EVALUATING THE IMPACT OF AUTONOMOUS VEHICLES ON ACCESSIBILITY USING AGENT-BASED SIMULATION —A CASE STUDY OF GUNMA PREFECTURE

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The emergence of autonomous vehicles is expected to shape the urban transportation system in various ways. In this study, a large-scale agent-based disaggregate simulation model, MATSim, is employed to measure the impact of autonomous vehicles on accessibility changes. This study used disaggregate spatial data from the Gunma Prefecture Person Trip Survey as the initial travel demand input for the model. Two new autonomous transport modes, namely shared autonomous vehicle (SAV) and private autonomous vehicle (PAV), are included in the simulation, in addition to the existing human-driven private vehicles. A scenario analysis is conducted using fleet size of SAV, ownership of PAV, operation cost, value of time changes as the key variables in the scenario setting. Based on the final travel demand results, a Hansen-type accessibility analysis is conducted, providing quantitative evidence to measure the potential impact of autonomous vehicles on accessibility changes in Japanese regional cities. Results suggest a considerable market share of AVs in scenarios with positive assumptions, and an overall accessibility increase in the scenario where PAVs were introduced. Particularly, suburban areas seemed to enjoy more accessibility gains, which might result in further urban sprawl in the future.

Key Words: autonomous vehicles, agent-based simulation, travel behavior, accessibility, person trip survey

1. INTRODUCTION

With the rapid development of V2V (vehicle-to-vehicle-communication), V2I (vehicle-to-infrastructure communication) and I2V (infrastructure-to-vehicle communication) technologies nowadays, the automobile industry has high expectations regarding autonomous vehicles (hereinafter AVs). Although fully autonomous vehicles (SAE Level 5) are not yet operational, automobile manufacturers are committed to this task and many have publicized plans to introduce fully autonomous vehicle by 2020. As a growing research field nowadays, many academic papers on the implication of AVs have been published, with most research efforts focusing on the effects of the new technology on both vehicle characteristics and users’ travel behavior. Such changes include more efficient use of road capacity and level of service with smoother acceleration and deceleration, a shift from human-driven vehicle ownership to AV ownership, higher tolerance to distance traveled, shorter in-vehicle times, but also an increase in vehicle kilometers traveled, and cost reductions in ride-sharing services as drivers would not
be needed anymore\(^9,10\).

Given the benefits listed above, AVs have been hailed by many as the future daily mobility tool, and thus it is expected that it will not only impact transportation systems, but also shape the urban land-use system in various ways. From a regional perspective, impacts on accessibility might influence people’s travel patterns and residential location choices in a longer time span\(^1\).

A few studies have analyzed the implications of AV introduction in different contexts, mostly relying on simulation analysis. For example, Gucwa\(^11\) employed the San Francisco Metropolitan Transportation Commission (MTC)’s Travel-Model-One and Citilabs Cube model to simulate travel behavior in the Bay Area. Assuming level-3 automation, he found an increase in VKT (Vehicle kilometers traveled) of 4% and 6.7% when value of time was set to (1) equivalent to high-quality rail, and (2) half of the current human-driven car, respectively. Roadway capacity was assumed to increase by 10% for both the scenarios. Liu et al.\(^13\) employed MATSim to simulate SAV service by evaluating several metrics, such as waiting time and VKT (vehicle kilometers traveled). They found an increase in VKT of 7.5%–12.7%, and in average waiting time of 3.1–3.2 minutes for their assumed scenarios.

Some studies have also been conducted to evaluate accessibility changes resulting from AV introduction. Meyer et al.\(^14\) studied the impact of AVs on accessibility in Swiss municipalities based on the Swiss National Transport Model. Three nationwide scenarios that differ in AV deployment strategies (i.e., type of roads or areas AVs can operate) and ownership were examined, and the induced travel demand was identified. Their findings suggest considerable overall accessibility gains in all the scenarios, while large cities suffer a small decrease in a fully shared-autonomous scenario. For example, when considering induced demand, and modest capacity increase settings, average accessibility gains were estimated at 10%. However, the absence of a detailed individual network loading model, (a BPR function was used instead\(^15\)) to calculate congested travel time limits their results since few traffic interactions are considered. In addition, the reduction of the driving burden is not considered in this study.

