WILLINGNESS TO PAY FOR SHARED AUTONOMOUS VEHICLES AS LAST-MILE MOBILITY: A CASE STUDY BETWEEN RAILWAY STATIONS AND UNIVERSITY CAMPUSES IN JAPAN

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Combining shared autonomous vehicles service with public transport systems as the last-mile transportation can improve people's egress travel, which in turn promote the use of public transportation. There are many studies that have analysed people's intention to use and trust in shared autonomous vehicles as the last-mile mobility service, while there are few studies that quantitatively investigate such intention and trust by monetary value. This study used a stated preference survey to quantitatively analyse students' willingness to pay for shared autonomous vehicles from railway stations to campuses of the Kobe University. The results showed that there was no specific resistance to using this service. For students, there is no significant difference between this service and taxi service. This result suggests that shared autonomous vehicle service should be prioritised in the last mile area where many students commute to school.

Keywords:*Automated mobility; Shared mobility; Shared autonomous mobility; Mixed logit model; Stated choice experiment; Willingness to pay; Last-mile transport*

1. Introduction

In recent years, as the economic growth, the rapid increase in the number of vehicles has led to the emergence of various traffic-induced problems such as traffic congestion and air pollution. One effective solution to these problems is to develop autonomous vehicles (AVs) [1)2)]. The reason is that AVs are operated by computer systems, which can be expected to maintain smooth traffic flow by keeping appropriate distances between vehicles, thereby reducing traffic congestion and indirectly mitigating air pollution and greenhouse gas emission. In addition, as the driving system of AVs does not depend on human drivers, it may contribute to solving the driver shortage due to the declining birth rate, and ensuring mobility for the elderly and handicapped. In fact, it is estimated that 17% of greenhouse gas comes from the transport sector [3)]. Some measures to reduce air pollution include introducing hybrid or electric vehicles and improved fuel efficiency. Additionally, the measures to reduce road accidents include the installation of road safety facilities and road improvements. However, AVs also have the potential to make a significant contribution to the sustainable development through the elimination of air pollution and reduction of traffic accidents.

According to SAE International, AVs are classified into six levels according to the degree of automation. They are level 0 (no driving automation), level 1 (driver assistance), level 2 (partial driving automation), level 3 (conditional driving automation), level 4 (high driving automation), and level 5 (full driving automation) [4)].

In Japan, AVs up to level 3 have been realised, and level 4 AVs are approved only in restricted areas[5)]. According to the "Public-Private ITS

Initiative/Roadmaps", the level 4 AVs are expected to be fully realised by 2025. Beyond that, level 5 AVs are also expected to be realised in the near future.

Furthermore, the advent of the autonomous driving technology may allow for the emergence of novel business models such as shared autonomous vehicles (SAVs), which could provide inexpensive mobility on-demand services and could play a vital role in sustainable transportation systems by providing convenient last-mile (LM) solutions, which could facilitate multimodality.[6] Additionally, this sharing economy could also reduce the number of private vehicles and promote the effective use of urban space through reducing parking spaces. Therefore, introducing SAVs is considered to contribute to the sustainable development more than private AVs.

Additionally, starting SAVs services in a small area is considered to be preferable. For example, Fu (2022) stated that there seemed to be merits in studying the potential for SAVs in small urbanized areas; university towns may be more feasible locations for early deployments[7]. He argued that the financial and operational problems could arise if SAVs services were introduced in large urban areas during the early adoption period. For this reason, the present study will focus on small districts, especially between railway stations and university campuses, which are about 1.1~3.8 km apart.

SAVs as egress transport modes are not only superior in the sustainability of LM transportation systems, but also in terms of promoting the use of public transportation (e.g. railways and buses) by improving the convenience of LM transport.

The characteristics of SAVs, in comparison to buses and taxis, as an egress mode were shown in Table 1. Generally speaking, taxis and SAVs are more flexible in determining their origin and destination points, while buses run and stop at pre-determined places[8]. In terms of cost, SAVs maybe more expensive than buses but cheaper than taxis. Therefore, the SAVs services have merits of flexibility that the taxis have and of affordability that the buses have[9]. As the convenience of egressing from transit increases, so does the attractiveness and competitiveness of public transport and, ultimately, the demand for public transport[10]. Increased public transport use would also help to solve traffic-induced problems such as air pollution and traffic congestion, contributing to the sustainable transportation systems. Therefore, the widespread use of SAVs as egress transport is considered to be of great importance.

As mentioned above, the implementation of SAVs as an egress mode has important implications for the sustainable development of transportation systems. In addition, in considering the potential for the SAVs as LM mobility services (LMMS), policy makers and investors should know in advance to what extent people will accept this service and specifically to how much people's willingness to pay (WTP) for this service. Thus, the main purpose of this study was to further understand the acceptability of SAVs as an LMMS by calculating the WTP for this service and propose several policy implications.

Table 1 Flexibility and cost for bus, taxi and SAV.

	Bus	Taxi	SAV
Flexibility	Low	High	High
Cost	Low	High	Medium

(Made by the authors)

It should be noted that, as mentioned earlier, AVs for mobile services (SAVs) up to level 4 is currently implemented to some extent, but SAVs of level 5 have not yet been implemented. Therefore, in order to propose several policy implications for the diffusion of SAVs of level 5, SAVs referred in this study are considered to be level 5. That is, SAVs do not require any human operation and the automated driving system performs the all driving role. Finally, the details of SAVs service in the present study are as follows:

(1) This is an autonomous taxi service which could provide the same service as taxi by autonomous driving system substituting human drivers.

(2) People can book this service via mobile applications and pay through the applications.

(3) The pick-up and get-off point can be chosen anywhere as long as they are in admissible areas.

(4) The interior and exterior of SAVs in this study is set up in the same way as a taxi, except that it does not have a driver's seat.

