# Assessing the Scale of Shared Autonomous Vehicles Competition with Existing Modes using Agent Based Simulation: A Case Study of a Greater Tokyo Railway Corridor

# エージェントベースシミュレーションを用いたシェア型自動運転サービスと既存交通手段の競合の評価 -東京都市圏鉄道コリドーを事例として-

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Shared Autonomous Vehicles (SAV) threaten to disrupt legacy transportation such as private cars and railways through decreased cost and increased flexibility. The scale of the transportation shift to SAV is uncertain especially in specific contexts such as Suburban Tokyo. In this study, an agent-based transportation simulation is constructed of a Tokyo rail corridor that extends from the centre of Tokyo to its rural edges. This simulation incorporates a multinomial logit mode choice model estimated from the 2018 Tokyo Person Trip Survey and extends it to model SAVs as a possible mode choice. Multiple scenarios are constructed by varying pricing, fleet size, and choice utility of SAV mode choice, creating a range of projections that explore the future size of SAV market share. The model estimates a relatively low projected market share, around 0.9% and 4.25% for Moderate and High Adoption scenarios respectively. The effect of lower fares or increased fleet size is determined to be weak, with the most optimistic SAV mode share being 5.98% of overall trips. This low market share means that SAVs are unlikely to disrupt suburban rail lines in greater Tokyo and may remain a niche transport choice like taxis today. This analysis is furthered by exploring how different built environments influences SAV adoption. It is found that SAV trips have a bias towards denser, more urban areas and thus compete with transit in those dense areas more than conventional car trips in auto-dependent suburbs.

## 1. Introduction

Billions of dollars, yen, and yuan have been invested into the development of self-driving or autonomous vehicles. The prospect of twining them with rideshare applications to create a fleet of low-cost shared taxis is known as Shared Autonomous Vehicles (SAV). These SAVs have been hyped to revolutionize travel as we know it, since they could reduce taxi costs by 80%[1],and eliminate the need for many to rely on driving and owning a car. However, these may have a counterintuitive outcome in transit-oriented areas, as SAVs may capture market share from transit instead of private cars. Exploring the scale of travel market disruption on the transit focused urban sprawl of suburban Tokyo is a vital endeavor, especially in quantifying the possible loss of ridership for legacy rail lines. This is made more acute as Tokyo is both transit-heavy as well as having a great deal of uneven car-friendly urban sprawl[2]. The unique structure of the suburban rail corridor exemplifies this urban archetype, with these rail lines passing rice paddies and forests in between stations surrounded by multi-story malls. The objective of this study is to gain a clearer picture of the scale of SAV adoption in this unique built environment, or in a question:

1. What is the projected market share of Shared Autonomous Vehicles across a Greater Tokyo rail corridor, explicitly considering the differences in built environment?

And secondarily:

2. What is the projected shift away from rail transit and other modes, explicitly considering the differences in built environment?

The complexity of travel mode choice and traffic/transit trips can be simulated using an agent-based simulation (ABM), which will be detailed later in this summary. The thesis is composed of a literature review of different forecasts of SAV impacts across the world and using different models. After this review, a summary of the methodology and the simulation model used in the study is detailed before the results and discussion section.