Childress et al.\(^16\) also conducted an analysis in the context of AVs for the Puget Sound Region, Washington State, USA. The study applied an activity-based travel model, SoundCast, which simulated individual travel choices across a day and long-term choices like residential and work location. Four scenarios concerning capacity change, parking cost change, and value of time changes were evaluated using indicators such as VKT and delay. Accessibility changes were also evaluated for the most aggressive AV scenario. Largely attributed to the convenience of AVs, simulation results suggest increases in VKT of 19.6% in the most optimistic scenario where 30% capacity increase, 65% reduction in value of travel time and 50% parking cost reduction are imposed—a finding consistent with the concerns of some scholars\(^17\). In the same scenario, aggregate logsum accessibility increased from 8.5% to 8.9% (for different income groups) for the whole Seattle area, with considerable higher increases in more remote areas. Nevertheless, this study did not consider the effect of AVs empty trips and used a relatively simple network assignment model and representation of shared AVs in their behaviors.

Addressing the limitations stated above, this study offers some insight into the implications of AV introduction in Japanese regional cities. By using high-resolution disaggregate spatial data and an activity-based agent-based simulation model, several AV evaluation criteria such as passengers’ waiting time and AV deadheading (empty driving) ratio are used to assess the feasibility of the mode within several scenarios. Furthermore, a Hansen-type accessibility\(^18\) analysis is conducted, to provide quantitative evidence on the potential impact of autonomous vehicles in a longer time horizon.

To the best of our knowledge, this is the first study addressing via agent-based simulation the effects of AVs on accessibility in Japan. As a developed country, Japan shares some similarities with Western Europe and the United States, while also possessing some distinct characteristics, such as a rapidly ageing society.

2. METHODOLOGY AND DATA

(1) Agent-based Simulation: MATSim

In this study, MATSim\(^19\), an open-source large-scale agent-based disaggregate simulation model is used. This toolkit adopts an activity-based agent-based co-evolutionary iterative loop to solve the traffic assignment problem, as shown in Fig.1.

The loop starts with an initial travel demand in the form of daily activity chains for every individual. Later in the mobsim (network loading) phase, the activity chain is loaded and assigned to the road network. After the end of one simulation day, a score is calculated for each agent’s activity chains (plans). This score can be interpreted as econometric utility\(^20\). Later in the replanning phase, every agent has to choose one plan to execute for the next iteration. The collection of plans is generated (mutated) from their previous plans (see 2.(3) simulation settings for more details).

The scoring function is formulated following
Charypar and Nagel\textsuperscript{21)}, where the utility of a plan $S_{\text{plan}}$ is computed as the sum of the utility of all activities $S_{\text{act},q}$ plus the sum of all travel (dis)utilities $S_{\text{trav,mode}(q)}$:

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

where $N$ denotes the number of activities; $q$ is the activity; and $\text{mode}(q)$ refers to the travel mode used by the agent following activity $q$.

The basic logic behind the iteration process is an extension of the route assignment loop in classical Stochastic User Equilibrium to other choice dimensions like mode departure time choice, at the individual (agent) level.

This algorithm makes it more authentic to simulate traffic assignment and people’s choice process, which is important to improve prediction validity. A more detailed description of the mechanics of the simulator is provided below borrowing from Nagel et al.\textsuperscript{22)}

First, the incorporation of activity-based agent-based simulation rather than continuous flows allows for the efficient capturing of travel demand heterogeneity. Second, switching towards daily plans from “route swapping” renders a more authentic simulation with all choice dimensions jointly calibrated. However, even given many constraints like Hägerstrand’s space-time prisms\textsuperscript{23)}, the attempt to identify the optimal all-day plan is computationally unmanageable. Meanwhile, lack of behavioral realism has always been an issue in traditional behavioral models since real travelers might not be able to compute the best responses\textsuperscript{24)}. Therefore, the agent’s daily planning problem is addressed here with a population-based search algorithm where each agent maintains and improves multiple candidate solutions. Thus, “a population of persons where every person has a population of plans”, the so-called co-evolutionary algorithm, is applied in MATSim.

(2) Data collection

This work uses data from Gunma Prefecture as the target area of analysis.

Gunma is in the north of Kanto region in Japan (Fig.2), with total population of 1,973,115.\textsuperscript{25)} Its population density is around 310 people per km$^2$. Being different from the main Tokyo metropolitan area, Gunma is in fact a car-dependent society with a total car ownership of 1,792,075 vehicles\textsuperscript{26)}. It is the prefecture with the highest car ownership (89.7 per 100 people) in Japan. Current mode share of Gunma is shown in Fig.3.

Several data sources are used in this study. The Gunma Person Trip Survey data in 2015\textsuperscript{27)} (PT data hereinafter) is used as the initial travel demand input in MATSim. The survey provides one-day activity chains including trip purpose, location, mode, and departure times. Sample size is 64,500 households in Gunma prefecture plus Ashikaga City in Tochigi prefecture\textsuperscript{27)}.