The remainder of this paper is structured as follows. Section 2 introduces literature review on SAVs as an LMMS and presents the originality of this study. Section 3 provides an overview of the case study area and survey design, and the details about the design of the stated choice experiment also be presented. Section 4 discusses the results of the model estimation and people's WTP value for a SAV service. The final section concludes the findings of this study.

2. Literature review

As discussed in Section 1, SAVs as LM service are expected to make a significant contribution to

Table 2 Surveys of preferences for using SAVs as LM mode.

Authors	Title	Location	Target of subjects	Sample Size
Yap et al. (2016)	Preferences of travelers for using automated vehicles as last mile public transport of multimodal train trips	The Netherlands	People who travelled at least twice a month on average and older than 18 years	761
Kondo et al. (2020)	Analysis of intention to use shared autonomous vehicles services as a travel mode from a railway station.	Japan	Car-sharing members and parking lots members of a company called Meitetsu Kyosho CO., LTD	2581
Abe (2021)	Preferences of urban rail users for first- and last-mile autonomous vehicles: price and service elasticities of demand in a multimodal environment	Metropolitan areas of Tokyo (Japan)	The users of railway stations	1708
Torabi et al. (2022)	Passengers' preferences for using emerging modes as first/last mile transport to and from a multimodal hub case study Delft Campus railway station	Delft Campus railway station (The Netherlands)	The users of Delft Campus railway station	293

the sustainable development of society, but their acceptability has been challenging. For this reason, a number of previous researchers have attempted to understand people's intention to use SAVs as an egress mode. Table 2 summarises surveys that were conducted to elicit people's preferences for the SAVs as an LM mode.

Yap et al. (2016) used the Mixed Logit (MXL) model to analyse people's intention to use SAVs as an LM transport. The results of the model parameter estimation showed that first class rail users have a high intention to use SAVs services[11]. In addition, in order to investigate whether automated driving technology itself makes a sense to people compared to driving themselves, this study also investigated whether car-sharing AVs (where people have to drive themselves from the train station to their destination, but the AVs can return automatically to the train station or drive automatically to pick new users up) and automatically driven AVs (where the SAVs will always drive automatically without any manual driving) were compared. The results showed that, by comparing the parameter estimates of in-vehicle time, the negative marginal utility of the in-vehicle time of automatically driven AVs was higher than the negative marginal utility of the in-vehicle time of car-sharing AVs. In other words, the negative utility brought by the in-vehicle time when people ride in a full SAV is greater than when they drive themselves. The reason for this is assumed to be that people are less likely to perceive the benefits of SAVs in terms of reduced driving load, as the journey from the train station to the final destination is a short distance.

Kondo et al. (2020) used the Rank Ordered Logit Model to investigate car-sharing members' and parking lots members' intention to use SAVs as LM transport by a Stated Preferences (SP) survey and found the following three main results[12]. (1) people are unwilling to share an SAVs ride with other unknown passengers; (2) people who have a job are more likely to use SAVs because they mainly intend to travel to work or for business purposes, and they are more concerned about the convenience of travel than the price; and (3) people who are more willing to use car-sharing services think that SAVs improve conventional car-sharing services (e.g. because of the autonomous technology, users no need to park vehicles at destination, and also no need to walk to access SAVs when begin their trip), so the intention to use SAVs is also high among these people.

Abe (2021) estimated Multinomial Logit (MNL) and MXL models using SP survey data asking about the choice between SAVs services and the LM mode respondents currently used[10]. He analysed the willingness of rail users to use SAVs as an LM mode and the price and waiting time elasticity of SAVs were also analysed. Note that the model was constructed separately for commuting and leisure purposes in his study. The results show that (1) financial compensation for sharing a ride with other passengers is lower for commuting purposes than for leisure purposes; (2) the elderly and disabled have a higher intention to use SAVs; and (3) modes (e.g. buses) with lower travel speed are more likely to be substituted by SAVs.

Torabi et al. (2022) conducted an SP survey asking about preferences regarding five emerging modes, including SAVs, as LM transport[13]. The SP survey was designed by setting up a hypothetical situation with various changes in weather conditions and luggage weights. The estimation was carried out using a nested logit model to calculate market shares, price elasticities and journey time elasticities after the introduction of the five terminal transport modes. The three main findings obtained are that (1) weather and luggage weight have a significant impact on choices; (2) more educated and higher income people are more receptive to SAVs; and (3) the elasticity of price to SAVs is greater than the elasticity of travel time to SAVs.

These existing studies analysed people's

acceptability of using SAVs as an LMMS and also compared the intention of “driving by themselves” with “driving fully by automated driving system” and the prior distrust or reluctance was observed, but none of these studies quantify this sort of unacceptability of using SAVs as an LMMS. In other words, people’s WTP value for self-driving technology as an LMMS was not clear. Furthermore, although some studies have quantitatively calculated the WTP value for automated driving technology [14)15)], it was the WTP for using SAVs as a means of transport for long distance journeys, and the WTP for SAVs for short distance journeys such as LM travel have not been analysed until now. In order to successfully introduce SAVs to the market as an LMMS with reasonable pricing, a deeper understanding about the acceptability of this service is strongly required, especially peoples’ WTP values for this service.

