



Article

The City-Wide Impacts of the Interactions between Shared Autonomous Vehicle-Based Mobility Services and the Public Transportation System

Sehyun Tak **1**, **Soomin Woo** **2**, **Sungjin Park** **3,*** and **Sunghoon Kim** **1,***¹ The Korea Transport Institute, 370 Sicheong-daero, Sejong City 30147, Korea; sehyun.tak@koti.re.kr² Civil and Environmental Engineering, University of California, Berkeley, CA 94720, USA; soomin.woo@berkeley.edu³ Department of Urban Design and Planning, Hongik University, Seoul 04066, Korea

* Correspondence: parks@hongik.ac.kr (S.P.); sunghoon.kim@koti.re.kr (S.K.)

Abstract: When attempts are made to incorporate shared autonomous vehicles (SAVs) into urban mobility services, public transportation (PT) systems are affected by the changes in mode share. In light of that, a simulation-based method is presented herein for analyzing the manner in which mode choices of local travelers change between PT and SAVs. The data used in this study were the modal split ratios measured based on trip generation in the major cities of South Korea. Subsequently, using the simulated results, a city-wide impact analysis method is proposed that can reflect the differences between the two mode types with different travel behaviors. As the supply–demand ratio of SAVs increased in type 1 cities, which rely heavily on PT, use of SAVs gradually increased, whereas use of PT and private vehicles decreased. Private vehicle numbers significantly reduced only when SAVs and PT systems were complementary. In type 2 cities, which rely relatively less on PT, use of SAVs gradually increased, and use of private vehicles decreased; however, no significant impact on PT was observed. Private vehicle numbers were observed to reduce when SAVs were operated, and the reduction was a minimum of thrice that in type 1 cities when SAVs and PT systems interacted. Our results can therefore aid in the development of strategies for future SAV–PT operations.

Keywords: public transportation; shared autonomous vehicles; local traveler choices; impact analysis; demand responsive transit



Citation: Tak, S.; Woo, S.; Park, S.; Kim, S. The City-Wide Impacts of the Interactions between Shared Autonomous Vehicle-Based Mobility Services and the Public Transportation System. *Sustainability* **2021**, *13*, 6725. <https://doi.org/10.3390/su13126725>

Academic Editor: Giuseppe Inturri

Received: 21 May 2021

Accepted: 9 June 2021

Published: 14 June 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Autonomous vehicles (AVs) represent the core technology that will revolutionize urban mobility in the future. AVs are considered upgraded versions of conventional vehicles that have high levels of automation to assist or replace human drivers. However, if we simply treat AVs as upgraded versions of vehicle control, the benefits of deploying expensive technology will be marginal, particularly in large urban road networks with high travel demands and limited space. Hence, recent studies have focused on the potential for operating AVs as urban mobility services, such as demand-responsive transit (DRT) and shared vehicles [1]. Numerous studies have attempted to assess the impacts of operating AVs for urban mobility services using various approaches, such as survey reports [2,3], economy-based analyses [4,5], and simulation models [6–8].

When attempts are made to adopt AVs into shared and demand-responsive services, public transportation (PT) systems are affected, thereby creating changes in mode share. This could potentially create a difficult dilemma for many European and Asian cities that heavily rely on their public transportation systems. To avoid future problems, the relationship between newly formed mobility services and PT systems should be analyzed. Extensive research has been conducted on DRT [9,10] to develop methods for evaluating DRT systems with flexible route services [11–13]. However, these studies have commonly

compared flexible route services with existing *PT* systems, while considering *PT* as a competitor. Other studies attempted to develop methods for allowing the interaction of flexible route services with existing *PT* systems [14–16]. However, these works mostly did not include AVs or shared vehicles within their concepts. Recent studies have begun to focus on evaluating shared autonomous vehicle (SAV) operations in urban areas [8,17,18]. Nonetheless, their common perspective was that *PT* is a competitor and is to be replaced by SAV-based services in the future. However, for cities that heavily rely on *PT*, such as Seoul of South Korea, in which the modal portion of *PT* is higher than 60%, this scenario could potentially create various problems, including public debts from bankruptcy, traffic congestion from modal shift, and a lack of mobility for the poor. Nonetheless, there has been a lack of discussion regarding the impact of SAV operations on existing *PT* systems and the interactions between the two [19].

In this study, we attempted to analyze the impacts of SAV operations on *PT* systems in metropolitan areas. First, we provide an analysis method based on an agent-based simulation to analyze how local travelers' choices change between SAVs and *PT*s. Then, using the properties of the simulated results, we proposed a city-wide impact analysis method that can reflect the differences in travel behaviors based on urban type. Using a combination of the two different analyses, we derived insights into the potential impacts of future SAV operations on existing *PT* systems in different types of cities. The definitions of the key terms in this study are provided as follows.

- Autonomous vehicles (AVs): upgraded versions of conventional personal vehicles that have high levels of automation to assist or replace human drivers.
- Shared autonomous vehicles (SAVs): AVs used for the purpose of providing vehicle sharing services.
- Public transportation (*PT*): Grouped travel systems generally operated on pre-defined schedules.
- Demand responsive transit (DRT): A *PT* service in which users have to book their trips in advance.

The remainder of this paper is organized as follows. Section 2 provides a literature review of related studies. Section 3 describes the types of cities based on travel behaviors and scenarios for analyses, along with a simulation-based method and a city-wide impact analysis method. Section 4 presents the results of the two analyses and discusses the impacts on *PT*. Section 5 presents the conclusion along with the suggestions for future research.

2. Literature Review

2.1. Agent-Based Simulations for Impact Analysis

Numerous studies have been conducted to anticipate the potential impacts of SAV operations, particularly in recent years. Various approaches have been proposed, and the use of agent-based simulations is one of the main branches in SAV impact analysis. Agent-based simulations have been broadly utilized because of their flexibility in designing experimental settings for various study purposes. Some simulations may be designed to analyze only local impacts on partial urban areas [20,21], or may be designed to analyze the impacts on large urban areas. Especially for the latter approach, the use of a multi-agent transport simulation (MATSim) [22] has been popular, because it has high applicability to large-scale urban areas, and it is high speed due to being based on mesoscopic traffic flow models; furthermore, the latter can also be used to obtain a sufficient level of detail by reflecting individual travelers' activity plans. The demand estimation in MATSim is usually performed based on individual agents' plans of movement between activity locations. The main differences from previous studies are the mode choice mechanisms of multi-agents. The mode is chosen by either discrete choice modeling [23] or utility scoring [24,25]. While using such a simulation toolkit, various studies have also differed in terms of evaluation targets. Some are more interested in the extents to which SAV operations can reduce traffic congestion in urban areas [26]; others are more interested in the changes in detailed travel behaviors within specified urban areas, such as vehicle kilometers traveled (VKT) [7,27] and passenger waiting times [28].

Several studies have designed their own simulations rather than using MATSim for various purposes. Some such studies involved analyzing the impacts of employing shared taxis in a large urban area. The common results of the related studies are that shared taxis reduce traffic congestion [29,30] and VKT [31] compared to the conventional taxi systems by reducing the fleet size. Others have tested the impacts of employing EVs in urban areas. These studies related to EVs for shared mobility services show that EVs may increase the VKT because of empty trips required for battery charging, but they can still reduce operational costs [32] and increase sustainability [33].

All the studies mentioned above used agent-based simulations for impact analysis of SAV operation from various perspectives. However, most of them considered the SAVs as a replacement for private vehicles and existing public transit. Discussions regarding the impacts of SAV operations on existing PT systems or the interaction between the two services are scarce.

2.2. City-Wide Impact Analysis

Most previous studies have analyzed the impacts of SAV operations at a large-scale urban level because of the anticipation of the city-wide deployment of SAVs. According to Narayanan et al. [34], city-wide impact analyses have been conducted from various perspectives, such as economic, urban traffic performance, and travelers' mode choice perspectives. In fact, all these studies can be seen as sustainability-related works on AV-based mobility services, since they all "attempt to understand and manage concomitant environmental, economic, and social issues" [35].

The usual method employed for city-wide economic analysis is to express the impacts in terms of cost. Based on an analytical calculation of the total trip distance and the required fleet size of autonomous taxis, Brownell and Kornhauser [4] estimated the cost per person, per day. Chen et al. [32] developed an agent-based simulation model of a hypothetical urban area and derived the operational cost per kilometer in an electric SAV environment using simulation tests. Ongel et al. [36] calculated the cost per passenger-km based on the analysis of various information sources for operational costs.

The results of previous studies are controversial in terms of urban traffic. Some studies have found that SAV operations can increase congestion in urban areas, particularly after peak hours because of the increased number of empty trips after providing services [37]. In contrast, the results of other studies indicate that congestion can be significantly reduced when the travel mode sharing level meets a certain value [29,30]. Similar results were obtained in VKT-based analysis. Some studies showed that there is an increase in VKT in the city-wide analysis because of empty vehicle trips [38,39]. Childress et al. [40] derived similar results; however, they also showed that there can be positive impacts when all vehicles become automated and shared.

Simulation-based analyses can be performed in terms of travelers' mode choices. Based on activity-based simulation results, Liu et al. [23] showed that private vehicle owners, particularly in rural areas, prefer SAV-based services. Another example of simulation-based analysis has shown that, if private vehicle usage is disabled, most travelers prefer to use SAV-based services rather than PT [6]. Survey-based analyses have also been conducted for the impacts on travelers' mode choices. The common result of such analyses is that conventional PT (or multimodal transit) users are positive about switching to SAV-based services; however, private vehicle owners are less likely to use SAVs [2,41]. Hence, the results of impact analyses on travelers' mode choices are still controversial.

In addition, there have been a few interesting studies analyzing the impacts on shared mobility caused by internal urban aspects, such as the accessibility of services influenced by demographic factors and transportation infrastructure [42]. There have also been a few studies on the impacts of external forces such as weather [43] and pandemics such as COVID-19 [44].

2.3. The Impact on Public Transit Systems

As described in the previous section, several existing studies have considered *PT* to be a competitor and an object to be replaced by *SAV*-based services in the future. However, it is difficult to expect that unmanned vehicles will completely take over existing systems in the future. Still, the adoption of *SAVs* will serve as a factor that continuously changes the shares of existing travel modes. Therefore, the impact of *SAV*-based services on existing *PT* systems or interactions between the two must be analyzed. Accordingly, Shen et al. [19] recently changed their ideal to *SAV* operations integrated with a *PT* system. They performed an agent-based simulation to evaluate an *SAV–PT* integrated system and suggested that replacing little-used bus routes with *SAVs* would significantly increase the efficiency of the integrated system. Subsequent studies have been conducted for further development of *PT–SAV* integration [45,46], and there is growing interest in this topic. The commonality of these recent studies was that they proposed integrated systems and then compared the results before and after applying the systems for testing the efficiency in terms of travelers' waiting times. However, they did not consider the detailed changes in the modal split ratio between *PT* and *SAV* when they interacted with each other in detail. Furthermore, the extent to which the interaction would reduce the number of private vehicles should also be considered in a city-wide analysis.

Therefore, the first objective of this study was to provide a simulation-based method to analyze the modal shift by local travelers between *PT* and *SAV* when the two modes interact with each other. Then, using the properties of the simulated results, the second objective was to propose a city-wide impact analysis method that can reflect the differences between urban types in terms of travel behaviors. The use of the combined approach of the two analyses (simulation and analytical methods) is a major difference between the current study and previous studies. Note that, in this study, we focus more on the impact of *SAV* operation on *PT* rather than evaluating the direct efficiency of the interaction system. Hence, we consider the following three criteria. The first is the matching ratio between service vehicles and passengers, which represents the service satisfaction of system users. The second is the mode choice ratio of travelers, which is closely associated with mobility service efficiency. The third is the rate of increase/decrease in the number of private vehicles, which is a major factor affecting urban congestion. The following section provides details of the analysis methods.

3. Methodology

In this study, we analyzed the impact of the introduction of shared mobility and autonomous driving on *PT* by applying an analysis method based on agent-based simulation to a city-wide analysis model. We used an urban perspective via the modal split ratio. As shown in Figure 1, the analysis method and procedure comprised four steps. In step 1, the types of cities for analyzing the impacts of the introduction of autonomous driving and shared mobility on *PT* were identified by reviewing existing reports related to autonomous driving and shared mobility. In step 2, scenarios were derived to analyze the impacts of the introduction of services and systems related to autonomous driving, shared mobility, and *PT* on future transportation. In step 3, agent-based simulation was performed to analyze the role of *PT* in the era of autonomous driving and shared mobility, and major factors required to analyze the introduction of shared mobility and autonomous driving were identified based on the scenario derived in step 2. Finally, in step 4, changes in *PT* caused by the introduction of autonomous driving and shared mobility were analyzed from a city-wide perspective using the simulation results obtained in step 3 for the target city and the types of change derived in step 2. In step 4, changes in the modal split ratio by type of city were also addressed. The impact of the introduction of shared mobility and autonomous driving on the efficiency of urban mobility was indirectly analyzed by estimating changes in the utilization of private vehicles, which are closely related to congestion.