Train and bus are excluded from the choice set because of their low modal share. After eliminating data with missing values, excluding persons who used bus or train at least once during the survey period, and trips either starting or ending outside the study area, the effective sample size was 53,814, which is around 2.53% of the whole target population.

TelPOINT Pack DB 2016\textsuperscript{29)} is used to get facilities data, which are used as the input for the accessibility computation. The data consist of records of facility types and geographical coordinates for 23 million facilities across Japan.

Network data were extracted from OpenStreetMap\textsuperscript{30)}. The study area bounding box covers totally 13,680km$^2$ (blue box in Fig.2). Road capacity extracted from the OpenStreetMap data, was scaled down by a 2.53% factor to match the sampling ratio. The total number of nodes and links are 313,501 and 866,784, respectively.
(3) Simulation settings

a) Network loading settings and traffic behavior

This study adopts with the MATSim’s default traffic flow model: QSim$^{31}$ to simulate network loading part in the iterative loop. QSim uses a computationally efficient queue-based approach but at the cost of reduced resolution. Basically, when vehicles enter a road segment, they are inserted into the tail of the queue of the road. The outflow speed is distinctive to each road and is specified by the capacity settings.

In this study, both private autonomous vehicle (PAV) and shared autonomous vehicle (SAV) are added as new transport mode alternatives, competing with human-driven private vehicles. Altogether, five travel modes are considered: human-driven vehicle (HV), SAV, PAV, bicycle, and walking.

HVs and PAVs are exclusive to an agent, that is, they are not shared with other agents. SAVs follow the behavior of current taxis, and ride sharing is not considered.

As a result of advanced driving assistance systems, AVs are assumed to have a positive effect in road capacity. This capacity gains are assumed to be a result of smaller vehicle gaps, smoother lane changes, a reduction in start-and-stop traffic behavior. Previous AV-related studies have also defined similar assumptions in start-and-stop traffic behavior. Previous studies are modified on the basis of the car (passenger with car ∩ with license) and “passenger with no car U with no license” in an attempt to distinguish whether the agent chooses to be a passenger because he or she has to or not.

SAV and PAV parameters defined in the simulation are modified on the basis of the car (passenger with car ∩ with license) coefficients for value of time variable. The constants of SAV and PAV are set based on car (passenger with car ∩ with license) and car (driver) mode, respectively.

Furthermore, AV driving control algorithms proposed in the literature also support our assumptions. For example, Huang et al.$^{32}$ designed a driving controller for automated vehicles to simulate mixed traffic with human driven vehicles. They observed a peak flow of 5000 vehicle per hour per lane on freeways under mixed traffic condition where the AV share is no less than 70%, compared to the human-drivers only case for which they observed a 2,000 vehicle per hour per lane flow. As such, based on these findings, and given the AV mode shares defined in 2,(5), we assumed a 0.8 PCU factor to reflect these benefits.

The SAV dispatching follows a rule-based heuristic, namely, demand-supply balancing. It is a strategy that dispatches the nearest idle taxi in oversupply situations and dispatches the taxi that just became idle, to the nearest request in undersupply situations. See Maciejewski et al.$^{33}$ for more details. In addition, each SAV trip is set with a pick-up and drop-off time of 120s together and no roaming behavior.

As for bicycle and walking modes, the former follows the so-called Seepage behavior$^{34}$ with 9km/h. The latter is performed via teleportation, where the distance is calculated as the beeline distance weighted by a factor of 1.3, and the speed is set as 4km/h.

b) Score settings and mode choice set

In this study, the travel utility for leg $q$ is given as:

$$ S_{\text{trav}, \text{mode}(q)} = C_{\text{mode}(q)} + \beta_m \times m_q + \beta_{\text{trav,mode}(q)} \times t_{\text{trav},q} $$

where, $C_{\text{mode}(q)}$ is a mode-specific constant; $\beta_m$ is the marginal utility of money; $m_q$ is the change in monetary budget caused by fares for the complete leg; $\beta_{\text{trav,mode}(q)}$ is the direct marginal utility of time spent traveling by mode; $t_{\text{trav},q}$ is the travel time between activity locations $q$ and $q+1$. In the case of SAVs, the waiting time is also included.

Parameters are calibrated using the PT data. With an effective sample size of 53,814, the total number of trips is 152,411. Five modes are included in the model calibration, car (driver), car (passenger with car ∩ with license), car (passenger with no car U with no license), bike, and walk.

