OWNERSHIP AND USAGE OF AUTONOMOUS VEHICLES AND THEIR IMPACTS ON PEOPLE'S LIVES

Capturing Ownership Behavior of Autonomous Vehicles in Japan Based on a Stated Preference Survey and a Mixed Logit Model with Repeated Choices[1]

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Abstract
Aiming to capture the impacts of autonomous vehicles (AVs) on people’s lives, this study implemented a web-based questionnaire survey to 1,002 people living in different parts of Japan in September 2016. The survey mainly includes the following contents: (1) actual travel behavior (both car and non-car, both short- and long-distance, as well as car ownership, and car usage (in-vehicle time use (multitasking behavior during travel))); (2) stated preference (SP) questions (three SP profiles per respondent) about both ownership and usage (both short- and long-distance) of AVs under different future scenarios, where usage refers to in-vehicle time use; (3) questions about changes in life (travel behavior, residential behavior, time use, tourism, use of AVs as a moving home/hotel/office, etc.). The present contents mainly focus on the ownership analysis based on a mixed logit model with repeated choices. At the time of the conference, analysis results about the impacts on people’s lives will be further reported.

Key Words: *autonomous vehicles, ownership, in-vehicle time use, SP survey, life-oriented impacts, Japan*

1. Introduction

Autonomous vehicles (AVs) (or self-driving cars) are expected to improve driving safety dramatically (Grand View Research, 2016). To testify the performance of various technologies equipped for AVs, an ever-increasing number of continuous on-site AVs experiments have been launched by research organizations and manufactories, such as Alphabet Inc., Tesla Motors Inc., Ford Motors Corp., General Motors of Audi, Google, and Nissan Motor Co., together with AV inventory companies. The Google-car has been self-driving for more than 2.0 million miles on urban streets mostly (Dolgov, 2016), and Tesla autopilot for 300 million miles[2] (Lambert, 2016). Summarized from 24 accident reports of the traffic accidents involving AVs, monitored by the California Department of Motor Vehicles (2016), from 2014 to 2016, 16 accidents occurred under AV-mode driving, and crash types were mostly rear-endings and slide-scrapes by adjacent vehicles at a relatively low driving speed. This is consistent with an analysis conducted by Schoettle and Sivak (2015) about self-driving vehicle crashes in real-word

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[2] Concerning the required driving distance for demonstrating the reliability of autonomous vehicles, Kalra and Paddock (2016) argued that it is almost not possible to empirically confirm driving safety based on driving distance only because fully autonomous vehicles would have to be driven hundreds of millions of miles and sometimes hundreds of billions of miles in terms of fatalities and injuries. They concluded that autonomous vehicle regulations should be adaptive.

driving. Schoettle and Sivak highlighted that AVs were not at fault in any crashes they were involved in, and the severity of crash-related injuries involving AVs has been lower than that for conventional vehicles. According to the WHO (2015), the total number of road traffic fatalities in the world has reached 1.25 million per year, i.e., more than 3,400 people die on the roads every day. Such a huge number of deaths and other types of traffic accidents are mainly caused by human errors. For example, by using a data from more than 2.0 million drivers in the US, Singh (2015) showed that 77–94% of car accidents are caused by human errors (recognition errors: 41% [±2.1%], decision errors: 33% [±3.7], and performance errors: 11% [±2.7%]). Such human errors are due to the limitations in the information processing abilities of human beings. With AV technologies, these human errors are expected to be dramatically reduced. Thus, the benefits of deploying AVs in the market are obvious.

However, safety improvements are not the only benefit of AVs. Drivers suffer from spending a certain length of limited time driving. Currently, there are 1.3 billion vehicles in use across the whole world[3]. For example, Americans spend an average of 17,600 minutes (about 12 days) driving per year[4]. How long does it people to obtain a driver's license? In Japan, the minimal time required for vehicles with a manual transmission is about 45 hours: about 20 for lecture-based learning and the other 25 for skill learning[5]. AVs can run automatically, just like a "moving home", "moving office", or "moving hotel". Therefore, people do not necessarily obtain a driving license, in theory. Thus, the use of an AV allows people to make more effective use of their time compared with a conventional car. In this sense, extensive use of AVs will save an enormous amount of time, which is a precious and scarce resource for everybody.

It is predicted that Level 4 AVs (high automation; see SAE International [2014]) will be available in the market in 2020, as announced by the CEO of Nvidia and the head of Audi of America during a keynote address at the Self-Driving Technology Conference (Ross 2017). In August 2016, Nissan Motor Company started to sell a small van equipped with partially autonomous driving functions on expressways for the first time in the domestic market of Japan, the target country of this study, and in the year of the 2020 Tokyo Olympics, thousands of driverless robot taxis are planned to run on selected road sections. Alto (2016) showed that even though only 1.3% of cars (about 1.16 million) sold in 2016 offered partial automation (Level 2: SAE International), the market share of AVs will grow explosively to about 15% of (15.4 million) vehicles with conditional/full automation (i.e., Level 3 / Level 4) at the global level in 2025.