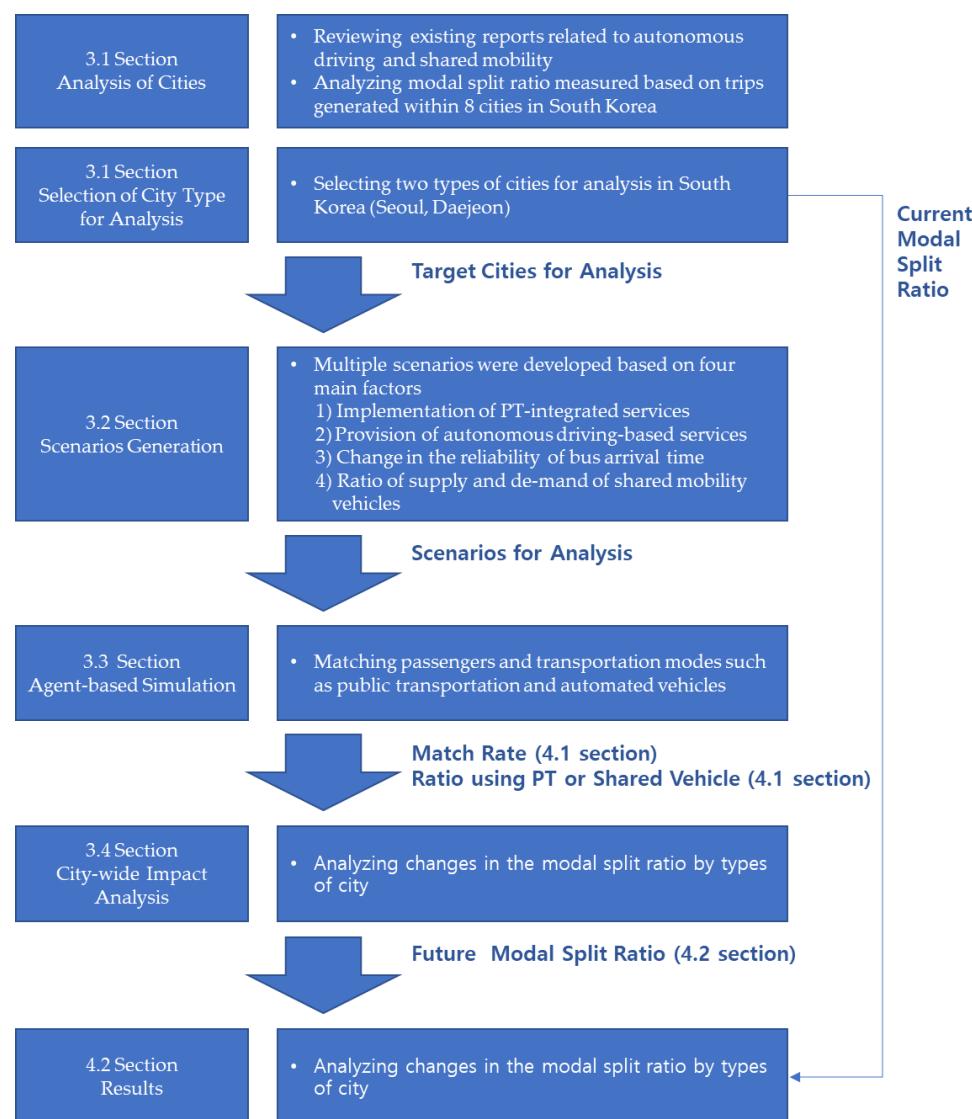


Figure 1. Analysis method and data flow.

3.1. Analyzed Cities and Selection of Types

The effects of introducing autonomous driving cars on PT vary according to the modal split ratio and city type. For example, in cities where mass-transition-based PT is developed, the effects of autonomous driving-based car-sharing systems could be relatively small. In contrast, in cities with high shares of private vehicles, introducing a SAV system can have a large effect. Hence, we classified the large metropolitan areas in Korea into two groups based on the utilization of transportation before analyzing the effects of introducing autonomous driving.

Table 1 shows the modal split ratio measured based on trips taken within each city in South Korea [47]. As shown in this table, Seoul, South Korea, has one of the best PT networks in the world, and has an exceptionally high modal score for PT. Next, Busan and Incheon have modal scores for PT of higher than 40%, followed by Gwangju, Daejeon, and Ulsan, which have low modal scores for PT (approximately 20%) and high proportions of private vehicles. An examination of the modal split ratio measured based on trips generated within each city shows that in the areas where new towns are located, many locations have higher proportions of PT use than 40%.

Table 1. Modal split ratios of metropolitan cities in South Korea.

Classification	Private Vehicles (%)	PT (%)	Mobility-on-Demand (%)
Seoul	27.7	63.1	9.2
Incheon	49.8	41.7	8.5
Busan	43.6	45.3	11.1
Daegu	55.3	33.6	11.1
Gwangju	63.9	23.2	12.9
Daejeon	63.8	26.5	9.7
Ulsan	65.4	23.5	11.1
Sejong	76.1	18.0	5.9

Most other metropolitan cities had modal splits of *PT* in the range of 10–20%, and modal splits of private vehicles above 60%. Few studies have predicted changes in traffic patterns and modal split ratios by city type, such as urban areas with well-established *PT* networks and suburban areas that have high dependence on private cars, while investigating changes in future traffic systems in terms of technology and services. In this study, the types of cities in South Korea were classified, and changes in the modal split ratio were analyzed according to the type of city based on the trend of the modal split ratio according to the types of cities suggested by Lang et al. [48].

Thus, cities were classified into the following two types before conducting the analysis: Type 1 cities are those that currently have high modal splits of *PT* and are moving toward choosing shared vehicle services, and their modal splits of *PT* and private cars are expected to be similar in the future. Type 2 cities are those that currently have high modal splits of private cars and where the users of private cars are more likely to choose shared vehicle services. Furthermore, based on the prediction of Lang et al. [48], the approximate estimates of changes in the modal split ratios of major cities in South Korea are summarized in Table 2, considering that the proportions of autonomous driving cars in mobility-on-demand for the urban and suburban areas are 88% and 87%, respectively.

Table 2. Classification of the types and modal split ratios of major cities in South Korea.

Classification	Private Vehicles (%)	PT (%)	Mobility-on-Demand (%)	
			(%)	AVs
Type 1 city	Seoul	13.67	49.14	37.19
	Busan	29.65	31.26	39.09
	Gwangju	40.94	25.23	33.83
Type 2 city	Incheon	35.83	27.72	36.45
	Daegu	41.36	19.58	39.06
	Daejeon	40.82	28.45	30.73
	Ulsan	42.89	25.05	32.06
	Sejong	53.09	20.01	26.90

It is assumed that Korean cities will experience similar changes in terms of the modal split ratio to those simulated in a study by Lang et al. [48]. Consequently, Seoul, which currently has a high modal split of *PT*, was selected as a type 1 city, and it is expected that existing users of *PT* and private cars will move to choosing shared vehicles in the future. Daejeon, which currently has a high modal split of private cars, was selected as a type 2 city, and the most of this share is expected to move to shared vehicle services.

3.2. Scenario Composition

To analyze the effects of the introduction of AVs and shared mobility on the PT and transportation systems, multiple scenarios were developed based on four main factors. As shown in Figure 2, 32 simulation scenarios were developed largely based on (1) the implementation of PT-integrated services, (2) the provisioning of autonomous driving-based services, (3) different levels of reliability for bus arrival times, and (4) changes in the ratio of supply and demand for shared mobility vehicles.

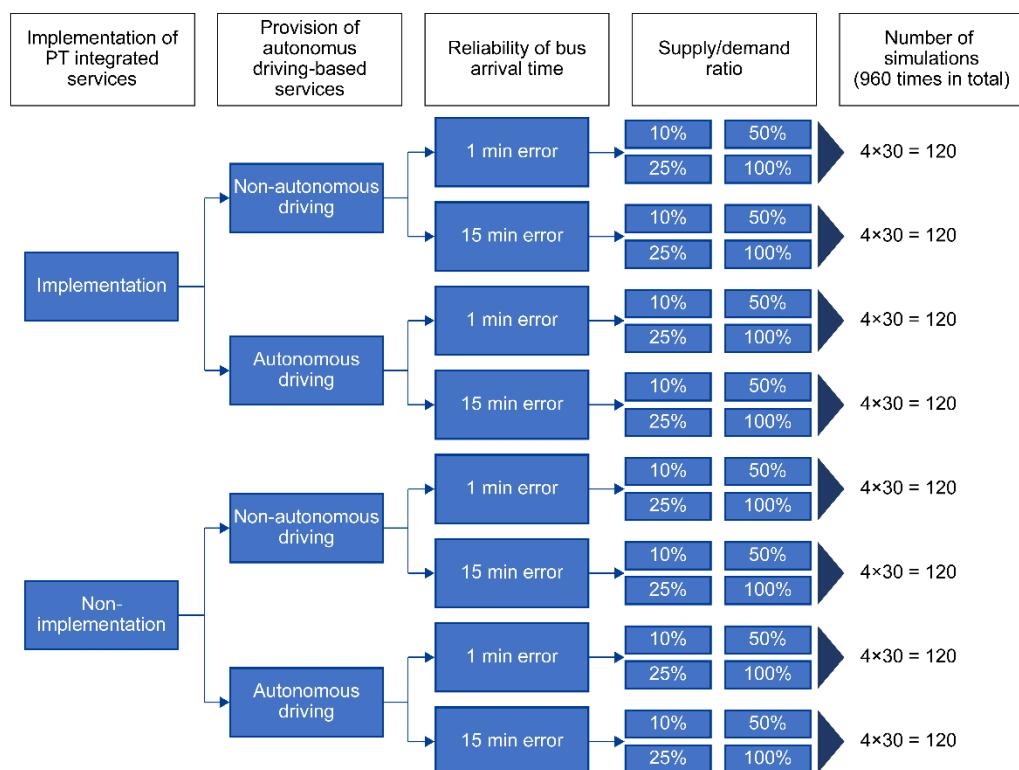


Figure 2. Scenario generation method.

To prevent the simulation results from representing only a specific demand pattern, repetitive simulations were performed 30 times based on a random traffic pattern for each scenario, and then the average value was set as the representative value for each scenario. Consequently, scenarios were generated by including/not including PT-integrated services, provisioning/not provisioning autonomous driving-based services, changing the reliability of bus arrival times, and altering the supply/demand ratio; and repetitive simulations were performed for each scenario, as shown in Figure 2. Hence, this study was based on the results of 960 simulations. Details regarding each scenario are provided below.

3.2.1. Scenarios According to the Implementation of PT-Integrated Services

The non-implementation state of shared mobility and PT-integrated services represents the current transportation system, in which shared mobility services are operated separately from PT. In other words, similarly to current Uber and taxi services, shared mobility services do not have a system for linked transfer between PT and shared mobility, and the inconvenience of a transfer can be minimized only through user experience.

The implementation of shared mobility and PT-integrated services represents the transportation system of the future, and indicates that mutually linked transfers are operated optimally. Passive services for this include integrated payments and reservations, and the provisioning of accurate transfer times; active services include bus signal adjustment to shorten travel time, sharing, and PT vehicle assignment based on the predicted information.

To reflect this scenario in the simulations of this study, in the non-implementation state of shared mobility and *PT*-integrated services, shared mobility and *PT* provided services independently of each other, and mutual transfer was not considered. In contrast, when shared mobility and *PT*-integrated services were active, shared mobility and *PT* provided services complementarily, and the disadvantages of shared mobility (e.g., refusal of dispatch for many detour requests) were resolved by *PT*.

3.2.2. Scenarios According to the Provisioning of Autonomous Driving-Based Services

The introduction of *AVs* will enhance shared mobility services. Hence, simulations were performed for different scenarios when shared mobility services were provided by *AVs* and non-autonomous vehicles. Based on this premise, the effects of autonomous driving technology on shared mobility and future *PT* were analyzed.

When shared mobility services are provided by *AVs*, optimization of passenger boarding is expected to be possible. When compared with the provisioning of shared services by non-autonomous vehicles, the provisioning of shared services by *AVs* should increase the average number of passengers, as a driver seat is no longer needed. To reflect this improvement in service performance, the average number of passengers for *AVs* was assumed to be higher by one (replacing drivers with passengers) than the average number of passengers for non-autonomous vehicles.

3.2.3. Scenarios According to the Travel Time Reliability of *PT* Services

When *PT*-integrated services are provided, a difference in travel time reliability of *PT* services should have a significant impact on the use of related services. As an example, we can assume a trip in which user A moves to bus stop 3 on the bus line using shared mobility, moves to bus stop 10 using another bus, and then moves to the final destination using shared mobility. In this case, for bus stop 3, where the user transfers from shared mobility to *PT*, the shared mobility vehicle must accurately predict the time when the bus starts from bus stop 1 and arrives at bus stop 3 to arrive at the bus stop punctually. Moreover, at bus stop 10, where the user transfers from *PT* to shared mobility for continuous linked transfer, the estimated arrival time must be provided accurately. In this example, if the error of the estimated arrival time is less than 1 min, continuous linked transfers are possible; however, if the error is as large as 15 min, such transfer delays will mean that the shared mobility service cannot be used.

As shown in this example, the reliability of a bus's travel time is essential when *PT*-integrated services are provided. In this study, to analyze the effect of the reliability of bus travel time on the shared mobility and *PT* usage pattern, scenarios were developed by distinguishing between 1 and 15 min travel time errors. In this way, the effects of *PT* service reliability on the modal split of *PT* and the total transportation system in the shared mobility era of the future were analyzed.

3.2.4. Scenarios According to Various Demand–Supply Ratios

The effects of shared vehicles on the transportation system were predicted to differ depending on the number of shared vehicles provided. For example, if the total traffic demand is 1000 and the number of shared vehicles provided is 10, the services can be provided only to a limited number of passengers, even though traffic demand is large; however, the average number of passengers riding per unit will increase. If the number of shared vehicles is 1000 with the same traffic demand, it is highly likely that the related services will meet the total traffic demand; however, the average number of passengers riding in one shared vehicle will converge to 1. In this case, *PT* usage will decrease, which is expected to have a negative effect on road congestion.