Driver and passenger mode are separated for the car mode in the PT data since these two are assumed to differ in marginal utility of time. And on the basis of the separation, passenger mode is further divided into two types: “passenger with car ∩ with license” and “passenger with no car U with no license” in an attempt to distinguish whether the agent chooses to be a passenger because he or she has to or not.

SAV and PAV parameters defined in the simulation are modified on the basis of the car (passenger with car ∩ with license) coefficients for value of time variable. The constants of SAV and PAV are set based on car (passenger with car ∩ with license) and car (driver) mode, respectively.

The basic idea behind this approach is that given that no observational data is available, parameters of AV must be approximated using existing modes. The willingness to choose the car (passenger with car ∩ with license) resembles AVs the most because the trip-maker might choose to be a passenger on his or her own initiative to avoid the driving burden, not because he or she does not own a car or license.

In addition, the availability rules and current share for each mode are summarized in Table 1.

On the basis of the rules set above, the marginal utility of each mode is calibrated using a Multinomial logit (MNL) mode choice model. Travel time of car and walk mode are calculated using the Google Distance Matrix API, with the input of coordinates of OD pairs, where time of day is set following the reported departure time in the PT survey. Bicycle travel time is calculated from the ratio of walk distance and bike speed, which is set to 9km/h. Car travel cost is set to 6.8yen/km, considering that the average fuel consumption in Japan is 21.9km/L$^{35}$, and the average gasoline price (regular) in Gunma is 150 yen/L$^{36}$ The calibration results are shown in Table 2.

Regarding the utility of activity $q$, $S_{\text{act},q}$ contains
two parts, the utility of performing activity q, \( S_{act,q} \), and late arrival penalty, \( S_{late\_arrival,q} \). As such:

\[
S_{act,q} = S_{dur,q} + S_{late\_arrival,q}
\]  

(3)

All settings are in accordance with the MATSim default setting method only differing in that factors such as early departure penalty is not included. By default, the marginal utility of performing an activity is set as the same absolute value as \( \beta_{dur} \) (drop the minus sign, which is 2.824/h in this study). And marginal utility of late arrival is set to three times that of \( \beta_{dur\_mode\_car} \).

c) Replanning settings

In application, the plan in the next iteration is generated with two operators: mutation and selection. The mutation operator modifies a certain component in the previously executed plan, and adopts this modified (mutated) plan for the next iteration. Each time a mutator is operated, the agent will reserve the previous plan as part of its plan memory. Once the number of plans in memory exceeds 5, the plan with the worst score is dropped.

Three types of mutation operators are used in this study, namely, reroute mutator, time allocation mutator, and subtour mode choice mutator. The three mutators conduct mutations in route choice, departure time choice and mode choice, respectively.

Specifically, the reroute mutator recomputes the fastest path for each activity in the plan while according to link travel times, which is calculated from the simulation of the previous iteration. The time allocation mutator randomly draws a value from a uniform distribution from minus 30min to plus 30min, then shifts the activity end time for the first activity and activity duration for the others with this value. The subtour mode choice mutator changes travel mode to a random other mode in subtour level: a consecutive subset of a plan that starts and ends at the same link. HV, PAV and bicycle mode mutations are constrained by the ownership attributes of each individual (the PAV ownership attribute is assigned in the scenario settings in individual level, and ownership attributes of different modes are not mutually exclusive). In other words, an agent cannot choose a mode other than HV (or PAV, bicycle) if the previous activity is fulfilled by HV (or PAV, bicycle) during a

### Table 1 Availability rules for each mode in calibration.

| Mode                      | Availability rules for a trip | Mode share in the initial travel demand |
|---------------------------|-------------------------------|----------------------------------------|
| Car (driver)              | 1. The trip-maker owns a car and license; 2. The previous trip used car mode; | 72.65% |
| Car (passenger with car \( \cap \) with license) | 1. There is at least one household member of the trip-maker who owns a car; 2. Trip purpose is not "pickup" or "work"; 3. The trip-maker owns a car and license; | 2.78% |
| Car (passenger with no car/ without license) | 1. The trip distance is less than the 99% percentile of bicycle mode. (in this case, 13,922m); 2. Trip-maker owns a bicycle. | 4.63% |
| Bicycle                   | The trip distance is less than the 99% percentile of walk mode. (in this case, 3,380m); | 8.46% |
| Walk                      | The trip distance is less than the 99% percentile of walk mode. (in this case, 3,380m); | 11.48% |