3. Survey

3.1. Survey location

The present study mainly aims to quantitatively analyse acceptability of SAVs as an LMMS. The investigation is focused on the railway stations near Rokkodai area of Kobe University (Kobe, Japan) and students’ WTP for using SAVs as an LMMS (from the railway stations they get off to their campuses). There are four campuses in the Rokkodai area, as shown in Fig. 1. Specifically, they

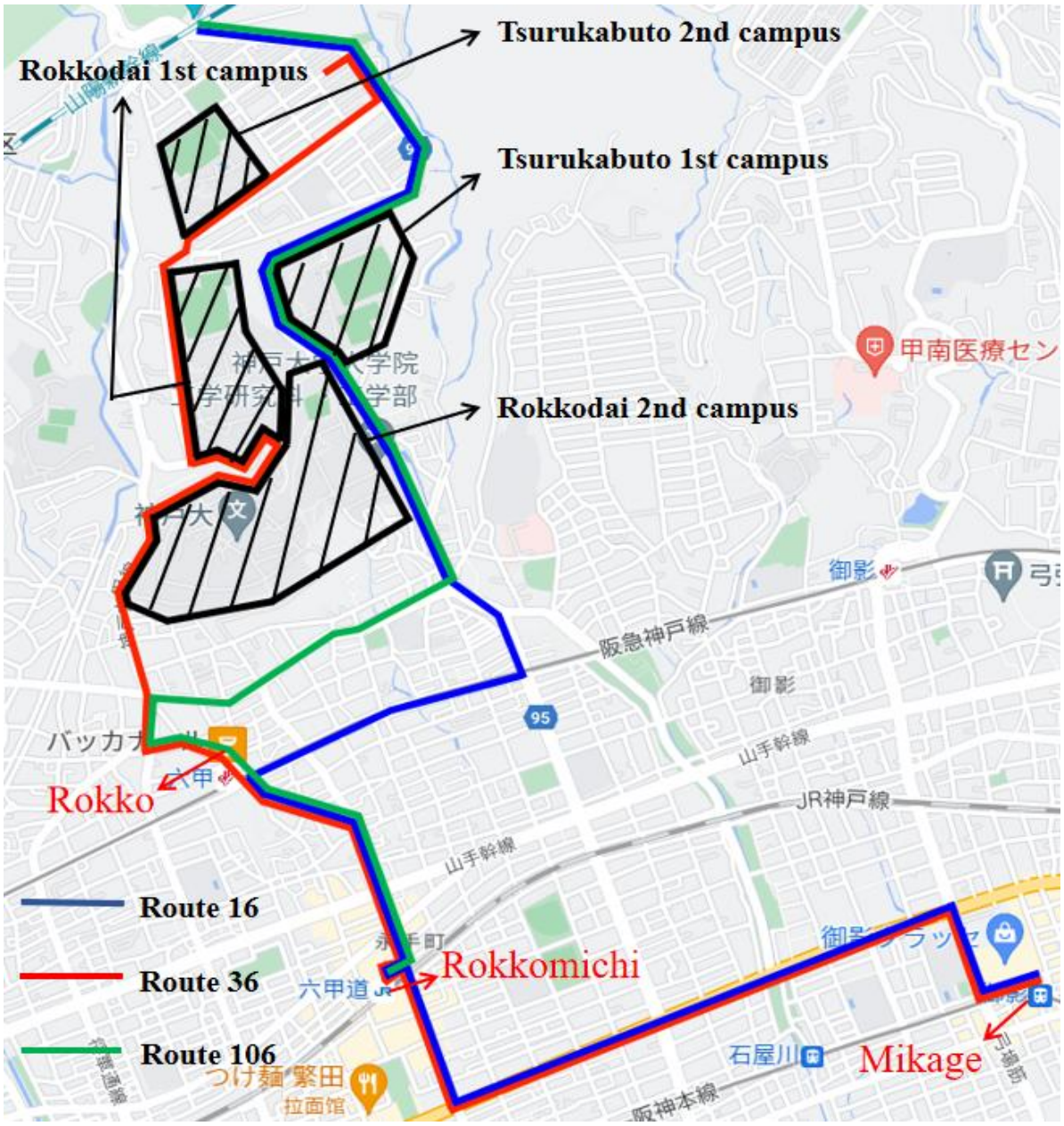


Fig. 1 Bus routes in study area. © Mapbox © OpenstreetMap © Yahoo Japan

are Rokkodai 1st (R1) Campus, Rokkodai 2nd (R2) Campus, Tsurukabuto 1st (T1) Campus and Tsurukabuto 2nd (T2) Campus. Fig. 1 shows the location of the four campuses.

According to Sanko (2020), the three most frequently used railway stations for students commuting to these campuses by rail are Hankyu Rokko (Rokko), JR Rokkomichi (Rokkomichi) and Hanshin Mikage (Mikage)[16]. In this study, these three stations will be referred to together as the nearest stations and they will be chosen as case study area for the reasons mentioned below.

First, data collecting was easy because the authors belong to the Kobe University. Second, this is a good area to study mode choice of LM. Different from many urbanised area in Kobe, in which only walking is enough for the access and egress modes, the campus (R1, R2, T1, T2) located on Rokko mountain hillside have not an easy access on foot from stations and demand other than walking exists.

Finally, the introduction of SAVs as an LMMS can be a desirable solution to solve the current traffic problem in the study area. Most students who get off from farther railway stations (e.g. Mikage and Rokkomichi) will choose buses as their LM mobility mode. Therefore, the concentrated use of buses by students causes congestion in buses and extra waiting times especially during morning peak hour, even though the interval of buses is less than 10 minutes at that time. Thus, adding new modes, such as SAVs, may be important to relieving the pressure on buses during morning peak hour, because there are no other convenient and affordable options than buses for students.

3.2. Campuses and stations

The Kobe University was founded in 1902 and has 10 faculties and schools, 15 graduate schools and numerous research centers and institutions. As of May 2022, it has 4073 staff (1556 faculty members and 2517 administrative staff) and 17,166 students[17].

There are three bus routes connecting between the nearest stations and the four campuses: routes 36, 16 and 106. Route 36 connects Mikage, Rokkomichi, Rokko, R2, R1, and T2. Route 16 connects Mikage, Rokkomichi, Rokko, and T1. Route 106 connects Rokkomichi, Rokko, and T1. More details of each bus route are shown on the map in Fig.1.