As mentioned above, the effects of shared mobility on *PT*, transportation systems, and road congestion are expected to differ depending on the supply and demand ratio. To analyze this situation through simulations, scenarios were defined by setting the ratio of shared vehicle supply to traffic demand (number of shared vehicles supplied/traffic

demand for shared vehicles $\times 100$) to 10, 25, 50, or 100. We assumed that the SAV services would not be expanded all over the urban road systems and that the supply/demand ratio will not exceed 50% in the near future, considering the current technologies and services. Hence, we intend to focus more on the ratios less than or equal to 50:50 and set the ratio values as above. The ratio of 100% was included in the set just to see a rough estimation of the long-term.

3.3. The Agent-Based Simulation Method

3.3.1. A Matching Algorithm for the Implementation of Autonomous Driving and Shared Mobility

Figure 3 shows the matching algorithm used in this study. The matching algorithm proposed in this study includes a traffic demand prediction module, which predicts the demand and outputs the origins and destinations for several hours later. The prediction is performed by a demand–supply optimal matching algorithm, which receives the demands of passengers and the vehicle information as input and matches them, and a system outputs the matched results to PT.

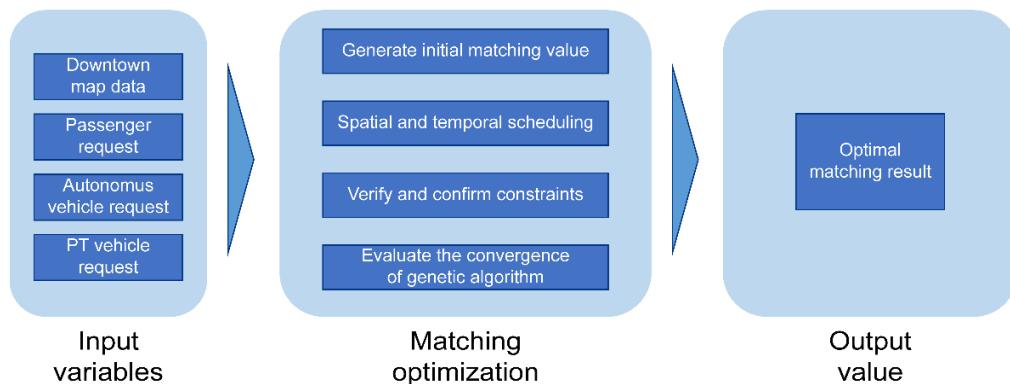


Figure 3. Matching algorithm.

The basic input values include the downtown map, the origin and destination (*O-D*) table for passengers, and the *O-D* table for AVs. The matching optimization algorithm determines the optimal matching value by generating initial values, performing spatial and temporal scheduling, checking the constraints, and evaluating whether the matching rate converges. The traffic demand prediction-based matching algorithm additionally has a demand prediction module which comprises a downtown, real-time, dynamic, asymmetric demand prediction module, an autonomous vehicle, and a PT *O-D* prediction module. It outputs the predicted demand, the AVs, and the PT *O-D* table, and then uses them as the inputs for the linked matching algorithm. The matching set generated by the first matching optimization module is given as follows:

$$M = (m_1, m_2, \dots, m_{2n}) \quad (1)$$

$$m_q = (ID_{pax,q,sequence}, ID_{AV,q}, x_{on,q}, x_{off,q}, t_{on,q}, t_{off,q}) \quad (2)$$

As two vehicles are arranged per passenger, $2 \times n$ matching sets are generated. Each of the q -th matching variables includes various information, as in Equation (2). $ID_{pax,q,sequence}$ is the passenger identification number at each sequence (first or second) of the matched vehicle and $ID_{AV,q}$ is autonomous vehicle's identification number. $x_{on,q}$ and $x_{off,q}$ are get-on and get-off locations, respectively. Additionally, $t_{on,q}$ and $t_{off,q}$ are get-on and get-off times, respectively.

The matching algorithm first uses vehicle and passenger matching types by default. From the viewpoint of passengers, the types of rides are classified into single-hop, where the passenger uses only one vehicle from the origin to the destination, and multi-hop, where the passenger uses multiple linked vehicles. Vehicles are classified based on the

numbers of passengers serviced as matching only one passenger or arranging multiple passengers for one vehicle and matching them by defining the get-on and get-off sequences.

The second basic element of the matching algorithm is the bypass burden. For smooth connection and transfer with *PT*, it is necessary to consider where and how much distance detours from the existing path should allow for each mode of transportation. As *PT* has fixed lines that cannot be changed, passengers must walk to the designated *PT* boarding location, or the linked private vehicle must take a detour to the transfer point.

The last basic element of the matching algorithm is the vehicle composition, which refers to the composition of the vehicle that matches the needs of passengers. The vehicle composition information comprises the existing origin and destinations, time information, and seat information; and additionally, the origins and destinations, time information, and seat information when *AVs* are cruising. When connected with the *PT*, the dispatch times of the *PT* and bus stop locations are added.

The matching algorithm of this study aims to maximize the number of passengers with the given vehicle resources. The ratio of the number of actual passengers to the requested passenger demand is defined as the matching ratio (*M*), and the objective function is used to maximize this ratio. The input variables applied to this algorithm mostly include passenger demand, *AVs*, and *PT* information.

First, the passenger demand input variables consist of the following:

$$R_{pax} = (r_{pax,1}, r_{pax,2}, \dots, r_{pax,n}) \quad (3)$$

$$r_{pax,i} = (ID_{pax,i}, O_{pax,i}, D_{pax,i}, t_{pax,i}^{\min, O}, t_{pax,i}^{\max, D}, \omega_{pax,i}) \quad (4)$$

where R_{pax} is the set of passenger demand; $r_{pax,i}$ for $i = 1, 2, \dots, n$ is the demand of each passenger; $ID_{pax,i}$ is the passenger's identification number; $O_{pax,i}$ is the origin; $D_{pax,i}$ is the destination; $t_{pax,i}^{\min, O}$ and $t_{pax,i}^{\max, D}$ are the maximum allowed start and arrival times, respectively; and $\omega_{pax,i}$ is the maximum walking distance for transfer.

The input variables of *AVs* are as follows:

$$R_{AV} = (r_{AV,1}, r_{AV,2}, \dots, r_{AV,m}) \quad (5)$$

$$r_{AV,j} = (ID_{AV,j}, O_{AV,j}, D_{AV,j}, t_{AV,j}^{\min, O}, t_{AV,j}^{\max, D}, c_{AV,j}) \quad (6)$$

where R_{AV} is a set of *AVs*; $r_{AV,j}$ for $j = 1, 2, \dots, m$ is the information of each *AV*; $ID_{AV,j}$ is the identification number of the vehicle; $O_{AV,j}$ and $D_{AV,j}$ are the virtual origin and destination sets for the cruiser, respectively; $t_{AV,j}^{\min, O}$ and $t_{AV,j}^{\max, D}$ are the virtual starting and arrival times, respectively; and $c_{AV,j}$ is the number of seats.

The input variables of the *PT* bus are as follows:

$$R_{bus} = (r_{bus,1}, r_{bus,2}, \dots, r_{bus,l}) \quad (7)$$

$$r_{bus,k} = (ID_{bus,k}, S_{bus,k}, T_{bus,k}, t_{bus,k}^{\text{first}}, t_{bus,k}^{\text{last}}) \quad (8)$$

where R_{bus} is a set of *PT* vehicles; $r_{bus,k}$ for $k = 1, 2, \dots, l$ is the information of each *PT* vehicle; $ID_{bus,k}$ is the identification number of the *PT* vehicle; $S_{bus,k}$ is the bus stop; $T_{bus,k}$ is the dispatch interval; and $t_{bus,k}^{\text{first}}$ and $t_{bus,k}^{\text{last}}$ are the first and last vehicle times, respectively.

3.3.2. Simulation Network and Settings

This agent-based simulation was based on a simplified Sioux Falls network. The simplified road network of Sioux Falls City in South Dakota and its demand data are often used for experimenting on transportation-related problems of route inefficiency and road vulnerabilities. This network includes 24 zones, 24 nodes, 24 links, and 528 origin-destination pairs, allowing an assessment of the city-wide impact of mobility services without the challenge of computing a large number of OD pairs with high complexity.

To analyze the effects of introducing the bus connection services together with private vehicles, the real bus routes of Sioux Falls were simplified to best fit the network, as shown by the nine routes of bus data in Figure 4. These bus networks represented the *PT* service in the network. A different color was assigned for each bus line, as shown in the simulations in Figure 4.

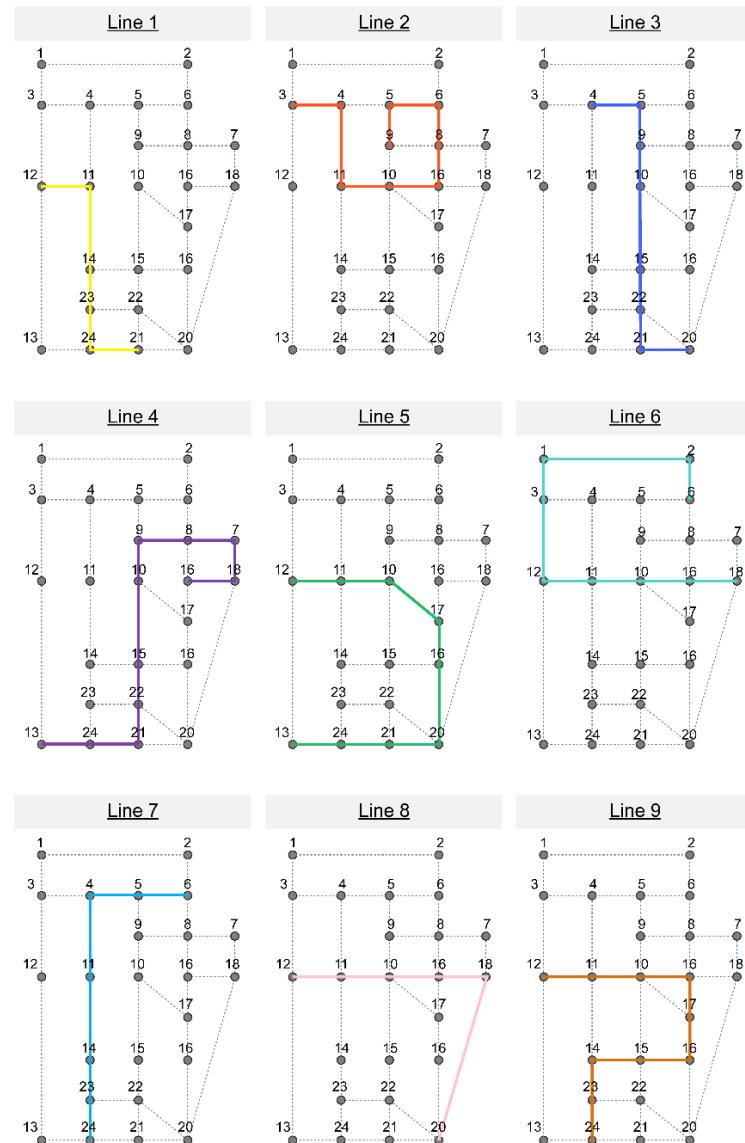


Figure 4. Bus lines for *PT* analysis.

3.4. City-Wide Impact Analysis Method by Type of City

In this study, changes in the transportation system according to the type of city were derived based on the shared vehicle match rate obtained through agent-based simulation analysis, the *PT* use rate of shared mobility service users, and the average passenger occupancy of shared vehicles. The derived outputs were the change in the modal split ratio and the change in the private vehicle use rate for each city; the calculation methods based on the type of city are described below. For descriptions of the variables, see Table 3.

Table 3. Descriptions of related variables.

Notation	Description
R_{match}	Shared vehicle match rate
P_{PT}	Ratio of PT connected service use among shared mobility users
P_{SV}	Ratio of shared vehicle use among shared mobility users
$M_{PT, current}$	Current modal split ratio of public transit
$M_{PT, future}$	Future modal split ratio of public transit reflecting the simulation result
$M_{PV, current}$	Current modal split of private vehicles
$M_{PV, future}$	Future modal split of private vehicles reflecting the simulation result
$M_{MOD, current}$	Current modal split ratio of mobility-on-demand
$M_{MOD, future}$	Future modal split ratio of mobility-on-demand reflecting the simulation result
C_{PV}	Estimated change rate of private vehicles usage
O_{SV}	Average number of passengers when using shared vehicles
O_{SAV}	Average number of passengers when using SAVs

3.4.1. Calculation Method of the Modal Split Ratio

As analyzed in the classification of types of cities in Section 3.1, in type 1 cities (e.g., Seoul), the changes in modal split for PT and private vehicles when shared mobility enters are similar. Furthermore, we found that when PT-integrated services are not implemented, the users of shared mobility use shared mobility only. Based on this research finding, the modal split equation with PT-integrated services was implemented for each type 1 city is as follows:

$$M_{PT, future} = M_{PT, current} - 0.5 \cdot R_{match} \quad (9)$$

$$M_{PV, future} = M_{PV, current} - 0.5 \cdot R_{match} \quad (10)$$

$$M_{MOD, future} = M_{MOD, current} + R_{match} \quad (11)$$

When PT-integrated services were implemented in a type 1 city, shared mobility users parallelly used shared mobility and PT. Based on this research finding, the modal split equation for the case of implementing PT-integrated services in a type 1 city is as follows:

$$M_{PT, future} = M_{PT, current} - 0.5 \cdot R_{match} + P_{PT} \cdot R_{match} \quad (12)$$

$$M_{PV, future} = M_{PV, current} - 0.5 \cdot R_{match} \quad (13)$$

$$M_{MOD, future} = M_{MOD, current} + R_{match} - P_{PT} \cdot R_{match} \quad (14)$$