### Table 2 MNL model calibration results for mode choice.

| Variable name                                                                 | Coefficient | t statistic |
|-------------------------------------------------------------------------------|-------------|-------------|
| Car (passenger with no car \( \cup \) with license) constant                 | -3.453      | -129.96     |
| Car (passenger with car \( \cap \) with license) constant                   | -4.599      | -153.75     |
| Bike constant                                                                | -1.416      | -55.27      |
| Walk constant                                                                | -0.708      | -28.33      |
| Travel cost/yen                                                              | -0.00424    | -6.93       |
| Travel time of car (driver)/h                                                | -2.824      | -7.65       |
| Travel time of car (passenger with no car \( \cup \) with license)/h         | -5.631      | -14.70      |
| Travel time of car (passenger with car \( \cap \) with license)/h            | -2.548      | -6.64       |
| Travel time of bike/h                                                        | -3.221      | -22.18      |
| Travel time of walk/h                                                        | -8.058      | -68.417     |

Goodness of fit

\[ LL(0) = -156087.7 \]

\[ LL(\beta) = -57356.3 \]

\[ -2[LL(0) - LL(\beta)] = 197462.8 \]

\[ \rho^2 = 0.633 \]

\[ \text{Adjusted } \rho^2 = 0.632 \]
tour. Note that these constraints are not imposed to SAV and walking; that is, these two modes are accessible to everyone in the mode choice mutator.

As for the selector part, to account for stochastic variations in agents’ behavior, this study uses an MNL model as the plan selection method:

$$P_i = \frac{e^{\mu S_i}}{\sum_j e^{\mu S_j}}$$  \hspace{1cm} (4)

where $i$ is the plan to be examined; $j$ is the plan the agent possesses in memory; $\mu$ is the scale parameter, which is normalized to be 1; and $S$ is the score of the plan.

In this study, the share of agents (or possibility) to execute the reroute mutator, time allocation mutator, subtour mode mutator and MNL selector is 0.05, 0.1, 0.15, and 0.7 in the replanning phase, respectively.

Note that travel origins and destination are not considered in the replanning phase. In other words, travel demand OD patterns are fixed.

(4) Accessibility computation

Accessibility can be defined as “the potential for interaction and exchange”\(^{18}\) or “people’s overall ability to reach services and activities, and therefore the time and money that people and businesses must devote to transportation.”\(^{40}\) Being different with classical mobility-based planning performance indicators such as automobile travel speed, delay, and travel cost, accessibility-based analysis is concerned with agents’ utility instead, thus measuring the transport system in a more comprehensive way.

Accessibility impacts persons’ choice in a longer time range, too. Choice makers weigh accessibility to make not only their daily travel choice but also their house-moving or building development choice conducted over longer time horizons such as decades or longer.

In this study, an economically interpretable accessibility assessment based on Hansen\(^{18}\) is adopted as follows:

$$A_i = \ln \sum_k e^{V_{ik}}$$  \hspace{1cm} (5)

where $k$ denotes possible destination; and $V_{ik}$ equals the disutility (marginal utility × travel time + constant) of traveling from location $i$ to destination $k$. The marginal utility is exactly the $\beta_{\text{trav,mode}(q)}$, and the travel time of each link is acquired after simulation converges. The logsum term of exponentials can be interpreted as the expected maximum utility\(^{20}\).

The procedure quantifies “how accessible a given location $i$ is to certain services”\(^{41}\), called outgoing accessibility. In application, the computation procedure is highly disaggregated and coordinate-based with single facility considered as the activity opportunity (destination $k$). However, the location to be evaluated is tessellated in 1km×1km cells.

For each pair of cell $l$ and service $k$, a Least Cost Path Tree is applied\(^{45}\) that determines the route with the least travel disutility.

In this study, the measurement of the time-dependent travel times is based on the morning peak on the mode of PAV and/or Human-driven vehicles.

Since the facility data used do not include information on size of facilities (i.e., area), the index used here focuses on the number of facilities, as measures of activity opportunities. Number of shopping and leisure facilities are used to calculate accessibility, although it is expected that these are highly correlated with other indicators such as employment. In total, 246,918 facilities are considered in the analysis.

(5) Scenario settings

Given the uncertainty associated with the future, a scenario analysis with different degrees in vehicle characteristics and travel behavior changes is used in this research. Among them, fleet size of PAV and SAV, operation cost, and value of time changes are considered as key variables in the scenario setting.