3.3. Survey design

The survey is divided into four sections, A-D, and the items surveyed are provided in Table 3.

Section (A) screened out those who are not target of the present study. Only the students who answered yes in both items (A1) and (A2) proceed to Section (A3) and other respondents will proceed to Section (D). Item (A3) is a brief explanation of the SAVs assumed in this study, mainly describing the features of the SAVs and the booking process mentioned in Section 1 of this paper.

Section (B) asks respondents about their current egress modes from the nearest stations to campuses and its level of service. Note that item (B2) was only asked of respondents whose current mode is walking, buses, and bicycles/motorcycles. According to Sanko (2020), which targeted the same study area, the egress modes from the nearest stations to campuses are mainly walking, buses, bicycles, and motorcycles[16]. Excluding “taxi” and “other” is a minor concern due to their lower market shares. Also, preferences to taxis and SAVs are elicited in stated choice survey in Section (C).

Table 3 Items surveyed

Section (A) Introduction of SAVs			
(A1) Is the campus you most frequently commute to R1, R2, T1, or T2?			
(A2) Do you use any one railway station of Rokko, Rokkomichi, or Mikage?			
(A3) SAVs service assumed in this study are explained			
Section (B) Current egress mode			
(B1) Most frequently used egress mode when commuting to university			
Select from “Walking”, “Bus”, “bicycle/motorcycle”, “Taxi”, and “Other”.			
For current walkers	For current bus riders	For current bicycle or motorcycle riders	For current taxi riders and others
(B2.a1) Walking time	(B2.b1) In-vehicle time by bus	(B2.c1) Travel time	
	(B2.b2) Waiting time at bus stops	(B2.c2) The monthly cost of parking	
(B3) The most frequently used pair of the nearest stations and campuses when commuting to university			
Section (C) SP survey (Only for those who choose “walking”, “bus”, or “bicycle and motorcycle” in B1)			
(C1) Stated choice survey for egress modes (Choosing preferred one from “Current egress mode (answered in B1)”, “SAV”, and “Taxi” for the journey of B3).			
Section (D) personal information			
(D1) Gender			
(D2) Grade			
(D3) Car driving licence holding			
(D4) Frequency of commuting to university			

Table 4 Grouping of 12 station-campus pairs.

The nearest stations→Campus	Taxi cost (midpoint value)	Taxi in-vehicle time	Distance	Group
Rokko→R1	660 JPY (660 JPY)	5 min	1.3 km	Group 1
Rokko→R2	660 JPY (660 JPY)	4 min	1.1 km	
Rokko→T1	660 JPY (660 JPY)	5 min	1.6 km	
Rokko→T2	680–750 JPY (715 JPY)	7 min	1.9 km	Group 2
Rokkomichi→R1	720–790 JPY (755 JPY)	9 min	2.0 km	
Rokkomichi→R2	660–700 JPY (680 JPY)	9 min	1.8 km	
Rokkomichi→T1	720–800 JPY (760 JPY)	7 min	2.1 km	
Rokkomichi→T2	1200–1300 JPY (1250 JPY)	9 min	2.6 km	Group 3
Mikage→T1	1100–1200 JPY (1150 JPY)	9 min	2.9 km	
Mikage→T2	1500–1700 JPY (1600 JPY)	12 min	3.8 km	Group 4
Mikage→R1	1400–1600 JPY (1500 JPY)	14 min	3.9 km	
Mikage→R2	1500–1700 JPY (1400 JPY)	12 min	3.1 km	

Therefore, those whose current mode is “taxi” or “other” will be directed to Section (D) when they finished the answer of item (B3).

Finally, all respondents were asked to answer their personal information in section (D).

3.4. Design of stated choice experiment

Respondents face three alternatives: “current egress mode”, “SAV”, and “taxi” and requested to choose one of them. Choosing these three alternatives has two reasons: (1) Examining the impact of SAVs on current modes; and (2) Comparing people’s preferences for “driving by others” and “driving by automated driving systems”.

Each alternative has 3 attributes: in-vehicle time, waiting time, and cost, which are important attributes for transport mode. The attributes’ levels for the “current egress mode” is the same as those reported by respondents: (B2.a1), (B2.b1), (B2.b2), (B2.b3), (B2.c1), and (B2.c2). On the other hand, the level of SAV and taxi attributes are set taking the taxi’s level of service in operation into account

Presenting reasonable attributes’ levels is important, and the attributes’ levels for SAVs and taxis are determined based on distances between the stations and campuses. The 12 realisable station-campus pairs (Table 5) in (B3) are divided into four groups of 1–4 taking their distances into account. Table 4 shows cost and in-vehicle time of taxi and distances (direct distances of taxi routes) according to Google Maps (Google Maps, Map Data©2022, accessed 5 November 2022). Note that the cost was presented in a range in Google Maps, so the midpoint values are shown in parentheses. The levels of taxi and SAV attributes were designed with a reference to values presented in Table 4. The cost and in-vehicle time of taxi are aggregated for each group and are presented in Table 5. The figures are simple arithmetic averages.

