
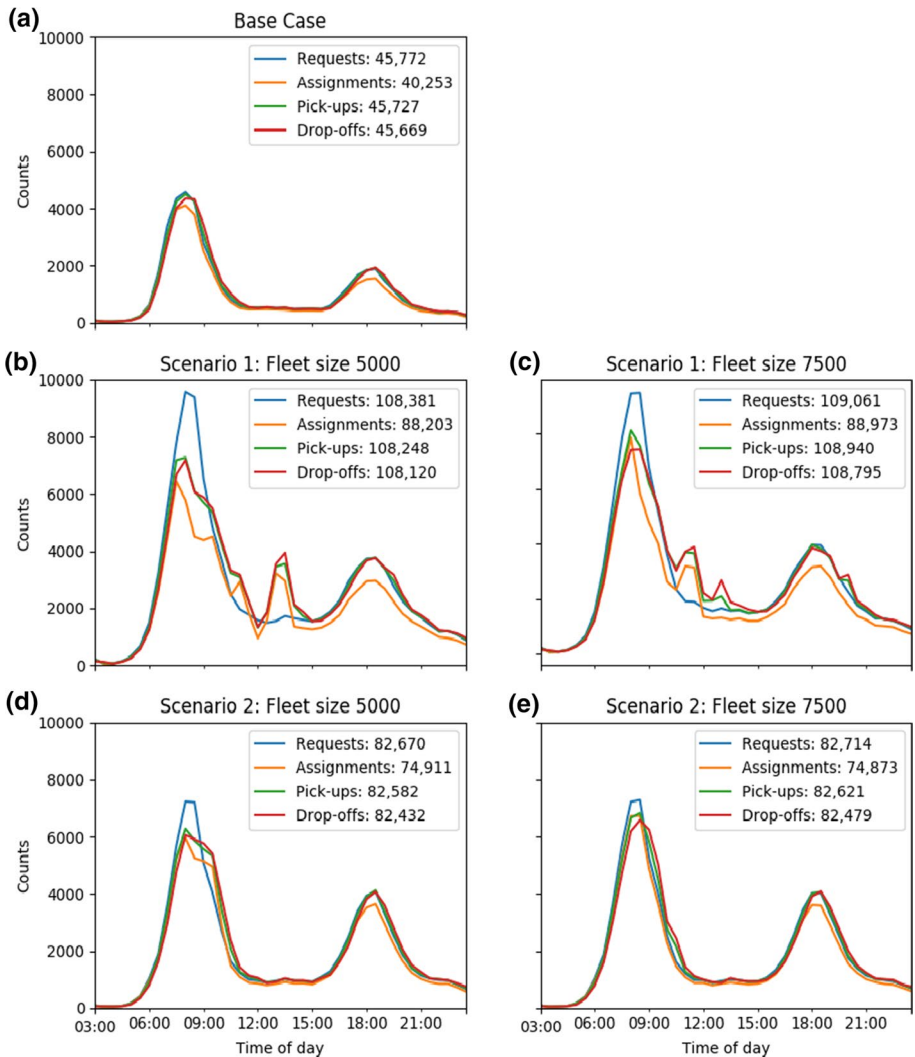
Fig. 11 Comparing on-demand service controller performance among the scenarios. For Scenarios 1 and 2, the results from increased fleet size are also shown

three scenarios. A performance summary across the various on-demand services in each scenario is given in Table 6.

Table 7 shows the driver subscriptions and assignments (supply-side), and passenger requests, pick-ups and drop-offs. An assignment indicates that a passenger pick-up schedule has been successfully sent to a given vehicle. Since some rides are shared, overall assignments are fewer than overall requests. In Scenario 2, the proportion of single rides demanded is the highest, hence the 91% request-assignment ratio compared to 81% in Scenario 1. Scenarios 1 and 2 are implemented under the initial assumption

that the overall on-demand fleet size does not change. Thus, across all three cases being compared, the total is 5000 vehicles. This implies that the city might regulate the overall fleet size, even while some conventional vehicles are replaced with AVs. These assumptions result in the high wait times observed in Table 2 for Scenario 1, even though these trips are still ultimately serviced (Table 3). To simulate a more realistic future where supply investments are made to meet rising demand (for instance, in Scenario 1, trip requests are more than twice those in the Base Case), we simulate Scenarios 1 and 2 with increased on-demand fleet sizes of 7500.

While the ABA does not change much with increased fleet sizes in either scenario, we do observe considerable improvement in waiting times under Scenario 1. These numbers are compared in Table 8. We find that while wait times reduce, in-vehicle travel times do not necessarily follow the same trend. One possible explanation might be that there is a bit more congestion due to the cruising of the additional fleet vehicles in addition to that induced by the region restriction. Another interesting outcome is that the reduction in waiting times is less drastic for the shared on-demand rides. We can rationalize this by considering that the increased availability of vehicles does not immediately result in lower pick-up times for shared ride requests.