There are several studies providing insights on the setting of these key variables. Johnson and Walker\(^{43}\) predicted that shared, electric autonomous vehicles will cost around 35 eurocents per mile (29yen/km) in 2035. And Stephens et al.\(^{44}\) suggested a $0.40–$0.60 per mile (27–41yen/km) in the American context. Compared to human-driven cost to date of about $2.00 per mile (136yen/km, NY), a reduction of around 20%–40% from current taxi fare in Japan is assumed for the operation cost of SAV. In terms of fleet size of autonomous vehicles, there are some references available, especially for SAV. Fagnant et al.\(^{9,10}\) employed MATSim to test the optimized fleet size with a rule that generates a new SAV for every traveler who has been waiting for at least 10 min after sending the request in the warming-up simulation. They found that 1,977 SAVs meet the demand of 56,324 agents (3.51% of the demand size) and 1,688 SAV meet it for the 60,551 case (2.78% of the demand size), respectively. More generally, Bansal and Kockelman\(^5\) forecast Level-4 automation market penetration would be 28.6% in 2035, using a binary logit model and Monte-Carlo simulation based on a state preference (SP) survey. As for the change in in-vehicle value of time, to the best of our knowledge there is no quantified evidence so far.

Regarding the SAV fare, the current taxi fare in Gunma Prefecture is as follows: a start fare of 710 yen for the first 2000m and 90 yen per 301m subsequently. In this study, a 320 yen per km fare is adopted as the benchmark for current taxis.

PAV ownership is assigned randomly among the whole population in all scenarios.
Based on the above, following scenarios are set (summarized in Table 3):

a) Scenario 1: Skeptical market—Can computers really be trusted?

In this scenario, the assumption is that in 2030, the technology is still not fully trusted. As some fatal accidents occurred in trial phases, people are holding a wait-and-see attitude and only innovators buy some PAVs. The government is also suspicious and is being strict in the regulations and subsidies of AVs.

This scenario shows a pessimistic view into the future and is a counterpart for other scenarios.

b) Scenarios 2–4: Booming market—Booming sales performance and satisfied governments.

In these scenarios, both AV vehicle manufacturers and SAV operating companies show very strong sale performance, thanks to rapid technology development, positive customers’ attitudes, as well as supportive governmental policies.

These scenarios offer a relatively optimistic prediction of the future with booming PAV and SAV markets. Scenario 2 and 3 are assumed here with different optimism levels. Scenario 4 is defined with relatively extreme settings for reference purposes.

c) Scenario 5: Exclusive sharing autonomy—Fast, cheap, comfortable, sharing autonomous units everywhere.

In this scenario, it is assumed that in 2030, both the technology and economy grow at a considerable pace. The government finds it a great way to improve people’s mobility and safety by franchising a fleet of SAVs with almost full control of them. People are very willing to use and have got accustomed to this novel transport of mode. As such in this scenario, no private ownership is allowed.

In addition to Scenarios 1–5, a base scenario is simulated in which the choice set is composed merely by HVs, bicycle, and walking.

### 3. SIMULATION RESULT

Simulations were conducted with 70 iterations for each scenario and results are described below. Mode share shows users’ modal preferences in each scenario. SAV metrics including passenger waiting time are then stated to evaluate SAV service from both demand (passenger) and supply (operator) side. Finally, analyses in travel distance and accessibility are conducted to evaluate the implications of AVs in traffic congestion, and changes in the spatial distribution of activity opportunities, which are associated with agents’ changes in short-to-long term travel-related decisions.

(1) Modal split result

As Fig.4 shows, the base scenario approximates

| Scenario | PAV ownership | SAV fleet size | Value of travel time for AV | Fare of SAV |
|----------|---------------|---------------|----------------------------|-------------|
| base     | Only HV, bike and walk applied. |             |                            |             |
| Parameters are set exactly the same as the calibration results. |             | 60% of current passengers’ (1.529/h) | 60% of current taxi’s fare (192yen/km) |
| 1        | 10% of agents’ number (5,381 agents) | 2% of agents’ number (1,076 units) | 60% of current passengers’ (1.529/h) | 60% of current taxi’s fare (192yen/km) |
| 2        | 30% of agents’ number (16,144 agents) | 5% of agents’ number (2,690 units) | 25% of current passengers’ (0.637/h) | 20% of current taxi’s fare (64yen/km) |
| 3        | 40% of agents’ number (21,526 agents) | 8% of agents’ number (4,305 units) | 10% of current passengers’ (0.255/h) | 10% of current taxi’s fare (32yen/km) |
| 4        | 50% of agents’ number (26,907 agents) | 10% of agents’ number (5,381 units) | 10% of current passengers’ (0.255/h) | 5% of current taxi’s fare (16yen/km) |
| 5        | None          | 5% of agents’ number (2,690 units) | 25% of current passengers’ (0.637/h) | 20% of current taxi’s fare (64yen/km) |

the observed mode share in the Gunma PT sample. One of the reasons bicycles and HV mode have a higher share may be the fact that parking issues are not considered in the calibration procedure, drawing a lot of people from walk mode to bike mode.