Table 5 Cost and in-vehicle time for taxi for each group

Group	Cost	In-vehicle time
Group 1	660.0 JPY	4.67 min
Group 2	727.5 JPY	8.00 min
Group 3	1200.0 JPY	9.00 min
Group 4	1500.0 JPY	12.67 min

Attributes’ levels for SAVs and taxis are determined using the similar method in Abe (2021)[10]. SAV cost (Table 6) is designed by multiplying the cost of taxis (Table 5) by 0.3, 0.5 and 0.7 and the taxi cost (Table 6) is designed to be the level 1 of SAVs plus 50, level 2 of SAV plus 100 and level 3 of SAV plus 150. The reason for designing the levels for cost of taxi in this way is to observe more information about people’s

Table 6 Levels of SAV and taxi attributes

		SAV			Taxi		
Group	Attribute	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
Group 1	Cost (JPY)	200	330	460	250	430	610
	In-vehicle time (min)	3	5	6	3	5	6
	Waiting time (min)	3	5	10	3	5	10
Group 2	Cost (JPY)	220	360	510	270	460	660
	In-vehicle time (min)	6	8	10	6	8	10
	Waiting time (min)	3	5	10	3	5	10
Group 3	Cost (JPY)	360	600	840	410	700	990
	In-vehicle time (min)	6	9	12	6	9	12
	Waiting time (min)	3	5	10	3	5	10
Group 4	Cost (JPY)	450	750	1050	500	850	1200
	In-vehicle time (min)	9	13	16	9	13	16
	Waiting time (min)	3	5	10	3	5	10

preferences for fares. Similarly, SAV and taxi in-vehicle time is designed by multiplying the taxi in-vehicle time (Table 5) by 0.7, 1.0 and 1.3. Note that cost and in-vehicle time are rounded to nearest multiples of 10 JPY and 1 minute, respectively. Finally, the waiting time for SAVs and taxis is assumed to be 3, 5 and 10 minutes, which also are based on Abe (2021)[10]. The details of attributes' levels for SAVs and taxis are presented in Table 6.

SP surveys are designed by D-efficient design, a method that employs the design with the lowest D-error[18]. In order to use D-efficient design, it is necessary to know the prior parameters[19]

Prior parameter values are determined based on previous studies analysing SAVs using discrete choice models. Prior parameters of SAV and taxi cost and SAV in-vehicle time are determined based on estimates reported in Carteni (2020)[15], which has similar study aims. The parameter of waiting time was based on estimates in mixed model of leisure trip by Abe (2021)[10]. The taxi in-vehicle time parameter was based on estimated in off-peak metro-taxi model by Chen, F et al. (2020)[20]. The values of waiting time and taxi in-vehicle time referenced parameters are then scaled to the parameters estimated by Carteni (2020)[15].

Finally, designs were generated by Ngene[19]. Given the alternatives, attributes, and levels mentioned in Table 6, four survey designs with 9 choice tasks were generated for each of Groups 1 to 4. The "S-estimate" output by Ngene, which represents the required minimum number of samples in order to obtain statistically significant parameter estimates (at the 95% level), is 27 for Group 1, 28 for Group 2, 22 for Group 3, and 31 for Group 4. Fig. 2 shows an example of choice tasks that are actually presented to respondents.

	Your current mode of transport	Shared automated vehicle	Taxi
Travel cost	Same as current※	200 JPY	610 JPY
In vehicle time	Same as current	5 min	3 min
Waiting time	Same as current	5 min	5 min

※If your current mode of transport is walking, the in-vehicle time would be the walking time.

Fig. 2 An example of choice tasks

4. Result

4.1 Descriptive statistics

The SP survey questionnaire was constructed in a web-based format by Google Forms. The target population of this survey was current students of the Kobe University. The questionnaire was distributed mainly through the authors' network. The data was collected between 5 and 15 December 2022, and finally 208 respondents completed the survey.

Tables 7 and 8 show descriptive statistics, with all

Table 7 Descriptive statistics of all respondents' characteristics (n=208)

	n	%
Gender		
Female	96	46.15
Male	108	51.92
No answer	4	1.92
Grade		
Undergraduate students	106	50.96
Master's students	76	36.54
Ph.D. students	20	9.62
Others	6	2.88
Car driving licence holding		
Yes	110	52.88
No	98	47.12
Frequency of commuting to university		
7 times a week	3	1.44
6 times a week	11	5.29
5 times a week	36	17.31
4 times a week	48	23.08
3 times a week	57	27.40
Twice a week	26	12.50
Once a week	24	11.84
Less than once a week	3	1.44
The campus most frequently commutes to is R1, R2, T1, or T2		
Yes	199	95.67
No	9	4.33
Using any one railway station of Rokko, Rokkomichi, or Mikage (Only people who commute to R1, R2, T1, or T2 can answer this question (n=199))		
Yes	136	68.34
No (using other stations)	6	3.02
No (not the railway user)	57	28.64

Table 8 Descriptive statistics of recent egress trips (n=137)

	n	%
Egress mode		
Walking	48	35.29
Bus	83	61.03
Bicycle	1	0.74
Motorcycle	1	0.74
Taxi	2	1.47
Others	1	0.74
Ownership of season pass for bus between the nearest stations and campuses (ask for those who use bus as egress mode (n=83))		
No	77	92.77
Yes	6	7.23
Stations-campuses pair he/she most frequently travels		
Rokko→R1	51	37.50
Rokko→R2	13	9.56
Rokko→T1	5	3.68
Rokko→T2	2	1.47
Rokkomichi→R1	48	35.29
Rokkomichi→R2	8	5.88
Rokkomichi→T1	1	0.74
Rokkomichi→T2	5	3.68
Mikage→R1	3	2.21
Mikage→R2	0	0.00
Mikage→T1	0	0.00
Mikage→T2	0	0.00

respondents' characteristics in Table 7 and characteristics of egress trips of current rail users in Table 8.

The representativeness of the respondents is worth mentioning. The undergraduate students who comprise 50.96% of respondents in this survey accounted for 0.92% of all undergraduate students at Kobe University, while graduate students who responded to this survey accounted for a higher percentage, 2.14% of all graduate students at Kobe University[21]. Thus, random sampling might be a potential issue in the survey. Nevertheless, these data can still provide adequate information for this study, but caution needs to be taken when generalising.