## 2. Literature Review

SAV research is an expanding field, with studies using myriad techniques to explore a variety of impacts. A detailed review by Narayanan et al.[3] highlights the use of surveys, optimization programming, and simulation-based studies to explore the impact of SAV on mode choice, land use, travel demand, emissions and many other factors. A complex outcome that has yet to be explored are questions of mode choice, as that involves the interplay between individual choices, SAV supply, and the characteristics of the transportation network. Agent based simulation (ABM) is a modelling method that recreates a system by simulating the interactions of many individual agents and is appropriate for the complexity of SAV simulation. The MATSim simulation framework developed by Maciejewski et al. [4] is the most popular for the simulation of SAV transportation models[5] and is selected for this study. MATSim has been used by Fagnant & Kockelman[6] , Gurumurthy et al. [7], Kamijo et al. [8] and many others to predict a rise in total Vehicle Kilometres Traveled (VKT) if SAVs replace private cars. A consensus of the near-term impact and competition with transit is less clear, with Oh et al. [9] predicting an adoption rate of up to 18.8% of all trips in Singapore, while a forecast by Gurumurthy et al[7] in Greater Chicago predicts a lower adoption rate of ~3%. SAV adoption seems quite dependent on the built environment, with denser, more transit-heavy areas having a high adoption rate and sparser, auto-dependent areas showing less disruption. Within Japanese studies the lack of clarity remains, with Mori et al.[10] predicting a market share of 4% of all trips in Nagoya, while Ishibashi & Akiyama[11] observing an SAV adoption rate of up to ~33% in Central Tokyo. Most of the above studies utilize an individual travel mode choice model built from survey data, guiding the individual agents' choices for an ABM or similar type of transportation system model. Building on these best practices, this study uses the MATSim framework with an external Mode Choice Model to create a simulation of a Tokyo rail corridor, extending from the CBD station of Shinjuku to the suburbs and rural areas at Tokyo's periphery.

## 3. Model Formulation & Methodology

The simulation model is built in three steps: the analysis and archetyping of the Odakyu rail Corridor, the estimation of a Multinomial Logit model as the individual mode choice model, and the construction of the transportation system in MATSim and

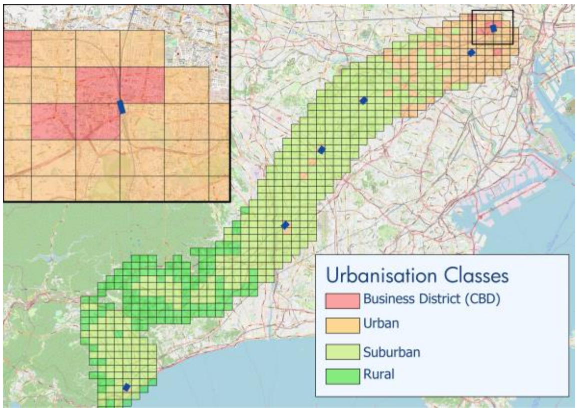


Figure 1. Map of Odakyu Corridor by Urban Typology

the calibration of the model. MATSim or Multi-Agent Transportation Simulation is an ABM that models the travel behaviour of individual agents across one day of a transportation network. It uses an iterative approach, improving agent's daily plans based on previous simulation outcomes, optimizing individual plans with overall traffic and system usage. In this study, the outputs of each simulation iteration are scored and replanned by a Multinomial Logit (MNL) model and then reinputted into the MATSim framework for individual route assignment and traffic simulation. This MNL model is first trained on actual travel modes then is extended to include SAV in its set of choices. Using this completed model, a set of possible scenarios is then simulated to give a range of potential SAV adoptions, as well as explore how key factors may influence this adoption rate.

To begin, a more holistic approach of understanding and quantifying the unique built environment across Greater Tokyo rail corridor is needed. This study focuses on a 5km range around the Odakyu-Odawara Railway Corridor, which goes from Shinjuku station (the busiest station in the world) to key commuter stations, going through sparse suburbs and forests and farms along the way. This nonlinear development can't be measured by a single indicator alone, so this study uses Principal Component Analysis to combine several variables into a single indicator that is an approximate measure of Urbanisation. This Urbanisation Index is calculated for 1km x 1km census blocks across the scope and is built by using indicators previously known to have great influence on travel behaviour[12]. These include Population Density, Intersection Density, Bus Stop density, % of area zoned for development and % zoned for high density development, No. of commercial addresses within an area, and distance from closest station, hub (station servicing two lines or more), and CBD (Shinjuku). Once every block was scored with the Urbanisation Index, they were classified using Jenks Natural Break Algorithm and qualitative methods into four distinct urban archetypes:

1. **CBD**, or blocks around Central Business Districts
2. **Urban**, or blocks generally within central Tokyo or at hub stations
3. **Suburban**, or blocks generally outside Central Tokyo
4. **Rural**, or blocks generally farmland or mountainous areas with low population

These are displayed in Figure 1.