For the PAV mode, in Scenarios 1–4 (no PAV applied in Scenario 5), nearly all the people who own a PAV prefer to use it in their daily activities, showing that only the acquisition cost behind the PAV ownership choice, though not explicitly simulated, might be the largest barrier against usage. The lower travel time parameter might explain this tendency.

It is more complex when it comes to SAV mode. Despite that SAV share increases with the fleet size in general for all five scenarios, we cannot say that fleet size affects the SAV share linearly (in the way
PAV ownership does). Value of travel time and SAV fare compositely affect the SAV share along with the fleet size.

In a sense, SAV might compete with HV and other unmotorized modes instead of PAV, with no apparent benefits over PAV in this context, except for acquisition costs. To support this argument, one can find that in Scenario 1, with negligible SAV share, the bicycle and walk modes maintain similar share compared to the base scenario. In other words, the modal shift mainly occurs between HV and PAV in Scenario 1, while an apparent change in unmotorized modes is observed between the base scenario and Scenario 5 (where no PAV is available).

Nevertheless, the results of Scenarios 2–5 still indicate a considerable market penetration for SAV given relatively optimistic settings, and hence a promising potential niche market under certain conditions.

(2) SAV metrics

For the all the five scenarios introducing SAVs, metrics for evaluating the service are: (1) passenger average waiting time from the user side, (2) fleet average served requests, (3) average inactive ratio, (4) average deadheading ratio (see Table 4).

First, it is apparent that passenger average waiting time increases with advantageous SAV settings. Under relatively lower benefits in value of travel time and fare, and a smaller fleet assumed for Scenario 1, requests that are not “fit” for the SAV mode (such as request locations that are far from any of SAV and would result in very long waiting time) are screened-out through the iteration process. On the contrary, with SAV benefits increasing, the demand for SAV would increase as well, resulting in higher passenger waiting times.

In its absolute value level, average passenger waiting time in all five scenarios fall in an acceptable range in general. Ninety-five percentiles of waiting time are about 10 min. This indicates the feasibility to promote the service at least from the demand side.

| Scenario | Passenger average waiting time (standard deviation) | Fleet average served request | Average inactive ratio (standard deviation) | Average deadheading ratio (standard deviation) |
|----------|-----------------------------------------------------|-----------------------------|---------------------------------------------|-----------------------------------------------|
| 1        | 86.4s (264.8s)                                      | 1.53                        | 98.6% (2.9%)                                | 15.9% (14.6%)                                |
| 2        | 145.2s (403.6s)                                     | 4.66                        | 93.9% (7.5%)                                | 17.7% (14.0%)                                |
| 3        | 180.8s (682.8s)                                     | 5.88                        | 90.5% (8.9%)                                | 14.0% (12.1%)                                |
| 4        | 174.4s (579.7s)                                     | 5.96                        | 90.2% (8.4%)                                | 12.0% (10.0%)                                |
| 5        | 189.1s (551.3s)                                     | 5.82                        | 92.6% (7.9%)                                | 21.4% (14.9%)                                |

Table 4 SAV metrics.

But it is also worth noticing that the no roaming behavior of SAVs probably results in lower waiting times because many of SAVs would serve their last passengers for a new trip after they finish their activities at certain locations with no waiting time, since the vehicle just stays where it dropped their last passenger until it is dispatched again.

Fleet average served requests and average inactive ratio suggest supply efficiency for the whole fleet, which increases with size. This suggests a higher operational efficiency with relatively sufficient SAV supply. However, the economies of scale effect is seemingly suppressed when SAV benefits (fare, value of travel time, and its fleet size) have been raised to a certain level: for Scenarios 3 and 4, this metric is found to keep steady instead. It is assumed that fleet average served requests increase also due to the no-roaming behavior.

The most thought-provoking metric is the average deadheading ratio, which stands for how much extra deadheading occurs in order to serve SAV requests. It is interesting to find a decreasing trend for scenarios with optimistic settings (Scenarios 2–4). In other words, despite a general assumption that deadheading ratio would increase with more requests to serve, this scale diseconomy effect was not observed in this study. In particular in Scenario 4 with the most optimistic settings, the deadheading ratio declines 30% compared with Scenario 2. A higher dispatching efficiency with the help of sufficient available vehicle supply might explain this effect.