4.2 Model specification

Included in the model estimation are SP data answered by those whose current egress mode is walking and buses. The reason for this is that, according to Table 8, walking and buses are the most frequently used egress modes. SP surveys are also conducted for those whose current egress mode is bicycle and motorcycle, but they are removed from the analysis since the two modes are used rarely. Therefore, the alternatives presented in the stated choice tasks are "the current travel mode" (walking for the current walkers, and buses for the current bus riders), "SAV", and "taxi".

There were 131 respondents whose egress mode was buses or walking. Ten respondents who provided obviously unreasonable information of travel time of buses or walking in section (B) were removed from the analysis and 6 respondents who holds the season pass of bus also be removed from the estimated model since they are captive of bus. The remaining 115 respondents consist of 60 from Group 1, 48 from Group 2, 5 from Group 3, and 2 from Group 4. In the following analysis, data from neither Groups 3 nor 4 were included, since the number of respondents completed the survey fell short of the S-estimate presented in Section 3.4. The remaining number of respondents in the following analysis is 108 (= 60+ 48).

For the level of service attributes, "In-vehicle time", "Waiting Time", and "Cost" are considered. Alternative-specific parameters were estimated for the "In-vehicle time", while generic parameters were estimated for the "Waiting time" and "Cost". For individual socio-economic attributes, "LF+Licnece", "LF+noLicence", "HF+Licence", and "HF+noLicence" were considered:

(1) "LF+Licnece": 1 for low frequent commuters (less than 3 times a week) with car driving licence holding; 0 otherwise.

(2) "LF+noLicence": 1 for low frequent commuters (less than 3 times a week) without car driving licence holding; 0 otherwise.

(3) "HF+Licence": 1 for high frequent commuters (greater than twice a week) with car driving licence holding; 0 otherwise.

(4) "HF+noLicence": 1 for high frequent commuters (greater than twice a week) without car driving licence holding; 0 otherwise.

This study uses MXL models. In estimating the MXL model, due to the main focus of this study being SAVs, all level of service attribute parameters related to SAVs (including cost and waiting time which are generic parameters, as well as alternative-specific constants: ASC) are set as random. Furthermore, the random parameters are specified as normally distributed.

4.3 Discrete choice model results

In this study, MXL models were estimated using the Apollo package in R[22]. Table 9 presents the estimates of egress mode choice models incorporating SAVs. In order to estimate the willingness of each different category of respondents to use automated driving technology as an LMMS, Model 1 (Table 9) excludes ASC. To more simple and aggregate models, Model 2 retains ASC. This was done in order to estimate aggregated respondents' "pure preference" in using automated driving technology as an LMMS.

According to Cartenì (2020)[15], ASC allows to estimate people's attitudes toward using automated driving technology. Since it was explained in section (A) of the questionnaire that SAVs in this study have the same interior and exterior as taxis, except that SAVs do not have a driver's seat, it is assumed that the only difference between SAVs and taxis for respondents is whether they are manned or unmanned. Thus, the difference between the ASC for SAVs and taxis reflects people's "pure preference" in using automated driving technology as an LMMS. Furthermore, therefore, the calculation of WTP value for automated driving technology can be based on the ratio of the difference between the ASC of SAVs and taxis with respect to cost.

Additionally, due to the parameter of cost being random in this study, the WTP value will no longer be simply calculated as a ratio of parameters with respect to cost by the estimates in Table 9. Therefore, WTP was directly estimated in the WTP space (Table 10).

The adjusted ρ^2 of the four models are shown in Tables 9 and 10, all higher than 0.65. In other words, there is no problem with the goodness of fit in these models. This section analyses the estimates of preference space (Table 9), while the estimates of

Table 9 Estimates in preference space.

Variable	Alternative	Model 1 (preference space)		Alternative	Model 2 (preference space)	
		Est.	t-value		Est.	t-value
Constant	SAV	NA	NA	SAV	3.13**	2.32
Standard deviation	SAV	NA	NA	SAV	2.51***	3.73
Constant	Taxi	NA	NA	Taxi	0	Fixed
Constant	Bus	NA	NA	Bus	-1.39	-1.37
Constant	Walk	NA	NA	Walk	2.57	0.68
Service attribute						
In-vehicle time (10^2min): mean	SAV	-0.52***	-3.11	SAV	-0.48***	-2.73
Standard deviation	SAV	0.45***	5.48	SAV	0.32**	2.15
In-vehicle time (10^2min)	Taxi	-0.11	-0.98	Taxi	-0.08	-0.69
In-vehicle time (10^2min)	Bus	-0.08	-1.13	Bus	-0.07	-0.93
Walking time (10^2min)	Walk	-0.65***	-3.05	Walk	-0.64***	-3.09
Cost (10^2JPY): mean	SAV, Taxi, Bus	-0.06***	-7.61	SAV, Taxi, Bus	-0.06***	-7.29
Standard deviation	SAV, Taxi, Bus	0.02***	6.60	SAV, Taxi, Bus	0.03***	5.46
Waiting time (10^2min)	SAV, Taxi, Bus	-0.25***	-4.90	SAV, Taxi, Bus	-0.25***	-4.90
Standard deviation	SAV, Taxi, Bus	0.15**	2.41	SAV, Taxi, Bus	0.16**	2.32
Personal attribute						
LF+Licnece	SAV	5.77***	3.47	SAV	NA	NA
LF+Licnece	Bus	-0.23	-0.20	Bus	NA	NA
LF+Licnece	Walk	3.37	0.65	Walk	NA	NA
LF+noLicnece	SAV	3.32**	2.15	SAV	NA	NA
LF+noLicnece	Bus	-1.86	-1.59	Bus	NA	NA
LF+noLicnece	Walk	2.35	0.46	Walk	NA	NA
HF+Licnece	SAV	3.69***	2.78	SAV	NA	NA
HF+Licnece	Bus	-0.77	-0.71	Bus	NA	NA
HF+Licnece	Walk	3.48	0.85	Walk	NA	NA
HF+noLicnece	SAV	1.48	1.20	SAV	NA	NA
HF+noLicnece	Bus	-2.00*	-1.91	Bus	NA	NA
HF+noLicnece	Walk	1.12	0.59	Walk	NA	NA
Sample size		108			108	
Number of observations		972			972	
Number of estimated parameters		21			13	
Log-likelihood at convergence		-341.18			-346.98	
Log-likelihood at zero		-1067.85			-1067.85	
ρ^2		0.6805			0.6751	
Adjusted ρ^2		0.6608			0.6629	

Note:

NA = not defined in the model.