A Multinomial Logit (MNL) Model is a statistical model that predicts the probability an individual will choose among multiple distinct choices, in this case between walking, biking, driving a car, taking a ride in a car, and taking rail transit. It is trained on data from the 2018 Tokyo Person Trip Survey,

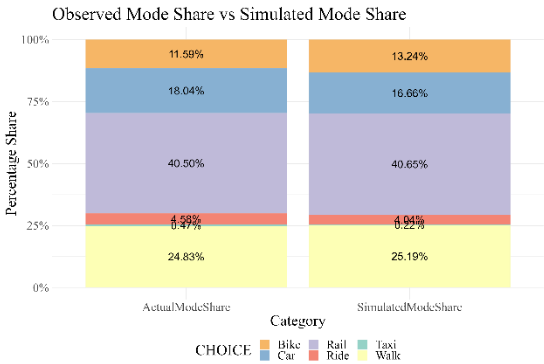


Figure 2. Mode Share of Observed vs Simulated Trips

which contains information about the actual daily trips of ~1% of the corridor's population. The model is based on a set of choice-specific utility equations, where the travel time, cost and other factors are used to determine which choice would have the highest utility, and thus the most likely choice. While a variety of factors were explored to create this model, keeping it limited to only travel time, cost, Urbanisation Index at the trips origin, and a random component reflecting unobserved baseline preferences (ASC) kept the balance between simplicity and predictive power

To model choice when SAVs are an option, an assumption is made that the utility equation is similar to that of current taxi, the most similar current mode, albeit with a reduced price due to zero wage cost. To model a situation where the low cost of SAVs shifts the baseline preference of individuals, the ASC or Alternative Specific Constants of taking a car as a passenger (Ride) and driving one's own car (Car) are chosen for a Moderate Adoption, and High Adoption scenario. The values of the final model are listed in Table 2.

Table 1. Results of Multinomial model parameter estimation

| ***Choice Attribute*** | ***Estimate*** | ***t-stat*** |
|---|---|---|
| ***Alternative Specific Constants*** | | |
| *ASC – Walk* | 0 | (-) |
| *ASC – Bike* | -1.849 | (-52.79) |
| *ASC – Car Driver* | -1.441 | (-30.79) |
| *ASC – Car Passenger* | -3.106 | (-53.99) |
| *ASC – Taxi* | -6.852 | (-41.04) |
| *ASC – Rail* | -2.915 | (-39.87) |
| ***Travel Time (/hr)*** | | |
| *TT – Walk* | -9.601 | (-71.56) |
| *TT – Bike* | -6.205 | (-52.70) |
| *TT – Car Driver* | -5.685 | (-28.21) |
| *TT – Car Passenger* | -7.803 | (-42.81) |
| *TT – Taxi* | -5.349 | (-5.49) |
| *In Vehicle TT – Rail* | -0.563 | (-7.21) |
| *Access TT – Rail* | -2.893 | (-31.68) |
| ***Travel Cost (/JPY)*** | | |
| *TC – Car Driver* | -0.00294 | (-5.31) |
| *TC – Taxi* | -0.00023 | (-2.86) |
| *TC – Rail* | -0.00141 | (-9.07) |
| ***Urbanisation Index*** | | |
| *UI – Car Driver* | -0.364 | (-39.30) |
| *UI – Car Passenger* | -0.150 | (-11.56) |
| *UI – Taxi* | 0.136 | (6.15) |
| *UI – Rail* | 0.051 | (6.21) |
| *Sample size* | 35923 | |
| *ρ2* | 0.519 | |
| *Adjusted ρ2* | 0.518 | |

The transportation network of the MATSim simulation was built by collecting data on the detailed road network from OpenStreetMap, and on the rail network and schedule from the Public Transportation Open Data Centre[13]. With the transportation demand taken from the Tokyo PT Survey, and the MNL model for mode choice, a baseline model was constructed. While MATSim has open-source modules for mode choice models, SAV modelling, and complex transit systems,