In a type 2 city (Daejeon), only the modal split of private vehicles was changed to shared mobility. Based on this research finding, the modal split equation when PT-integrated services are not implemented in a type 2 city is as follows:

$$M_{PT, future} = M_{PT, current} \quad (15)$$

$$M_{PV, future} = M_{PV, current} - R_{match} \quad (16)$$

$$M_{MOD, future} = M_{MOD, current} + R_{match} \quad (17)$$

Furthermore, the modal split ratio equation for implementing PT-integrated services in a type 2 city is as follows:

$$M_{PT, future} = M_{PT, current} + P_{PT} \cdot R_{match} \quad (18)$$

$$M_{PV, future} = M_{PV, current} - R_{match} \quad (19)$$

$$M_{MOD,future} = M_{MOD,current} + R_{match} - P_{PT} \cdot R_{match} \quad (20)$$

3.4.2. Calculating the Expected Rate of Increase or Decrease for Private Vehicles

According to the simulation results explained in the previous section, the introduction of autonomous driving and shared mobility is closely related to changes in the average number of passengers. Once autonomous driving and shared mobility are introduced, and these services are integrated with *PT*, the average number of passengers of shared vehicles is expected to increase to 2.8 persons. However, if shared mobility is operated with non-autonomous vehicles and *PT*-integrated services are not implemented, the average number of passengers is expected to converge to 1. This change in the number of passengers is closely associated with the number of vehicles running on the road. For example, if the demand for single-passenger vehicles is changed to shared mobility based on autonomous driving, for which the average number of passengers is 2.8, the number of private vehicles running on the road will decrease at a ratio of $1/(2.8-1)$. In contrast, if the demand for buses is changed to shared mobility based on autonomous driving, for which the average number of passengers is 2.8, the number of private vehicles running on the road will increase at a ratio of $1/2.8$. This change in the number of private vehicles running on the road indirectly indicates an increase or decrease in overall road congestion. If the predicted change in *PV* (C_{PV}) is a positive number, it indicates increased congestion due to the increased use of private vehicles. If the estimated change in *PV* (C_{PV}) is negative, it indicates decreased congestion due to the decreased use of private vehicles.

The estimated change in *PV* (C_{PV}) is calculated differently when the service is provided based on non-autonomous vehicles and when the service is provided based on *AVs*. The estimated change rate of private vehicles (C_{PV}) when the service is provided based on non-autonomous vehicles is as follows:

$$C_{PV} = \left(M_{PT,current} - M_{PT,future} \right) + \frac{(M_{PV,current} - M_{PV,future})}{(O_{SV}-1)} \quad (21)$$

for $M_{PT,current} \leq M_{PT,future}$

$$C_{PV} = \frac{(M_{PT,current} - M_{PT,future})}{O_{SV}} + \frac{(M_{PV,current} - M_{PV,future})}{(O_{SV}-1)} \quad (22)$$

for $M_{PT,current} > M_{PT,future}$

When calculating the estimated change rate of private vehicles (C_{PV}) in case the service is provided based on *AVs*, the average number of passengers for autonomous driving service is applied, and the equation is as follows:

$$C_{PV} = \left(M_{PT,current} - M_{PT,future} \right) + \frac{(M_{PV,current} - M_{PV,future})}{(O_{SAV}-1)} \quad (23)$$

for $M_{PT,current} \leq M_{PT,future}$

$$C_{PV} = \frac{(M_{PT,current} - M_{PT,future})}{O_{SAV}} + \frac{(M_{PV,current} - M_{PV,future})}{(O_{SAV}-1)} \quad (24)$$

for $M_{PT,current} > M_{PT,future}$

4. Results

4.1. Results of Agent-Based Simulation Analysis

As shown in Figure 5, when the supply/demand ratio was 10%, the portion of *PT* users among shared mobility passengers was high at 41%. In other words, when the number of shared mobility vehicles was relatively small, a large portion of shared mobility passengers used *PT*-integrated services, thereby using both shared mobility and *PT*.

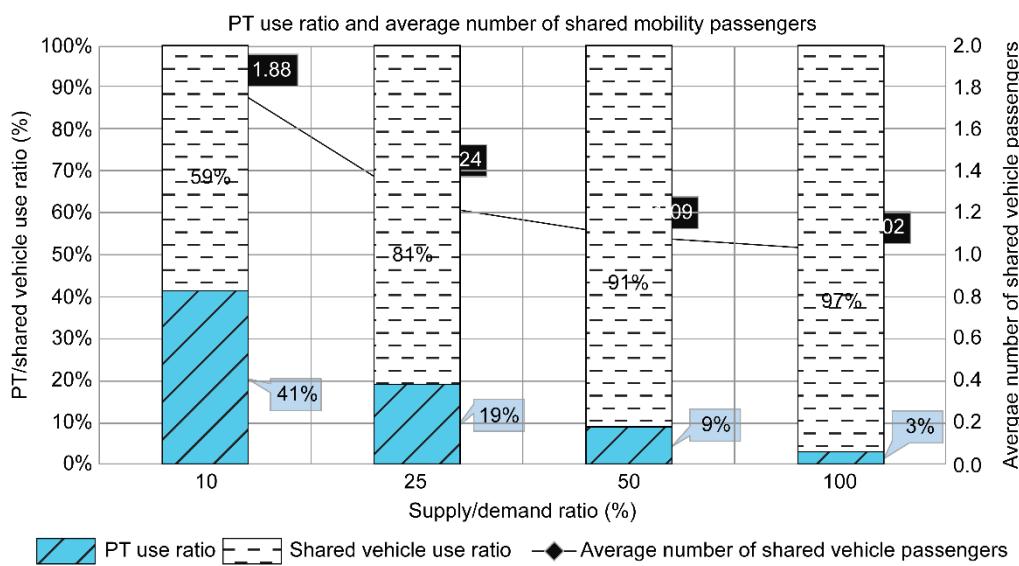


Figure 5. PT use ratio and average number of shared mobility passengers.

However, as the supply/demand ratio gradually increased, the number of passengers who used both shared mobility and *PT* slowly decreased, and the *PT* use ratio decreased to 3% when the supply/demand ratio was 100%. In other words, most passengers using shared mobility only used shared mobility for transportation.

The supply level of shared mobility also shows a close correlation with the average number of shared vehicle passengers. As indicated by the solid line on the graph in Figure 5, when the supply/demand ratio is 10%, the average number of passengers is 1.88, indicating that many users prefer shared mobility. However, as the supply/demand ratio increased, the average number of passengers gradually decreased and converged to 1. In other words, when the supply/demand ratio is low and *PT*-integrated services are implemented, users actively use *PT*, and the average number of passengers and the shared vehicle match rate become larger than when the supply/demand ratio is high. This result suggests that in the early stage of introducing shared vehicles, active provisioning of *PT*-integrated services will have a positive effect on the use of both shared vehicles and *PT*.

Analysis of the Effects of Shared Mobility and PT Integration on the Match Rate of Shared Vehicles

Figure 6 shows the simulation results for the changes in the match rate for users and shared vehicles when the supply/demand ratio increased from 10% to 100%. As shown in the graph, when the shared vehicle supply rate increased with the demand for shared vehicles, the shared vehicle match rate also increased. However, the shared vehicle match rate showed differences between the implementation and non-implementation of *PT*-integrated services. Thus, providing *PT*-integrated services is greatly helpful for improving the shared mobility match rate when the shared vehicle supply to demand ratio is low, at 10–25%. However, with an increase in the shared vehicle's supply/demand ratio, the differences in match rate between the implementation and non-implementation become smaller, and they are highly similar when the supply/demand ratio is 100%.

The difference in the shared vehicle match rate between the non-implementation and implementation of *PT*-integrated services was large when the supply/demand ratio was low, and the difference became smaller when the supply/demand ratio was high. Thus, the pattern of using personal mobility appears identical: as the shared vehicle supply level increases, the average number of passengers in the vehicle decreases and the ratio of connection with *PT* also decreases, as shown in Figure 5.

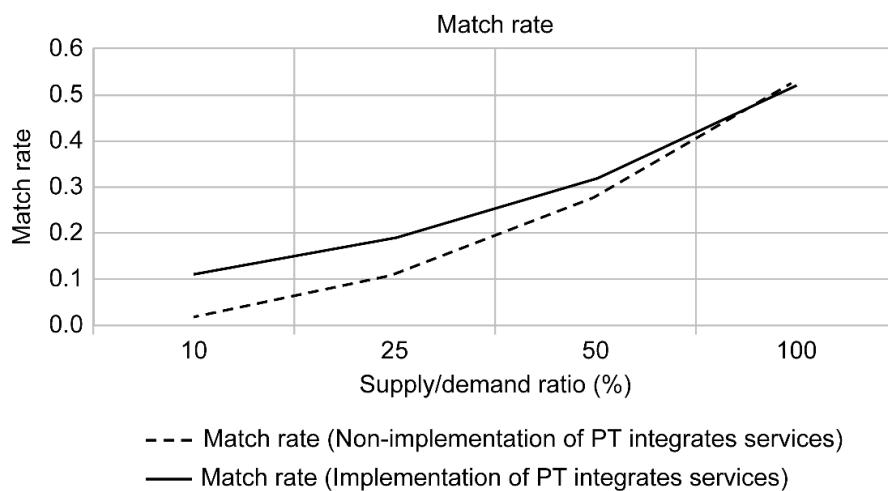


Figure 6. Effect of the provisioning of *PT*-integrated services on the match rate.

Figure 7 shows the changes in the shared vehicle match rate according to changes in the reliability of bus travel time. As shown in this graph, the reliability of bus travel time has a significant impact on the shared vehicle match rate. When the reliability of bus travel time improves from 15 min to 1 min, the shared vehicle match rate increases by 0.033 on average in the entire range of the supply/demand ratio.

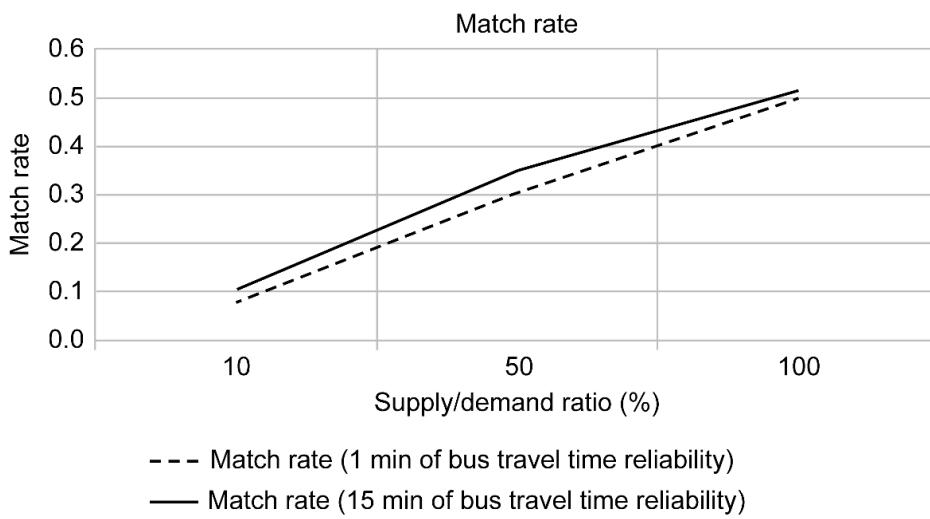


Figure 7. Effect of the reliability of bus travel time on the match rate.

Figure 8 shows the *PT* use ratio and the average number of shared mobility passengers when the reliability of bus travel time is 15 min. As the error in the reliability of bus travel time increases from 1 min to 15 min, the *PT* use ratio among the shared mobility passengers drops to almost zero. In other words, even if *PT*-integrated services are implemented, if the reliability of *PT* travel time is not secured, the role of *PT* almost disappears regardless of the supply/demand ratio. Furthermore, as the role of *PT* decreases, the average number of shared mobility passengers also converges to zero. Thus, *PT* reliability is essential for increasing the average number of shared mobility passengers.

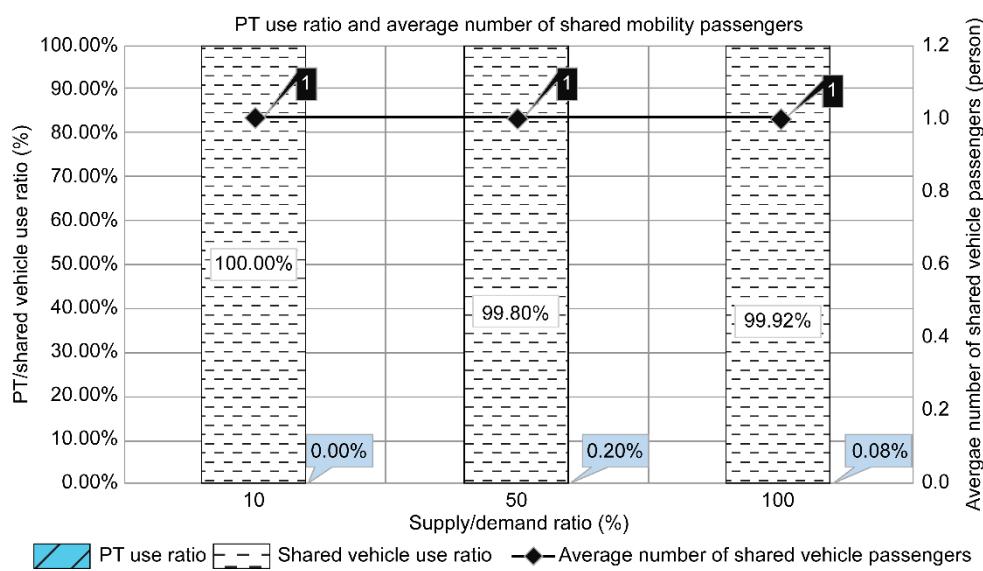


Figure 8. Changes in the *PT* use ratio and the average number of shared mobility passengers (reliability of 15 min bus travel time) according to the supply/demand ratio.