*,**,*** = statistically significant at the 10%, 5%, 1% level.

Modified Latin Hypercube sampling (MLHS) draws was applied in both models and the number of draws is 2000.

WTP space (Table 10) will subsequently be discussed in Section 5.3.

Mean estimates of cost and SAV in-vehicle time are all negative in Models 1 and 2, which is consistent with the common sense. The standard deviation of the two parameter estimates is all significant at 5% level in both models. This suggests that there is taste heterogeneity in students' preferences for cost and SAV in-vehicle time.

Estimates for in-vehicle time of buses and taxis are not statistically significant, but the parameter estimates of SAV in-vehicle time and walking time are significant in both models. One possible reason for this could be the students' attitudes toward SAVs and walk. First, with respect to SAVs, since SAVs are a new service that relies on computer systems for driving, it is unlikely that people will fully trust the safety of this automated driving technology service. Therefore, this distrust may make students more sensitive to the changes of SAV in-vehicle time than the same changes of bus and taxi in-vehicle time. As for walk, the campus is located on a hillside, so commuting to university by walking uphill places a greater burden on the body; therefore, students are also likely to be more sensitive to the changes of walking time than the

Table 10 Estimates in WTP space.

Variable	Alternative	Model 1 (WTP space)		Alternative	Model 2 (WTP space)	
		Est.	t-value		Est.	t-value
Constant: mean (JPY)	SAV	NA	NA	SAV	-42.11*	-1.94
Standard deviation (JPY)	SAV	NA	NA	SAV	33.08**	2.48
Constant: mean (JPY)	Taxi	NA	NA	Taxi	0	Fixed
Constant: mean (JPY)	Bus	NA	NA	Bus	32.06*	2.07
Constant: mean (JPY)	Walk	NA	NA	Walk	64.31	1.29
Service attribute						
In-vehicle time: mean (JPY)	SAV	9.83***	3.18	SAV	10.50***	3.56
Standard deviation (JPY)	SAV	8.57***	7.69	SAV	8.07***	5.97
In-vehicle time (JPY)	Taxi	3.69*	1.90	Taxi	4.07**	2.04
In-vehicle time (JPY)	Bus	2.24*	1.95	Bus	1.99*	1.77
Walking time (JPY)	Walk	6.95***	3.91	Walk	8.34***	4.11
Cost: mean (JPY)	SAV, Taxi, Bus	-0.07***	-5.98	SAV, Taxi, Bus	-0.07***	-5.94
Standard deviation (JPY)	SAV, Taxi, Bus	0.03***	5.18	SAV, Taxi, Bus	0.03***	4.56
Waiting time: (JPY)	SAV, Taxi, Bus	5.75***	4.98	SAV, Taxi, Bus	6.32***	5.30
Standard deviation (JPY)	SAV, Taxi, Bus	5.22***	4.92	SAV, Taxi, Bus	5.49***	4.74
Personal attribute						
LF+Licnece (JPY)	SAV	-94.14***	-3.01	SAV	NA	NA
LF+Licnece (JPY)	Bus	-0.10	0.00	Bus	NA	NA
LF+Licnece (JPY)	Walk	37.43	0.70	Walk	NA	NA
LF+noLicnece (JPY)	SAV	-52.17*	-1.84	SAV	NA	NA
LF+noLicnece (JPY)	Bus	29.52*	1.68	Bus	NA	NA
LF+noLicnece (JPY)	Walk	114.34**	2.38	Walk	NA	NA
HF+Licnece (JPY)	SAV	-45.67*	-1.78	SAV	NA	NA
HF+Licnece (JPY)	Bus	25.45	1.54	Bus	NA	NA
HF+Licnece (JPY)	Walk	77.60*	-1.63	Walk	NA	NA
HF+noLicnece (JPY)	SAV	-15.65	-0.63	SAV	NA	NA
HF+noLicnece (JPY)	Bus	36.05**	2.17	Bus	NA	NA
HF+noLicnece (JPY)	Walk	99.18**	2.21	Walk	NA	NA
Sample size		108			108	
Number of observations		972			972	
Number of estimated parameters		21			13	
Log-likelihood at convergence		-345.37			-351.45	
Log-likelihood at zero		-1067.85			-1067.85	
ρ^2		0.6766			0.6709	
Adjusted ρ^2		0.6569			0.6587	

Note:
NA = not defined in the model.
*,**,*** = statistically significant at the 10%, 5%, 1% level.
MLHS draws were applied to both Model, and the number of draws is 2000.

changes of bus and taxi in-vehicle time.

For waiting time, the negative parameter estimates (Models 1 and 2) are also consistent with the common sense. Here, The standard deviation of waiting time estimate is significant at 1% level in both models, which means that there is also taste heterogeneity in students' preferences for waiting time. Furthermore, the absolute value of waiting time parameter is smaller than the value of SAV in-vehicle time in both models. The reason for this may be that the distrust of using SAVs outweighs the dislike of waiting.