Table 2. SAV Mode Share Across Different Adoption Scenarios

**Status Quo**

| | **FS x 0.7** | **Base Fleet Size** | **FS x 1.5** |
|---|---|---|---|
| Subsidised | 0.28% | 0.25% | 0.30% |
| Base Price | 0.30% | 0.24% | 0.29% |
| Surcharge | 0.26% | 0.27% | 0.27% |

**Moderate Adoption**

| | **FS x 0.7** | **Base Fleet Size** | **FS x 1.5** |
|---|---|---|---|
| Subsidised | 1.14% | 0.91% | 1.34% |
| Base Price | 0.71% | 1.02% | 0.73% |
| Surcharge | 0.71% | 0.80% | 0.72% |

**High Adoption**

| | **FS x 0.7** | **Base Fleet Size** | **FS x 1.5** |
|---|---|---|---|
| Subsidised | 4.26% | 5.17% | 5.98% |
| Base Price | 4.48% | 2.42% | 3.51% |
| Surcharge | 3.51% | 3.50% | 3.51% |

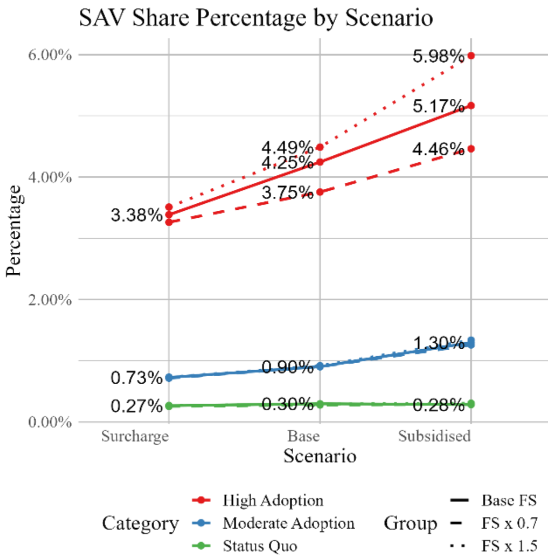


Figure 3. SAV Mode Percentage across All Scenarios

incorporating them together provided difficulties in scope and complexity, with the

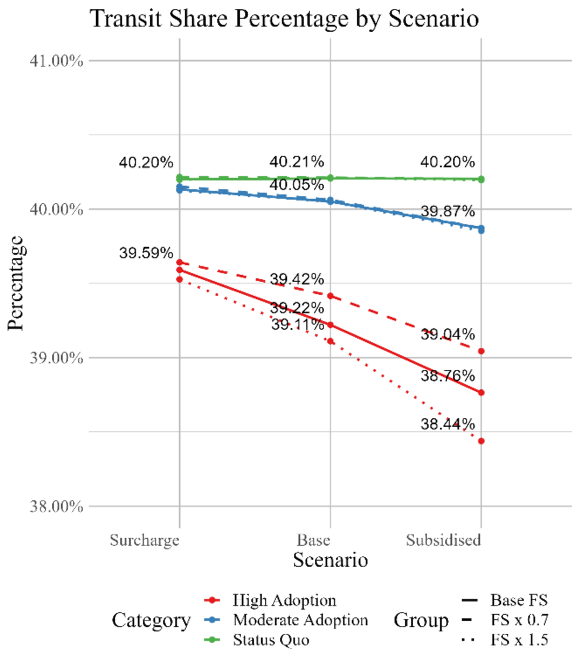


Figure 4. Rail Transit Mode Percentage across All Scenarios

omission of bus transit, and limiting out of scope trips to primary roads only, etc. Despite this, the model was calibrated to have a minimal amount of error when determining individuals' choice of travel mode, as seen in Figure 2.