Table 4 shows changes in the shared vehicle match rate, *PT* use ratio, and average number of shared vehicle passengers according to the error in the reliability of bus travel time. A negative value in the table indicates a decrease in the shared vehicle match rate, *PT* use ratio, or average number of shared vehicle passengers as the error of bus travel time changes from 1 min to 15 min.

Table 4. Changes in the shared vehicle match rate, change of *PT* use ratio, and average number of shared vehicle passengers according to the error of the reliability of bus travel time.

Item	Supply/Demand Ratio (%)		
	10	50	100
Change of shared vehicle match rate	-0.03	-0.05	-0.02
Change of <i>PT</i> use ratio	-48.0%	-10.8%	-3.4%
Change of average number of shared vehicle passengers (persons)	-0.88	-0.9	-0.2

As shown in this table, as the error of the reliability of bus travel time increased, the shared vehicle match rate, *PT* use ratio, and average number of shared vehicle passengers all considerably decreased. Thus, even when shared mobility is activated and *PT*-integrated services are implemented, the reliability of *PT* services needs to be secured, and this reliability has a positive impact on the activation of shared mobility as well as the use of *PT*.

4.2. Analysis of City-Wide Impacts by Type of City

4.2.1. Analysis of Changes in Modal Split Ratio by Type of City

Figures 9–11 show the changes in the modal splits of *PT*, mobility-on-demand, and private vehicles according to whether *PT*-integrated services were implemented when autonomous driving and shared mobility were introduced into a type 1 city. As shown in the figures, if the supply/demand ratio of shared vehicles increased, the modal splits of *PT* and passenger vehicles decreased, whereas the modal split of mobility-on-demand increased.

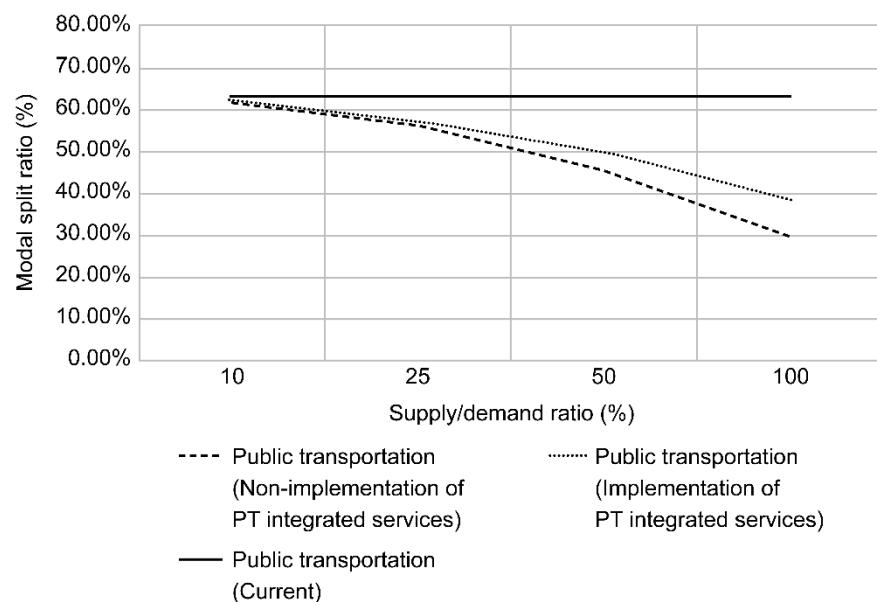


Figure 9. Changes in the modal split of PT (city type 1) depending on whether or not the PT-integrated services were implemented when autonomous driving shared mobility was introduced.

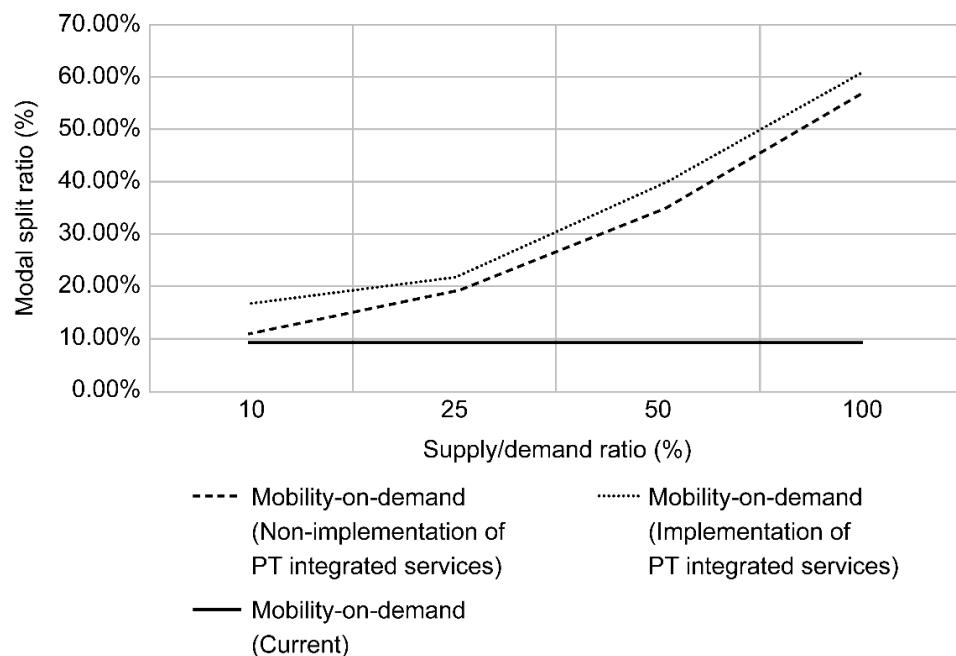


Figure 10. Changes in the modal split of mobility-on-demand (city type 1) depending on whether or not the PT-integrated services were implemented when autonomous driving shared mobility was introduced (city type 1).

The change trend of the modal split ratio showed differences depending on whether PT-integrated services were implemented. When the supply/demand ratio was 10%, the modal split of PT was 0.27% higher when PT-integrated services were implemented than when they were not implemented. This difference increased with the supply/demand ratio. When the supply/demand ratio was 100% and PT-integrated services were implemented, the modal split of PT increased by 9.02%.

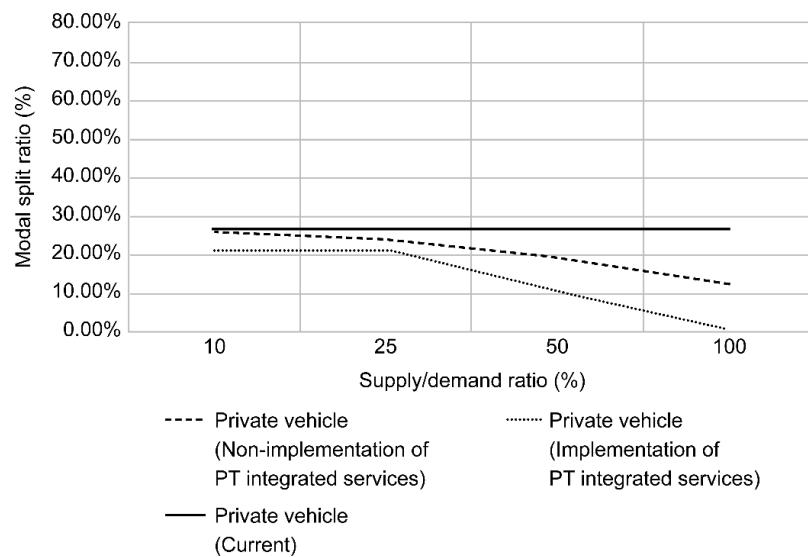


Figure 11. Changes in the modal split of private vehicles (city type 1) depending on whether or not the *PT*-integrated services were implemented when autonomous driving shared mobility was introduced (city type 1).

Figures 12–14 show the changes in the modal splits of *PT*, mobility-on-demand, and private vehicles depending on whether *PT*-integrated services were implemented when autonomous driving and shared mobility were introduced into a type 2 city. As shown in the figures, the modal split of *PT* was constant, regardless of the supply/demand ratio of the shared vehicle. However, as the supply/demand ratio of the shared vehicles increased, the modal split of private vehicles decreased, whereas the modal split of mobility-on-demand increased. The changes in the modal split ratio show some differences depending on the implementation of *PT*-integrated services. The modal split of *PT* was similar to the modal split of *PT* when the *PT*-integrated services were not implemented changed little. It increased by 4.51%p (supply/demand ratio 10%) at the maximum and 1.56%p (supply/demand ratio 100%) at the minimum only when *PT*-integrated services were implemented. The modal split of mobility-on-demand increased sharply with the supply/demand ratio by 11.72%p (*PT*-integrated services not implemented, supply/demand ratio 10%) or a minimum of 62.72%p (*PT*-integrated services not implemented, supply/demand ratio 100%).

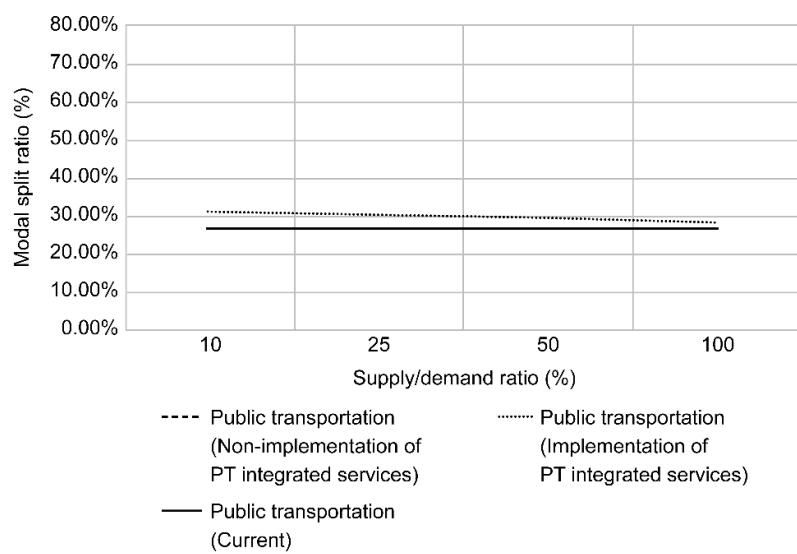


Figure 12. Changes in the modal split of *PT* depending on whether *PT*-integrated services were implemented or not when autonomous driving shared mobility was introduced (type 2 city).

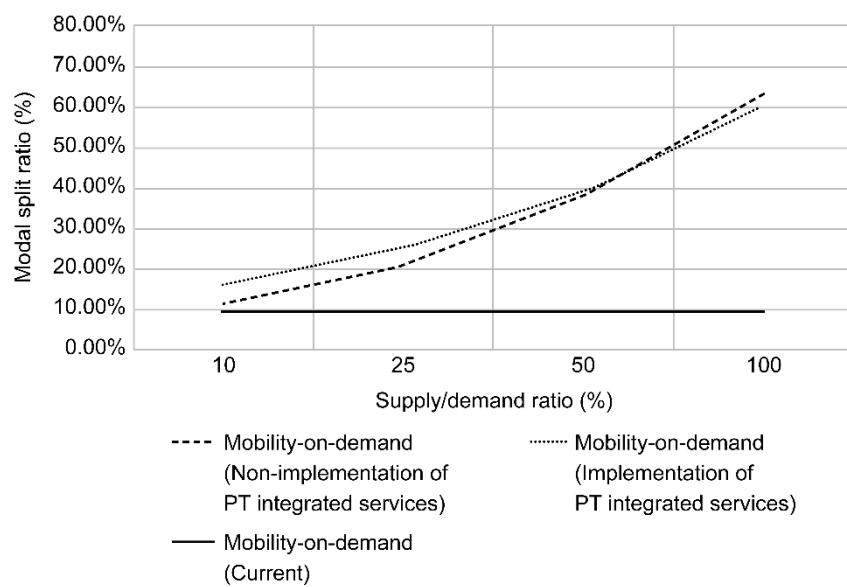


Figure 13. Changes in the modal split ratio of mobility-on-demand depending on whether PT-integrated services were implemented or not when autonomous driving shared mobility was introduced (type 2 city).

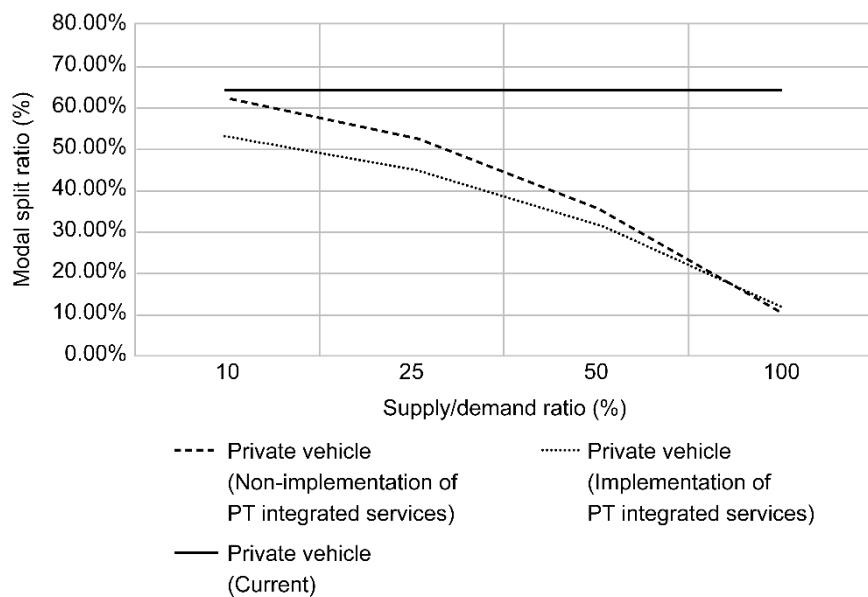


Figure 14. Changes in the modal split of private vehicles depending on whether PT-integrated services were implemented or not when autonomous driving shared mobility was introduced (type 2 city).