A comparison between Scenarios 2 and 5 suggests an analysis of the effect of PAVs, since the only difference between these two scenarios is that whether PAVs are allowed or not. The number of served requests increases with around 25% (around 2% of the total trips) at a cost of 30% increased average waiting.
Table 5 Total daily travel distance.

| Scenario | Total daily travel distance | Ratio change versus the base |
|----------|----------------------------|------------------------------|
| Base     | 8.340×10^7 km              | -                            |
| 1        | 8.369×10^7 km              | +0.35%                       |
| 2        | 8.779×10^7 km              | +5.26%                       |
| 3        | 9.001×10^7 km              | +7.93%                       |
| 4        | 9.123×10^7 km              | +9.39%                       |
| 5        | 8.756×10^7 km              | +4.99%                       |

An increase in total VKT is observed with the SAV introduction. This might result in more traffic congestion in the future all else being equal. Nevertheless, the level of increase does not seem to be that high considering the potential AV benefits upon road capacity, which in this analysis was considered, though in a rough manner, by using a 0.8 PCU factor.

(4) Accessibility analysis

The accessibility analysis area is shown in Fig. 5. All the following plots are measured within the same area.

Fig. 6 first shows the HV accessibility result of the base scenario. It can be observed that the result matches the development patterns of Gunma: in large cities such as Takasaki and Maebashi, the accessibility is clearly higher than other places.

Fig. 7–Fig. 10 depict the PAV accessibility changes against the base scenario (HV) for the four scenarios with PAV applied. For these scenarios, they are deliberately plotted in the same scale to be comparable. The black box in the legend in the left indicates the value range for each scenario.

On average, accessibility increases by 23.2%, 31.8%, 36.3%, and 36.3% for the four scenarios, respectively. The accessibility gains are accounted for the decrease in value of travel time.

Spatially, we can find higher accessibility gains in remote areas than in cities. This observation is consistent with the basic hypothesis of this research and with the findings of Meyer et al. and Childress et al.

Accessibility increases in particularly remote areas will likely encourage people to travel further and may promote further suburbanization in the future.
4. LIMITATIONS AND FUTURE WORK

Although the findings in terms of accessibility changes support our basic hypothesis, some limitations need to be highlighted. First of all, this study uses the current travel demand data as the input for the simulation and does not consider new travel demand generation or destination choice changes in the replanning phase. In this case, the induced trips and potentially longer distance with AVs cannot be captured, which is probably another important factor to influence modal shift. In order to address this limitation, generating a synthetic population and building a travel demand model to simulate travel patterns is necessary. In addition, modeling of vehicle ownership is necessary to improve the simulation interpretability and forecast reliability.

Given that the simulations were done for sample, waiting time and matching probabilities of SAV would possibly be affected as the overall road network size remains the same and only road capacity is scaled down. As such, the density of SAV supply (fleet) to one single passenger become sparser, thus increasing the SAV picking-up distances, and waiting times and decreasing matching probabilities for passengers. Furthermore, these effects are most likely to be non-linear given changes in the density of demand. Deadheading ratio might be affected in a similar manner. In order to conduct a population level simulation, calibrating an activity-based model to predict travel demand (activity schedules) in a synthetic population, as concerned above, is the next stop of this study.

In addition, the mode choice calibration is based on current choice preferences. An SP survey to capture attitudes on unexisting modes would be a welcome contribution.

As for the accessibility computation, accessibility of shared mobility modes is of significance to provide more substantive evidence. Other accessibility indicators such as employment, as well as measures of opportunity size (e.g., area) should be incorporated in the analysis.

Finally, as a simulation study, authors are fully aware that due to not only the uncertainty of future development but also in terms of simulation settings, any attempt to predict future implications of AVs should be understood as mapping potential outcomes to further inform policy design and implementation, while acknowledging its limitations.

5. CONCLUSION

This study used MATSim, an agent-based simulation model to analyze the effects of AVs in Japanese regional cities. With two new modes, shared AVs and
private AVs, added to agents’ mode choice, modal shifts were observed given scenario definitions. Based on predicted modal split, an accessibility analysis was conducted within the Gunma area. This study found an overall accessibility increase in the scenario where PAVs were introduced. Particularly, suburban areas seemed to enjoy more accessibility gains, which might result in further urban sprawl in future.

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