Using the baseline model as a starting point, the taxi choice is replaced by the SAV choice with its new utility and cost assumptions to forecast the new modal split when SAVs are introduced. To explore a range of possibilities, different prices and fleet size (vehicle supply) scenarios are simulated, along with three sets of utility assumptions mentioned above:

1. **Status Quo**: Same parameter as taxi
2. **Moderate Adoption**: ASC similar to Car passengers
3. **High Adoption**: ASC similar to Car Drivers

Simulating each combination of price, fleet size, and base values toward shared mobility gives a good range of possible market share of

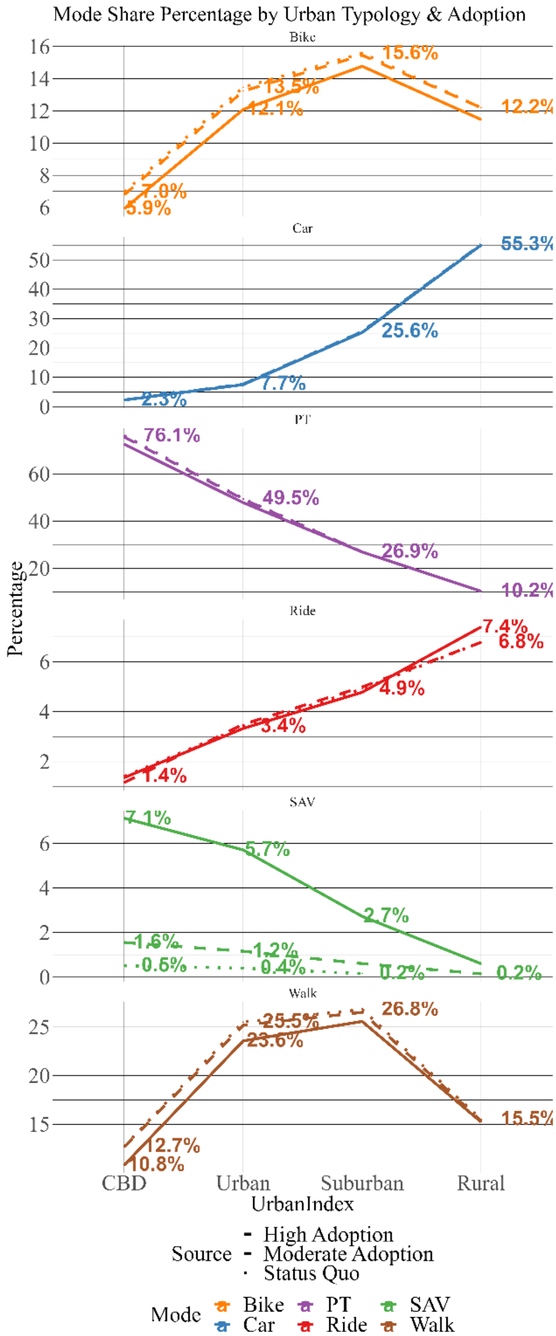


Figure 5. Mode Share of All Modes by Urban Typology & Adoption Scenario

SAVs and its subsequent impact on transit use.

## 4. Results

The observed SAV market share of every scenario is listed in Figure 3. As observed the adoption rate is relatively low even in the High Adoption scenarios, only going up to ~6% in very optimistic conditions. Examining the impact on transit in Figure 4, it is observed that there is only a slight decrease in ridership, amounting to around 5% decrease in transit use. Even more interesting are the results when broken down by urban typology, as seen in Figure 5.

When examining the operations of the SAV fleet, a complicated picture of financial and operational health emerges. Showcased in Figure 6, which breaks down the financials of the Moderate Adoption scenarios, profit or loss is dependent on the pricing of fares and fleet coverage.

## 5. Discussion

SAV Adoption was quite low, ranging in the single digits and even <1% for the Status Quo scenarios. These status quo scenarios have a very high baseline bias against SAVs, with other factors such as price and availability having very little effect. This may be due to current values to taking taxis, treating shared mobility as an option taken only in special circumstances such as overnight or a business trip. Analysing Moderate and High adoption scenarios, SAV market share does increase markedly to decrease in fare price, albeit from a low base. This is mirrored in the opposite yet relatively minor change in rail transit mode share, displayed in Figure 4. This shift of trip mode choice is larger than for car to SAV trips, hinting that policies and programs to adopt SAVs may do more harm to transit than good. With Status Quo and Moderate Adoption scenarios having almost negligible changes due to pricing, it may not be effective to use pricing or fleet size policy to influence car-to SAV shifts. Examining figure 6, scenarios where the fare price was priced at cost (Subsidized) run at a loss, further highlighting the weakness of a pricing policy.