Table 5 shows the changes in the modal split of PT depending on whether PT-integrated services were implemented by the type of city. As shown in this table, the implementation of PT-integrated services positively affected the modal split of PT in every city type. However, the effects and roles differed by city type. In a type 1 city where the existing PT was well maintained and there was a high modal split of PT, the introduction of shared mobility service lowered the modal split of PT in general. However, we found that implementing PT-integrated services could lower the reduction of the PT use rate through autonomous driving. In a type 2 city where the modal split ratio of the existing PT was low, the negative effect of introducing shared mobility services on PT was somewhat insignificant. Unlike type 1 cities, we found that the implementation of PT-integrated services increased the modal split of PT in the city. Therefore, it is expected that introducing

PT-integrated services and shared mobility services will improve the satisfaction of citizens regarding *PT* in type 2 cities.

Table 5. Changed in the modal split of *PT* by the type of city according to the introduction of autonomous driving shared mobility.

Classification	Supply/Demand Ratio (%)				
	10%	25%	50%	100%	
Type 1 city	Current	63.14%	63.14%	63.14%	63.14%
	Non-implementation of <i>PT</i> -integrated services	61.88%	56.19%	45.46%	29.68%
Type 2 city	Implementation of <i>PT</i> -integrated services	62.15%	57.25%	50.02%	38.70%
	Current	26.45%	26.45%	26.45%	26.45%
Type 2 city	Non-implementation of <i>PT</i> -integrated services	26.45%	26.45%	26.45%	26.45%
	Implementation of <i>PT</i> -integrated services	30.96%	30.06%	29.33%	28.01%

Figures 15 and 16 show the changes in the modal splits of *PT* and mobility-on-demand according to the reliability error of arrival time for *PT* when autonomous driving and shared mobility were introduced into a type 1 city. As shown in the figures, the effect of reliability of arrival time on the modal split ratio was insignificant in a type 1 city.

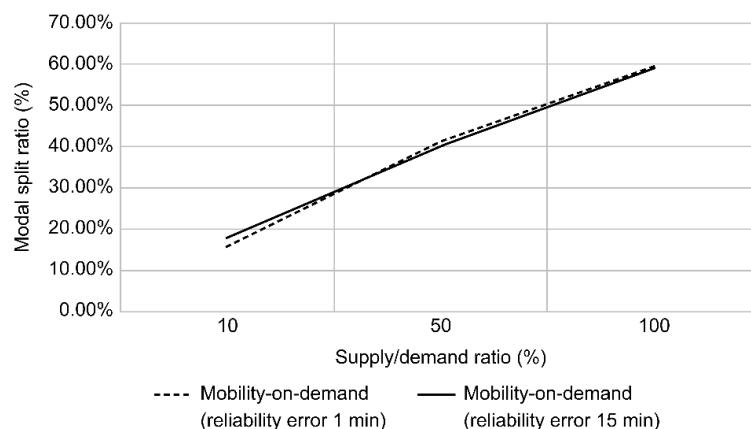


Figure 15. Changes in the modal split of *PT* according to the reliability error of arrival time for *PT* when autonomous driving shared mobility was introduced (type 1 city).

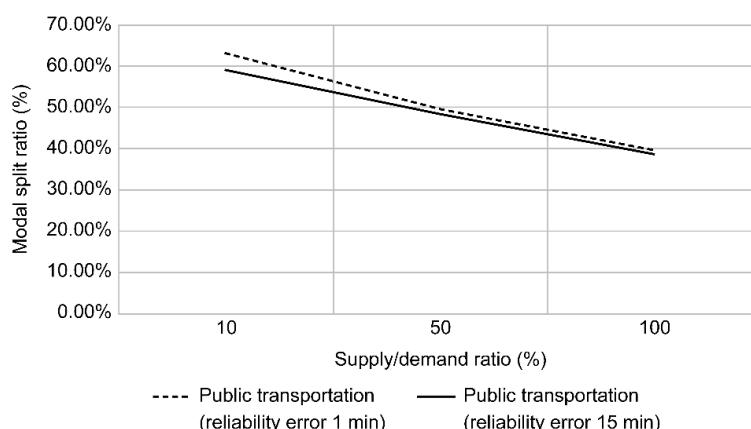


Figure 16. Changes in the modal split of mobility-on-demand according to the reliability error of arrival time for *PT* when autonomous driving shared mobility was introduced (type 1 city).

Figures 17 and 18 show the changes in the modal splits of *PT* and mobility-on-demand according to the reliability error of arrival time for *PT* when autonomous driving and shared mobility were introduced into a type 2 city. As shown in the figures, in a type 2 city, the reliability of arrival time had a considerable impact on the modal split ratio. In this type of city, we observed that an up to 32% modal split of *PT* could be secured through the reliability of arrival time for *PT*. This was analyzed to increase the modal split of *PT* by up to 5.28%p (supply/demand ratio 10%) compared to the case where the reliability error of arrival time for *PT* was 15 min.

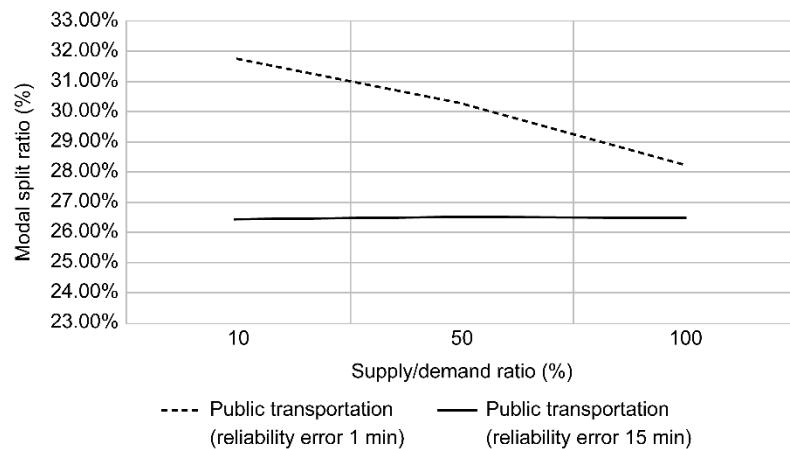


Figure 17. Changes in the modal split of *PT* according to the reliability error of arrival time for *PT* when autonomous driving shared mobility was introduced (type 2 city).

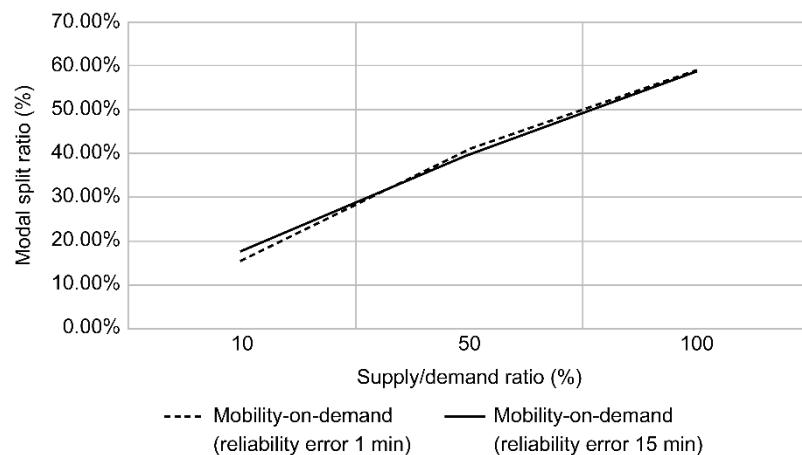


Figure 18. Changes in the modal split of mobility-on-demand according to the reliability error of arrival time for *PT* when autonomous driving shared mobility was introduced (type 2 city).

As shown in Figure 17, the changes in the reliability error of the arrival time for *PT* had almost no effect on the modal split of mobility-on-demand. From this analysis, it can be inferred that in a type 2 city, the reliability of arrival time for *PT* will decrease the modal split of private vehicles more effectively. For effective application of *PT* and shared mobility to a city, it is essential to achieve reliability of the arrival time for *PT*.

Table 6 shows the changes in the modal split of *PT* according to the type of city, based on the changes in the reliability of arrival time for *PT*. As shown in this table, the reliability of arrival time for *PT* had a positive effect on the modal split of *PT* in both types of city. However, the effects and roles differed according to the type of city. In a type 1 city where the existing *PT* was well maintained and the modal split of *PT* was high, the effect of reliability of arrival time for *PT* on the modal split of *PT* was insignificant.

Table 6. Changes in the modal split of PT by type of city according to the reliability of arrival time for PT.

Classification	Supply/Demand Ratio (%)		
	10%	50%	100%
Type 1 city	Current	63.14%	63.14%
	Reliability error 15 min	59.14%	48.20%
	Reliability error 1 min	62.92%	49.49%
Type 2 city	Current	26.45%	26.45%
	Reliability error 15 min	26.45%	26.51%
	Reliability error 1 min	31.73%	30.30%

In a type 2 city where the modal split of existing PT is low, the reliability of arrival time for PT is expected to improve the current modal split of PT by up to 5.28%p (supply/demand ratio 10%). However, if the reliability of arrival time for PT is not achieved, the modal split ratio of the PT will be similar to the current value. To summarize these results, the reliability of arrival time for PT is extremely important for increasing the modal split of PT in a type 2 city.

4.2.2. Analysis of the Change Rate of the Private Vehicle Traffic by Type of City

Figure 19 shows the estimated change rate of private vehicles depending on whether PT-integrated services were implemented and whether services based on AVs were provided. As shown in this figure, when PT-integrated services are implemented, the use rate of passenger vehicles is expected to stay the same or is expected to decrease. By contrast, if PT-integrated services are not implemented, the use rate of passenger vehicles should increase sharply. From this result, it is inferred that when a shared mobility service is implemented alone, traffic congestion will increase because of the increase in vehicles in a type 1 city. Providing shared mobility services with AVs together with the implementation of PT-integrated services is an important factor when estimating change rate of private vehicles. As shown in Figure 19, providing services related to AVs in general is more advantageous for reducing the use rate of passenger vehicles. In particular, it is expected that road congestion in cities such as Seoul can be reduced only when shared mobility services are provided based on AVs while implementing PT-integrated services.

Figure 20 shows the estimated change rate of private vehicles depending on whether PT-integrated services were implemented and whether services based on AVs were provided for a type 2 city. Unlike type 1 cities, the use rate of passenger vehicles decreased in all cases except for one scenario (PT-integrated services not implemented, service based on non-autonomous vehicles) when shared mobility services were introduced in a type 2 city. This result proves that when shared mobility services are introduced into a type 2 city, congestion will decrease or a similar level will be maintained. It was observed that, in general, the reduction rate of passenger vehicles was large when shared mobility services based on autonomous driving were provided or PT-integrated services were implemented. In particular, the reduction rate when autonomous driving and PT-integrated services were simultaneously implemented was 25.19%p (supply/demand ratio 10%) to -54.60%p (supply/demand ratio 100%), which yielded the largest suppression effect.

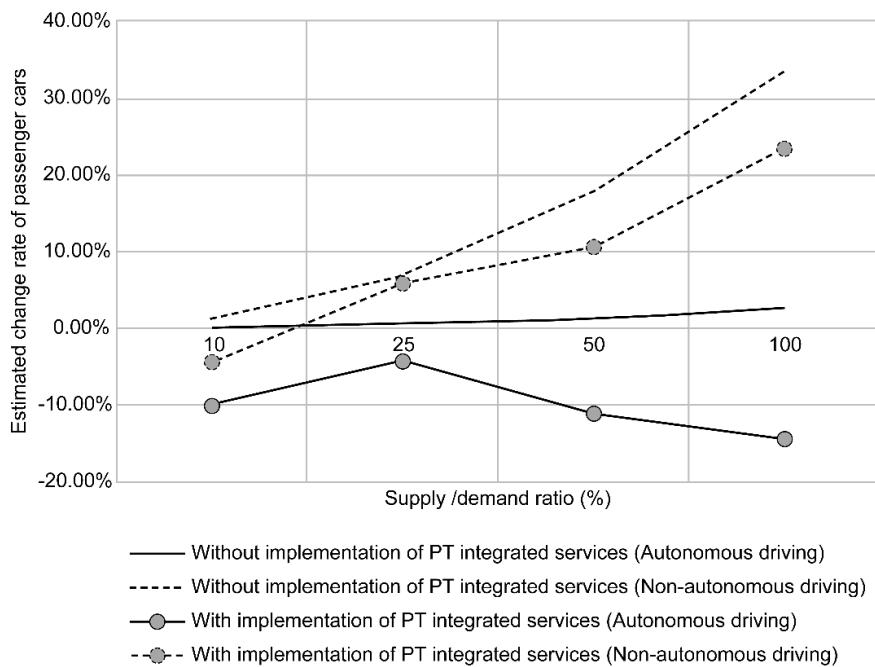


Figure 19. Estimated change rate of private vehicles depending on whether *PT*-integrated services were implemented or not and whether services based on AVs were provided or not (type 1 city).