A graphical summary of the service controller performance across all these cases is shown in Fig. 11. Despite the slight increase in trip times observed with increased fleet sizes, overall travel times of on-demand rides in Scenario 1 are lower. This can be seen from the closer tracking of the drop-off curve to the request curve in (c) compared to those in (b).

Conclusion

In this paper, we have demonstrated how user-centric impacts of new vehicle technologies and future urban mobility policies can be captured by the activity-based accessibility (ABA) measure, which takes advantage of the rich data and outcomes of the activity-based model and the mesoscale agent-based traffic simulation frameworks. This study is the first to utilize the ABA for analyzing different ridesharing strategies. We show that the socioeconomic impacts of future mobility policies can be analyzed at person-level granularity by calculating the ABA changes for useful insights in the evaluation of future urban mobility strategies. We also measure the response of current and future mobility-on-demand services under these strategies in a Virtual City network that can be regarded as a micromodel of Singapore. Two scenarios were implemented and compared to the Base Case. In Scenario 1, a restriction policy was implemented in which private vehicles and non-automated on-demand service vehicles were excluded from the central business district. In Scenario 2, the cheaper automated mobility-on-demand service replaced the entire supply of on-demand vehicle fleet network-wide. We assessed the impacts on the population at the individual level by comparing the activity-based accessibility relative to the Base Case, both in temporal and monetary terms.

In this study, the policy of automating all on-demand services results in the best outcomes in terms of accessibility and network performance. Nevertheless, the restriction policy does not result in desirable accessibility outcomes except for two exceptional cases: the first is in time savings in a suburban zone that relies heavily on traditional mobility-on-demand services for non-CBD destinations; the second is in monetary savings for the residents of a zone that has excellent public transportation coverage with close proximity to

the CBD. We also show that the level of service improvements can be achieved with investment in mobility-on-demand services if policies similar to that of the restriction strategy explored here are to be aggressively pursued.

The results presented in this paper are an initial step in evaluating a range of future urban mobility strategies under a wide range of uncertainty in networks and their inhabitant populations. Here, we approximated accessibility by benchmarking on the maximum utility in the case of a perfect network (i.e. zero travel cost and zero travel time). However, for a more intuitive conceptual definition of accessibility, we propose a new benchmark based on the extreme case of the absence of a transportation network (i.e. no consumption of transportation services), which can be realized by assuming that walking is the only available mode of transport for all individuals. This will enable us to obtain accessibility directly as a measure of consumer benefit, which would be more readily apprehended as a measure of accessibility compared to the relative cost approach applied here. Furthermore, while the generalization of the methods presented here to other utility-maximizing ABM frameworks is straightforward in principle, its adjustment to other similar-structure models (such as DaySim, Bradley et al. 2010) or different design architectures (such as Activity-Sim, Galli et al. 2009) more often applied in practice is yet to be showcased.

Our analyses of the on-demand service controller performance indicate immediate avenues for future investigation, some of which are underway. In particular, we would like to measure the response of the controller under various fleet management strategies. The current version has a parking and rebalancing component, which would become critical to deploy in a much larger coverage area. We note that there are current efforts in determining the optimal parking strategy for on-demand service vehicles. In a recent contribution, Xu et al. (2017) used a simulation-based approach to study the tradeoff between parking and cruising under a variety of conditions. With our detailed simulation framework, we can also contribute further to this area. Two other notable efforts that focus on the impacts of fleet size have been introduced by Boesch et al. (2016) and Wang et al. (2018). There is clearly great interest in finding the best pathways for optimal on-demand service performance. This is even more critical, given financial constraints and environmental concerns relating to the energy needs of future on-demand mobility paradigms. Further interests are in the long-term impacts of AMoD scenarios such as location effects, which may vary by implementation strategy. These have not been studied as part of this work, but such effects can be studied via the ABA using an integration between SimMobility LT and MT simulators, which we intend to explore in future research. Furthermore, we only considered only the direct effects of AMoD. An extension to this study would entail a full cost–benefit analysis, thereby accounting for various external effects.

Finally, the simulation platform described in this paper, SimMobility, has been enhanced for energy computations and calibrated for urban typologies that represent key mobility characteristics on a global scale (Oke et al. 2019). The aim is to develop a new integrated framework for analyzing the impacts of future mobility strategies and emerging vehicle technologies that account for not only ABA, benefits and costs but also energy consumption and level of service. The ABA would especially serve as a versatile and indispensable tool for further scenario exploration based on the individual population characteristics and thus contribute to robust decision-making by policymakers and planners.

Author's contribution The authors confirm the contribution to the paper as follows. BN-B, JO, CA, MB-A: study conception and design. BN-B, NK, JO: analysis and interpretation of results. BN-B, JO, NK, CA: manuscript preparation.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there are no conflicts of interest.

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