Estimates of personal attributes were examined in model 1. Irrelevant to whether holding a car driving licence, low frequent commuters are more likely to use SAVs service than high frequent commuters. The reason for this may be because low frequent commuters will be more willing to choose some expensive but comfortable and faster modes. It should be noted, however, that low frequent commuters prefer SAVs to taxis which are also expensive but convenient. This may be due to the fact that low frequent commuters have a lower "inertia" on their current modes and are more willing to replace traditional modes with the emerging modes. In addition, among low frequent commuters, those with a car driving licence are more likely to use SAVs than those without a car

driving licence.

Furthermore, the result also reveals the effects of licence holding on the intention to use SAVs. Independent of the frequency of commuting to university, holding car driving licence positively affects the utility of SAVs. In other words, those who hold a car driving licence have a higher intention to use SAVs than taxis. The possible reason is that those who have actual driving experience can recognise the advantages of automated driving technology (higher safety than driving by human) more than those who do not have driving experience. Additionally, similar to the phenomenon observed in the group of low frequent commuters, among students with a car driving licence, low frequent commuters are more likely to use the SAVs than no low frequent commuters.

Finally, in Model 2, the positive mean and standard variation of ASC variable are all significant at 5% level, which means that students have a positive preference in using automated driving technology as an LMMS and there is taste heterogeneity in this preference among them.

4.4 The WTP of SAVs

Regarding students' WTP for using an SAV service, their average values (Table 10) of in-vehicle time saving are 9.83 (in Model 1) and 10.50 (in Model 2) JPY/min and the standard deviations equal to 8.57 (in Model 1) and 8.07 (in Model 2) JPY/min. Moreover, the average values of SAV waiting time saving are 5.75 (in Model 1) and 6.32 (in Model 2) JPY/min and the standard deviations equal to 5.22 (in Model 1) and 5.49 (in Model 2) JPY/min.

About different groups of categories, students of "LF+Licnece" group present a positive and largest WTP value equal to 94.14 JPY (Table 10) which means that for changing from taxis to SAVs as an LMMS, they are willing to pay 94.14 JPY/trip. Furthermore, students of "LF+noLicence" and "HF+Licence" groups are willing to pay 52.17 JPY/trip and 45.67JPY/trip, respectively, for using SAVs as an LMMS when changing from taxis.

Next, we discuss the aggregated students' WTP for using SAVs as an LMMS through Model 2. According to the results of Model 2 (Table 10), students' average WTP value for automated driving technology is -42.11 JPY/trip (Table 10). This means that, respondents indicate a positive intention to use automated driving services as an LMMS. In other words, students are willing to use SAVs from railway stations to campuses even if the cost of SAVs is 42.11 JPY higher than the cost of taxi. An amount of 42.11 JPY is 20.05% of the cost of buses (210 JPY), and only 6.38% of the cheapest actual taxi cost (660 JPY) in the 12 the nearest stations-campuses pairs, which is a relatively small amount for the Japanese. Thus, students' WTP for using SAVs as an LMMS is considered to be almost the same as that of taxis. That is to say, for these students, "driving by drivers" and "driving by automated driving systems" have little influence on their choice between SAVs and taxis. Nevertheless, although they do not have a high willingness to use SAVs as an LMMS, at least they are not averse to using this service. The result is contrary to the WTP value (2.31€ ≈ 346.17JPY) calculated by Cartenì (2020)[15]. This may be due to the following two reasons.

(1) The respondents of this survey were all young people (current students at Kobe University). Young people may be more receptive to new technologies and services.

(2) Since the subject of this study is SAVs as an LMMS, the distance travelled in SAVs is short. Therefore, passengers may have less distrust and fear to using SAVs.

5. Discussion and conclusion

5.1 Conclusion

In order to smoothly introduce SAVs to the LM market, this study examined students' WTP for using SAVs as an LMMS by SP survey and a discrete choice model. The targeting respondents are students from Kobe University who travel from the nearest stations to the campuses in Rokkodai area. In particular, this study mainly focused on quantitatively calculating students' WTP for using SAVs as an LMMS. As a result, the following findings were obtained.

(1) Students are more sensitive to in-vehicle times in SAVs than in the taxis.

(2) Students who hold car driving licences or have a low frequency of commuting to university are more likely to use SAVs as an LMMS.

(3) Low frequent commuters with car driving licences have the highest WTP value (94.14 JPY) for switching from taxis to SAVs, and low frequent commuters without car driving licences have the similar WTP value as high frequent commuters with car driving licences (52.17 JPY and 45.67 JPY).

(4) Comparing to taxis students are willing to pay extra 42.11 JPY for using SAVs as an LMMS. Therefore, there is no great difference between SAVs and taxis in LM trips to students. In other word, students do not have a prior reluctance or great acceptability in using SAVs when travel in the LM trip.

5.2 Policy implications

According to the results of this study, several policy implications can be derived. First, SAVs as an LMMS can be regarded as a realistic option for students. Thus, this service should be introduced at first in the market as an LMMS and selecting LM places where young people are the main trip makers as the introduction area. Second, because the indifference of automated driving technology for students, SAVs have no advantage over taxis in the LM area. Therefore, the pricing of SAVs should not exceed the price of taxis and in order to attract people currently using other egress modes (e.g., buses or walking) to SAVs, lowering the price or raising the speed maybe the best way. Finally, since only students with a low frequent commuting have larger willingness to pay for this LMMS, a season pass system may be a good idea to attract high frequent commuters.

6.3 Limitations

Limitations in this study should be mentioned. Sample should be expended considering the diversification of age. Since the survey targets were only students, the WTP value of young people towards SAVs as an LMMS was clarified. However, this study cannot clearly distinguish whether the main reason for this positive WTP is caused by young people or short distance movement or even the combination of this two. Therefore, it is necessary to conduct an unbiased survey that includes other age groups in the survey.

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