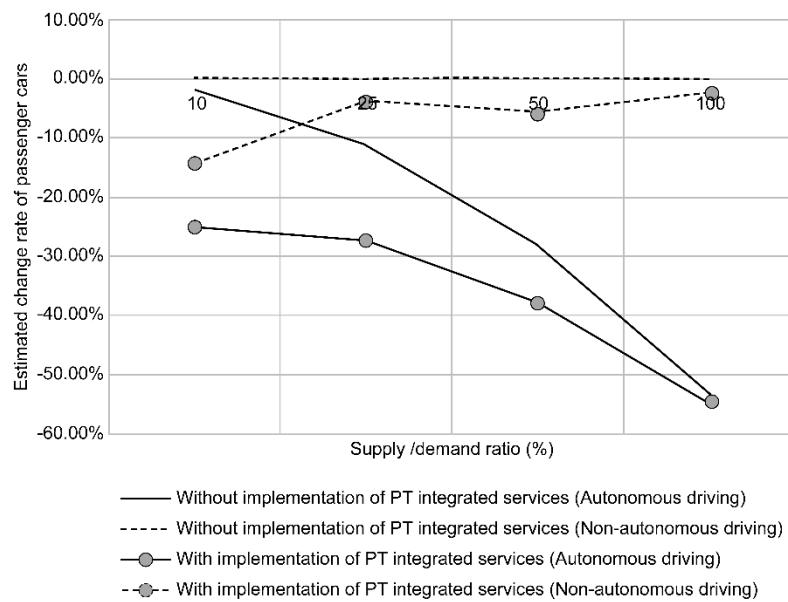


Figure 20. Estimated change rate of private vehicles depending on whether *PT*-integrated services were implemented and whether services based on AVs were provided (type 2 city).

Table 7 shows the estimated change rate of private vehicles by city type. As shown in this table, the use of passenger vehicles is expected to decrease only when *PT*-integrated services and shared mobility services based on AVs are provided simultaneously in a type 1 city. In other cases, road congestion is expected to increase because of shared mobility, and countermeasures must be established, such as limiting the supply of shared vehicles.

Table 7. Estimated change rate of private vehicles by type of city.

Classification		Supply/Demand Ratio (%p)			
		10%	25%	50%	100%
Type 1 city	Non-implementation of PT-integrated services	Non-autonomous driving	1.26%p	6.95%p	17.68%p
		Autonomous driving	0.10%p	0.54%p	1.37%p
	Implementation of PT-integrated services	Non-autonomous driving	-4.31%p	5.89%p	10.60%p
		Autonomous driving	-10.00%p	-4.19%p	-11.16%p
Type 2 city	Non-implementation of PT-integrated services	Non-autonomous driving	0.00%p	0.00%p	0.00%p
		Autonomous driving	-2.00%p	-11.00%p	-28.00%p
	Implementation of PT-integrated services	Non-autonomous driving	-14.19%p	-3.61%p	-5.76%p
		Autonomous driving	-25.19%p	-27.17%p	-37.76%p

In a type 2 city, it is expected that shared mobility will have a positive effect on reducing congestion. In particular, the congestion reduction effect is expected to be the largest when PT-integrated services and autonomous driving are simultaneously provided. However, a considerable congestion reduction effect is expected only by the application of AVs.

Figure 21 shows the estimated change rate of private vehicles according to the changes in the reliability error of the arrival time for PT. As shown in this figure, the reliability of bus travel time has a significant effect on the estimated reduction rate of passenger vehicles. Providing the same shared mobility service when the reliability error of arrival time for PT was 1 min additionally reduced the passenger vehicle use by 1.72%p (non-autonomous driving, supply/demand ratio 100%) to -8.72%p (non-autonomous driving, supply/demand ratio 10%) compared to when the reliability error of arrival time for PT was 15 min. However, we found that introducing shared mobility services based on AVs together with achieving reliability of arrival time for bus traffic was more effective at reducing congestion in a type 1 city.

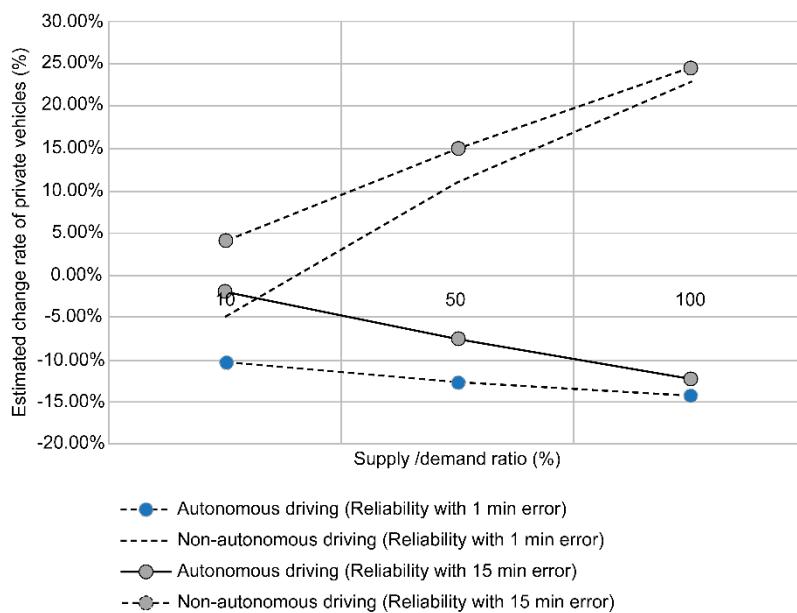
**Figure 21.** Estimated change rate of private vehicles according to the reliability error of arrival time for PT (type 1 city).

Figure 22 shows the effect of a change in the reliability error of arrival time for PT on the estimated change rate of private vehicles in a type 2 city. As shown in this figure,

the reliability of bus travel time significantly reduced the use of passenger vehicles. This effect was the largest when the reliability error of the arrival time for PT was 1 min and the shared mobility services were provided by AVs. This scenario reduced the use of passenger vehicles by -25.96% to -49.04% when compared with the scenario with the smallest effect on non-autonomous vehicles, which was when the reliability of arrival time for PT error was 15 min. In other words, it is expected that the reliability of arrival time for PT and the application of AVs will significantly suppress traffic congestion.

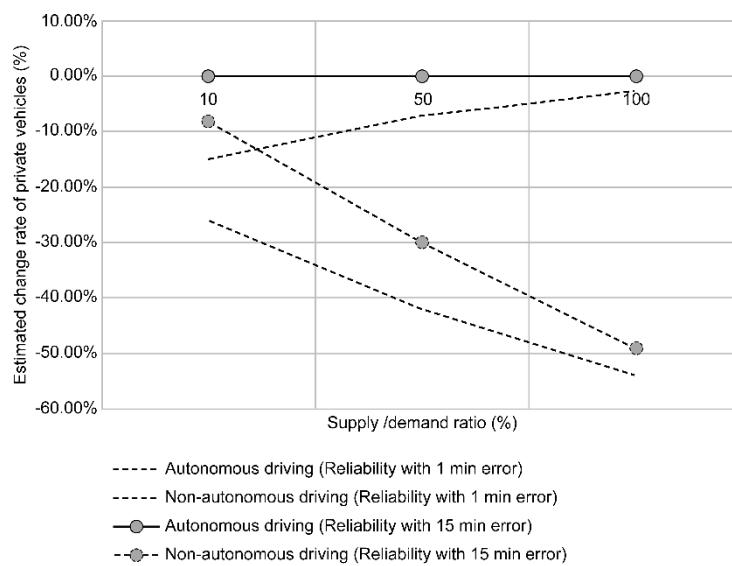


Figure 22. Estimated change rate of private vehicles according to the reliability error of arrival time for PT (type 2 city).

Table 8 shows the estimated change rate of private vehicles for each city type according to the change in the reliability of arrival time for PT. As shown in this table, the reliability of arrival time for PT could reduce the use of passenger vehicles in both types of city. However, the effect differed depending on the type of city. In a type 1 city, the use of passenger vehicles decreased by 10% or more when shared mobility services based on AVs were provided and the reliability error of arrival time for PT was 1 min. In a type 2 city, it is expected that the introduction of shared mobility will have a positive effect on the reduction of road congestion in general. In particular, the congestion reduction effect is expected to be the largest when the reliability of the arrival time for PT is achieved and AVs are applied simultaneously. However, a considerable road congestion reduction effect is expected with the application of AVs only (supply / demand ratio is 50% or 100%) or when the reliability of bus arrival time is achieved (when the supply / demand ratio is 10%).

Table 8. Estimated change rate of private vehicles according to the reliability of arrival time for PT by type of city.

Classification		Supply/Demand Ratio (%p)			
		10%	50%	100%	
Type 1 city	Non-implementation of PT-integrated services	Reliability with 15 min error	4.00%p	14.94%p	24.46%p
		Reliability with 1 min error	-4.72%p	10.95%p	22.74%p
	Implementation of PT-integrated services	Reliability with 15 min error	-2.00%p	-7.53%p	-12.27%p
		Reliability with 1 min error	-10.26%p	-12.54%p	-14.27%p
Type 2 city	Non-implementation of PT-integrated services	Reliability with 15 min error	0.00%p	-0.06%p	-0.04%p
		Reliability with 1 min error	-14.96%p	-7.00%p	-2.81%p
	Implementation of PT-integrated services	Reliability with 15 min error	-8.00%p	-30.06%p	-49.04%p
		Reliability with 1 min error	-25.96%p	-42.00%p	-53.81%p

5. Conclusions

In this study, we aimed to analyze the impacts of SAVs on PT systems in metropolitan areas. First, we developed an analysis method based on an agent-based simulation to understand how local travelers' choices changed between SAVs and PT. Then, using the properties of the simulated results, we proposed a city-wide impact analysis method that can reflect the differences in travel behavior by urban type. Based on this combined approach of the two different analyses, we analyzed the potential impacts of future SAV operations on existing PT systems, in different types of cities.

As a result of the analyzes, different impacts were derived for metropolitan cities based on private vehicle traffic (type 2 city). In a metropolitan city where a relatively high level of PT services is provided and the use of passenger vehicles is close to saturation, the following measures and preparations are required to reduce congestion and activate PT services: The simulation results showed that in a metropolitan city, the introduction of shared mobility and expansion of supply level significantly decreased the demand for private vehicles but also increased the modal change from PT to shared mobility.

In a metropolitan city, if shared mobility is expanded to provide convenience of using transport services and to expand the opportunities for service options, it could decrease the modal split of PT and increase road traffic. This could be a new dilemma for many European and Asian cities wherein significant amounts of daily travel are done by public transportation. To avoid this dilemma, a new operating strategy must be established. Depending on the traffic demand pattern and PT lines in the city where shared mobility is applied, the introduction of shared mobility can have advantages, but it also has clear limitations, such as an increase in vehicle traffic on the road. To overcome these limitations, we need the following conditions: the usable hours of shared mobility must be limited, PT-centered lines must be activated, and flexibility in PT operations must be achieved.

Therefore, the implementation of integrated mobility providing the optimal mobility service should be promoted simultaneously with the introduction of AVs. As shown in the simulation results, the integrated services of PT and other modes of transportation could offset traffic congestion and other adverse effects. Furthermore, in the era of autonomous driving and shared mobility, extra efforts should be made to improve the level of service of PT. For this, efforts need to be made to secure the flexibility of PT operations, achieve reliability for travel times, and secure efficiency for intensive line operations.

In a type 2 city where the modal split ratio for private vehicles is high and PT is operated only for core lines, the following measures and preparations are required to reduce traffic congestion and to maintain a desirable level of PT. If the modal split of private vehicles is high, the modal shift from private vehicles to shared mobility can have a significant effect, depending on the supply level of shared mobility. Hence, we must consider introducing and expanding shared mobility as an alternative for demand management, congestion management, and pollution management. In addition, to reduce additional disadvantages due to the introduction of shared mobility, measures such as redesigning stops for shared mobility, expansion of waiting facilities, and establishment of transfer facilities or PT-shared mobility transfer facilities are required. To reduce traffic on the road while maintaining the modal split of PT at a viable level, improving PT, for instance, via the reliability of bus travel time, is indispensable. To that end, improvement measures such as the development and application of a signal optimization system for sections with low reliability of travel time, and the introduction of bus-only lanes are required. Furthermore, to achieve flexibility of bus operations when the supply of shared mobility is expanded, a real-time coordination system for bus lines and dispatches must be introduced, and integrated mobility services that provide optimal mobility services to users by linking PTs and other modes of transportation must be implemented simultaneously in the future. The work of Shen et al. [19] supports the point that increased coordination between PT and SAV would lead to higher efficiency. To actively respond to the demand for shared mobility and PT in the mid to long-term, it is necessary to review special measures to increase the operational efficiency of shared services by introducing AVs. In fact, to

achieve flexible coordination, the information sharing system should be well-organized between public (*PT*) and private businesses (*SAV*). Hence, the local authorities have to actively support the data governance for *PT–SAV* interactive systems.

Although this study has provided insightful analyses, it possesses a few limitations. We estimated the rate of change of private vehicles, under the assumption that it would reflect the changes in the congestion levels within cities. Hence, a more direct approach for estimating future congestion levels should be considered in future studies. Moreover, this study classified cities into only two different types depending on the characteristics of the *PT* system and privately owned vehicles. Alternative approaches may be explored in further studies for classifying city types based on other urban attributes, such as urbanization and street patterns. In addition, some economy-based analyses may support the points made in this study for the future task of properly beginning *SAV* operations.

It is difficult to know whether the development of autonomous driving technology will be completed and unmanned vehicles will be commercialized in the near future. However, *AV* technology continues to be applied for shared vehicles and acts as a factor that significantly changes the roles of the existing modes of transportation. Currently, shared mobility is becoming a competitive mode for taxi and rental car services, and its role will increase when car sharing and ride sharing are implemented with *AVs* in the future. Furthermore, when the technology of *AVs* is developed and shared mobility is expanded, it is expected that the role of shared mobility will be considered as a viable mode of transportation—that is, a vehicle that can provide mobility services, rather than standing as an asset.