Separating the results by urban typology in Figure 5, the trend for higher SAV adoption in denser areas is apparent. This is most likely due to the network effects and vehicle density being able to meet demand with low wait times and predictable service. SAV adoption could have a strong yet localized disruptive effect on travel from CBDs, with High Adoption market share going up to 7%.

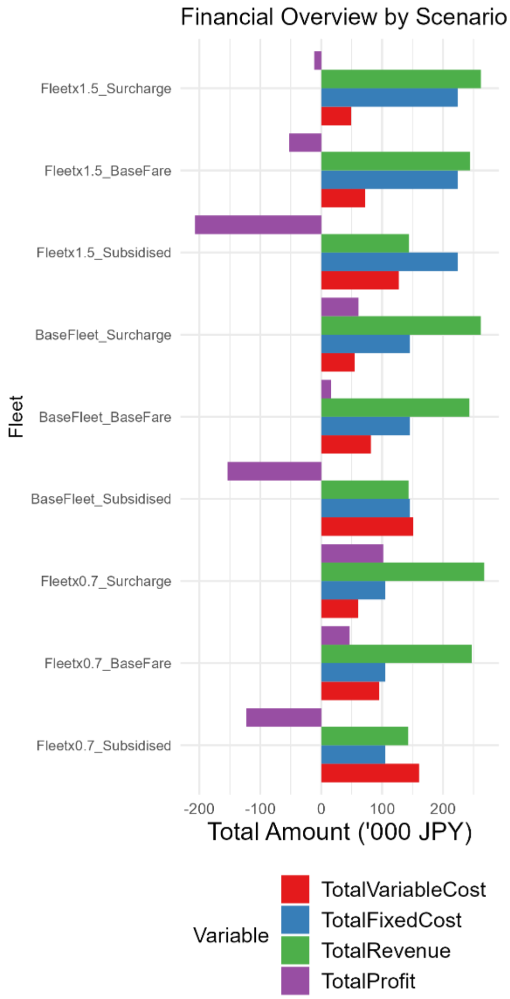


Figure 6. Financial Overview of Moderate Adoption Scenarios

The largest modal shift to SAVs is from rail transit, largely since both share a bias towards density. Yet this too is limited, with a decrease in the most SAV optimistic scenario amounting to a ~5-6% of transit ridership. The shift is minimal and most likely will not jeopardize the viability of legacy rail infrastructure.

This result falls in between the results by other researchers, with the closest being Mori et al.[10] 4% SAV market share when simulating Nagoya. The result of Oh et al. of 18.8% of trips in Singapore[9] and Gurumurthy et al of 3% in Chicago[7] fall within the observed pattern of SAV usage increasing towards denser built environments. It seems that in the suburban Tokyo environment the twin systems of rail and car dependence are so strong, that SAVs will have minimal impact and may require little regulation. SAVs might have a micro-impact around stations or other urban choke points and need a necessary regulation to prevent localized traffic.

Limitations include the small simulated population ratio of model, with only ~1% of the population simulated. The difficulty in computation, and simulation construction necessitated the low simulated population, and other shortcuts such as the omission of buses, omission of long-term trends of demographic decrease or decrease in car-ownership, and omission of Private Autonomous Vehicles (PAV).

Ultimately, SAVs are predicted to have a quite low adoption rate, and a small effect on transit necessitating no need for regulation. Commuter railways will still reign over all other travel modes in Greater Tokyo. The hype of autonomous mobility should instead be focused on Private Autonomous Vehicles, with next steps being to extend the simulation of this study by incorporating PAVs.

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