In consideration of the type of city, further research needs to be done to study the changes in the roles and functions of *PT* and shared mobility according to the technological development steps. Furthermore, it is expected that the effects of introducing autonomous driving and shared mobility services will appear differently depending on urban conditions, such as the level of urban transportation. Therefore, for future studies, *PT* service strategies and shared mobility service strategies must consider the level of autonomous driving technology, time of commercialization, and supply stage.

There are many policy aspects to consider in regard to autonomous and shared transportation services. First, it is critical to conduct a pilot operation of an actual mobility service, in order to find a service model that fits the local conditions and characteristics of each city and redefine the public transportation function. This may require establishing a legal basis to materialize and operate such a service. Second, the equitable use of the services must be ensured so that the vulnerable populations, such as the disabled, the elderly, children, and low-income groups, will not be excluded from the benefits. Shared transportation can improve efficiency, especially in large cities by alleviating the undersupply issue of public transit services and complementing the peak hour supply, but in doing so, the vulnerable population should not be overlooked. Third, there are vulnerable and scarce areas, such as rural and mountainous regions, where public transit services do not operate as efficiently as other areas. In such areas, shared transportation can be used to improve the access to mobility and social welfare for the residents. For instance, policies can be implemented to allow flexible operation of the passenger transport service laws and to modify standards for transportation platform industries. Fourth, it will be necessary to control the dead cruising of autonomous vehicles with no passengers and the possible increase of passenger demand that may occur with a new transportation service. The government agencies and industries must discuss policies to help solve the issues that can exacerbate climate change. Potential policies include incentivizing the shared use of automated vehicles, pricing of automated driving infrastructure, and financing for public transit operations.

Author Contributions: Conceptualization, S.T. and S.K.; methodology, S.T. and S.W.; validation, S.T. and S.P.; formal analysis, S.T.; investigation, S.K., S.T. and S.W.; data curation, S.T.; writing—original draft preparation, S.T. and S.K.; writing—review and editing, S.K. and S.P.; visualization, S.T. and S.K.; supervision, S.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Ministry of Land, Infrastructure, and Transport (MOLIT, KOREA) (Project ID: 21AMDP-C160548-01, project name: Development of Autonomous Mobility Service Technology to support the Transport Vulnerable (National R&D Project)).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data set files are available from the public repository (GitHub) database (<https://github.com/Dr-SKim/2021-05>) (accessed on 14 June 2021), doi: 10.5281/zenodo.4885184).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. De Almeida Correia, G.H.; van Arem, B. Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility. *Transp. Res. B Methodol.* **2016**, *87*, 64–88. [[CrossRef](#)]
2. Krueger, R.; Rashidi, T.H.; Rose, J.M. Preferences for shared autonomous vehicles. *Transp. Res. C* **2016**, *69*, 343–355. [[CrossRef](#)]
3. Menon, N.; Barbour, N.; Zhang, Y.; Pinjari, A.R.; Mannerling, F. Shared autonomous vehicles and their potential impacts on household vehicle ownership: An exploratory empirical assessment. *Int. J. Sustain. Transp.* **2019**, *13*, 111–122. [[CrossRef](#)]
4. Brownell, C.; Kornhauser, A. A driverless alternative: Fleet size and cost requirements for a statewide Autonomous Taxi Network in New Jersey. *Transp. Res. Rec.* **2014**, *2416*, 73–81. [[CrossRef](#)]
5. Clements, L.M.; Kockelman, K.M. Economic effects of automated vehicles. *Transp. Res. Rec.* **2017**, *2606*, 106–114. [[CrossRef](#)]
6. Heilig, M.; Hilgert, T.; Mallig, N.; Kagerbauer, M.; Vortisch, P. Potentials of autonomous vehicles in a changing private transportation system—A case study in the Stuttgart region. *Transp. Res. Procedia* **2017**, *26*, 13–21. [[CrossRef](#)]
7. Fagnant, D.J.; Kockelman, K.M. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. *Transportation* **2018**, *45*, 143–158. [[CrossRef](#)]
8. Jäger, B.; Brickwedde, C.; Lienkamp, M. Multi-agent simulation of a demand-responsive transit system operated by autonomous vehicles. *Transp. Res. Rec.* **2018**, *2672*, 764–774. [[CrossRef](#)]
9. Daganzo, C.F. An approximate analytic model of many-to-many demand responsive transportation systems. *Transp. Res.* **1978**, *12*, 325–333. [[CrossRef](#)]
10. Wilson, N.H.M.; Hendrickson, C. Performance models of flexibly routed transportation services. *Transp. Res. B* **1980**, *14*, 67–78. [[CrossRef](#)]
11. Diana, M.; Quadrifoglio, L.; Pronello, C. A methodology for comparing distances traveled by performance-equivalent fixed-route and demand responsive transit services. *Transp. Plan. Technol.* **2009**, *32*, 377–399. [[CrossRef](#)]
12. Li, X.; Quadrifoglio, L. Feeder transit services: Choosing between fixed and demand responsive policy. *Transp. Res. C* **2010**, *18*, 770–780. [[CrossRef](#)]
13. Qiu, F.; Li, W.; Haghani, A. A methodology for choosing between fixed-route and flex-route policies for transit services. *J. Adv. Transp.* **2015**, *49*, 496–509. [[CrossRef](#)]
14. Chang, S.K.; Schonfeld, P.M. Integration of fixed- and flexible-route bus systems. *Transp. Res. Board J. Transp. Res. Board* **1991**, *1308*, 51–57.
15. Aldaihani, M.M.; Quadrifoglio, L.; Dessouky, M.M.; Hall, R. Network design for a grid hybrid transit service. *Transp. Res. A* **2004**, *38*, 511–530. [[CrossRef](#)]
16. Li, X.; Quadrifoglio, L. Optimal zone design for feeder transit services. *Transp. Res. Rec.* **2009**, *2111*, 100–108. [[CrossRef](#)]
17. Chen, T.D.; Kockelman, K.M. Management of a shared autonomous electric vehicle fleet: Implications of pricing schemes. *Transp. Res. Rec.* **2016**, *2572*, 37–46. [[CrossRef](#)]
18. Mendes, L.M.; Bennàssar, M.R.; Chow, J.Y.J. Comparison of light rail streetcar against shared autonomous vehicle fleet for Brooklyn–Queens connector in New York City. *Transp. Res. Rec.* **2017**, *2650*, 142–151. [[CrossRef](#)]
19. Shen, Y.; Zhang, H.; Zhao, J. Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore. *Transp. Res. A* **2018**, *113*, 125–136. [[CrossRef](#)]
20. Dia, H.; Javanshour, F. Autonomous shared mobility-on-demand: Melbourne pilot simulation study. *Transp. Res. Procedia* **2017**, *22*, 285–296. [[CrossRef](#)]
21. Overtoom, I.; Correia, G.; Huang, Y.; Verbraeck, A. Assessing the impacts of shared autonomous vehicles on congestion and curb use: A traffic simulation study in the Hague, Netherlands. *Int. J. Transp. Sci. Technol.* **2020**, *9*, 195–206. [[CrossRef](#)]
22. Horni, A.; Nagel, K.; Axhausen, K.W. *The Multi-Agent Transport Simulation MATSim, the Multi-Agent Transport Simulation MATSim*; Ubiquity Press: London, UK, 2016. [[CrossRef](#)]
23. Liu, J.; Kockelman, K.M.; Boesch, P.M.; Ciari, F. Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. *Transportation* **2017**, *44*, 1261–1278. [[CrossRef](#)]

24. Hamadneh, J.; Esztergar-Kiss, D. Impacts of shared autonomous vehicles on the travelers' mobility. In Proceedings of the MT-ITS 2019—6th International Conference on Models and Technologies for Intelligent Transportation Systems, Cracow, Poland, 5–7 June 2019. [CrossRef]
25. Vosooghi, R.; Puchinger, J.; Jankovic, M.; Vouillon, A. Shared autonomous vehicle simulation and service design. *Transp. Res. Part C: Emerg. Technol.* **2019**, *107*, 15–33. [CrossRef]
26. Simoni, M.D.; Kockelman, K.M.; Gurumurthy, K.M.; Bischoff, J. Congestion pricing in a world of self-driving vehicles: An analysis of different strategies in alternative future scenarios. *Transp. Res. C* **2019**, *98*, 167–185. [CrossRef]
27. Moreno, A.T.; Michalski, A.; Llorca, C.; Moeckel, R. Shared autonomous vehicles effect on vehicle-Km traveled and average trip duration. *J. Adv. Transp.* **2018**, *2018*, 8969353. [CrossRef]
28. Bischoff, J.; Maciejewski, M. Autonomous taxicabs in Berlin—A spatiotemporal analysis of service performance. *Transp. Res. Procedia* **2016**, *19*, 176–186. [CrossRef]
29. Martinez, L.M.; Viegas, J.M. Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. *Int. J. Transp. Sci. Technol.* **2017**, *6*, 13–27. [CrossRef]
30. Alazzawi, S.; Hummel, M.; Kordt, P.; Sickenerger, T.; Wiesoette, C.; Wohak, O. Simulating the impact of shared, autonomous vehicles on urban mobility—A case study of Milan. *EPiC Ser. Eng.* **2018**, *2*, 94–110. [CrossRef]
31. Lokhandwala, M.; Cai, H. Dynamic ride sharing using traditional taxis and shared autonomous taxis: A case study of NYC. *Transp. Res. C* **2018**, *97*, 45–60. [CrossRef]
32. Chen, T.D.; Kockelman, K.M.; Hanna, J.P. Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. *Transp. Res. A* **2016**, *94*, 243–254. [CrossRef]
33. Dlugosch, O.; Brandt, T.; Neumann, D. Combining analytics and simulation methods to assess the impact of shared, autonomous electric vehicles on sustainable urban mobility. *Inf. Manag.* **2020**, *103285*. [CrossRef]
34. Narayanan, S.; Chaniotakis, E.; Antoniou, C. Shared autonomous vehicle services: A comprehensive review. *Transp. Res. C* **2020**, *111*, 255–293. [CrossRef]
35. Williams, E.; Das, V.; Fisher, A. Assessing the Sustainability Implications of Autonomous Vehicles: Recommendations for Research Community Practice. *Sustainability* **2020**, *12*, 1902. [CrossRef]
36. Ongel, A.; Loewer, E.; Roemer, F.; Sethuraman, G.; Chang, F.; Lienkamp, M. Economic assessment of autonomous electric microtransit vehicles. *Sustainability* **2019**, *11*, 648. [CrossRef]
37. Alam, M.J.; Habib, M.A. Investigation of the impacts of shared autonomous vehicle operation in Halifax, Canada using a dynamic traffic microsimulation model. *Procedia Comput. Sci.* **2018**, *130*, 496–503. [CrossRef]
38. Fagnant, D.J.; Kockelman, K.M. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transp. Res. C* **2014**, *40*, 1–13. [CrossRef]
39. Masoud, N.; Jayakrishnan, R. Autonomous or driver-less vehicles: Implementation strategies and operational concerns. *Transp. Res. E* **2017**, *108*, 179–194. [CrossRef]
40. Childress, S.; Nichols, B.; Charlton, B.; Coe, S. Using an activity-based model to explore the potential impacts of automated vehicles. *Transp. Res. Rec.* **2015**, *2493*, 99–106. [CrossRef]
41. Wang, K.; Akar, G. Factors affecting the adoption of autonomous vehicles for commute trips: An analysis with the 2015 and 2017 Puget Sound travel surveys. *Transp. Res. Rec.* **2019**, *2673*, 13–25. [CrossRef]
42. Shokoohyar, S.; Sobhani, A.; Narges, S.R.R. On the determinants of Uber accessibility and its spatial distribution: Evidence from Uber in Philadelphia. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2020**, *10*, e1362. [CrossRef]
43. Shokoohyar, S.; Sobhani, A.; Sobhani, A. Impacts of trip characteristics and weather condition on ride-sourcing network: Evidence from Uber and Lyft. *Res. Transp. Econ.* **2020**, *80*, 100820. [CrossRef]
44. Shokoohyar, S.; Shokoohyar, S.; Sobhani, A.; Gorizi, A.J. Shared mobility in post-COVID era: New challenges and opportunities. *Sustain. Cities Soc.* **2021**, *67*, 102714. [CrossRef]
45. Salazar, M.; Rossi, F.; Schiffer, M.; Onder, C.H.; Pavone, M. On the interaction between autonomous mobility-on-demand and public transportation systems. In Proceedings of the 2018 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, HI, USA, 4–7 November 2018; pp. 2262–2269. [CrossRef]
46. Pinto, H.K.R.F.; Hyland, M.F.; Mahmassani, H.S.; Verbas, I.Ö. Joint design of multimodal transit networks and shared autonomous mobility fleets. *Transp. Res. C* **2020**, *113*, 2–20. [CrossRef]
47. Korea Transport Database. National Passenger OD Totalization and Future Demand Forecast of Korea in 2017. 2018. Available online: <https://www.ktdb.go.kr/www/selectPblcteWebView.do?key=36&pblcteNo=429> (accessed on 12 March 2021).
48. Lang, N.S.; Reusmann, M.; Collie, B.E.; Wegscheider, A.K.; Moavenzadeh, J.; Loane, M. Reshaping Urban Mobility with Autonomous Vehicles—Lessons from the city of Boston. World Economic Forum: June. 2018. Available online: http://www3.weforum.org/docs/WEF_Reshaping_Urban_Mobility_with_Autonomous_Vehicles_2018.pdf (accessed on 12 March 2021).