There are some observations of the so-called 'peak-car' phenomenon in developed countries. In particular, young people are less likely to own/use a car, which differs from their parents' generations (Zhang et al., 2017). If so, how will the deployment of AVs affect such a phenomenon? If the reasons why some drivers become less likely to own/use a car and some non-drivers hate to own/use a car are because of the driving risk and time loss, all of the above advantages of AVs are expected to mitigate the resistance to owning/using a car. Thus, it is natural to expect a huge share of AVs in the future. Would that be the case? Unfortunately, these issues have not well investigated in existing studies. In other words, there are still many unknowns about the ownership behavior of AVs in future and its influential factors. More research should be accumulated.

Motivated by the above-mentioned background, this study aims to provide additional insights into policymaking based on a case study in Japan, by further clarifying factors that affect the deployment of AVs. This is done by investigating AV ownership behavior in Japan based on a stated preference (SP) survey, where SP attributes are specified with reference to revealed preference (RP) data. In the survey, the SP choice set includes a conventional vehicle and three types of AVs: full automation (*Full* AV: Level 5), high automation (*High* AV: Level 4), and conditional automation (*Conditional* AV: Level 3), as defined by SAE International (2014). The five SP attributes selected for this study were: additional purchase cost, permanent parking cost, insurance, diffusion rates of AVs, and release timing of AVs to the market. Focusing on the main effects of these SP attributes, this study derived 18 SP profiles based on an orthogonal fractional factorial design. In the survey, respondents were asked to report their SP answers by assuming that their future income levels would follow the current (negative or positive)

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[3] https://www.statista.com/statistics/281134/number-of-vehicles-in-use-worldwide/ (Accessed Dec 16, 2017)
[4] http://newsroom.aaa.com/2016/09/americans-spend-average-17600-minutes-driving-year/ (Accessed Dec 16, 2017)
[5] https://xn--94qw00l56cisb.net/?p=120

growth rate of income. The survey targeted both long- and short-distance trips made by not only current car users, but also public transport users. It was implemented online to 1,002 respondents recruited from the whole of Japan in September 2016, where the collected respondents followed the distribution of age and gender of the population in three types of regions. Each respondent answered three SP profiles, and the total sample size was 3,006 SP responses. The analysis of this only focuses on car users (576), who provided 1,728 SP responses.

In the remainder of this paper, Section 2 reviews the existing literature. Section 3 describes the SP-off-RP survey, followed by some aggregate analyses in Section 4. Section 5 explains the model structure employed in this study. Section 6 presents and discusses model estimation results. This study is concluded in Section 7.

2. Literature Review

Recent years have observed more and more studies on AVs in the context of both passenger and freight transport, in terms of driving safety (Schoettle and Sivak, 2015; Lambert, 2016), vehicle ownership, and usage, as well as travel mode choice (Becker and Axhausen, 2017), traffic flow and management (Zhang et al., 2015; Lamotte et al., 2016; Talebpour and Mahmassani, 2016; Chen et al., 2017; Lamotte et al., 2017), system design and optimization (Zhu and Ukkusuri, 2015; Fagnant and Kockelman, 2016; Levin and Boyles, 2016; Chen et al., 2017), regulations (James et al., 2014; Meyer, et al. 2017; Favarò et al., 2018), and impacts of AV deployment (Fagnant and Kockelman, 2015; Wadud et al., 2016). Related to regulations, Kyriakidis et al. (2015) argued that software hacking/misuse and legal and safety issues are still the main concern of the public, especially in developed countries, where there are more concerns about vehicle data transmission. Fagnant and Kockelman (2015) discussed the barriers of deploying AVs in terms of high initial costs, different licensing and testing standards, liability, security concerns, and lack of privacy standards.

2.1 Safety

Using data obtained from AV manufacturers testing on California public roads from 2014 to 2017, Favarò et al. (2018) presented trends of disengagement reporting, associated frequencies, and average mileage driven before failure, as well as an analysis of triggers and contributory factors. Positive impacts of AVs on driving, such as fatigue driving reduction and crash prevention (Bansal et al., 2016; Fagnant and Kockelman, 2015; Schoettle and Sivak, 2014), have been confirmed, while concerns about system failures and breeching errors have been pointed out (Bansal et al., 2016; Schoettle and Sivak, 2014). In the UK, Hulse et al. (2018) conducted an online survey on 1,000 respondents regarding their perceptions about AV safety and acceptance, and found that AVs were positively perceived as a “somewhat low risk” form of transport; however, they still had several concerns. Salonen (2018) conducted an interesting study on a driverless (autonomous) shuttle bus operated in a city of Finland, where a total of 19,021 passengers travelled 3,962 km on autonomous buses on a specific route in summer 2015. Collecting data from 197 passengers, Salonen found that passengers perceived better driving safety in the driverless bus; however, many passengers, especially females, answered that sense of in-vehicle security (e.g., to be a victim of a crime) in the driverless shuttle bus was worse or much worse compared with a conventional bus.

2.2 Public acceptance, ownership, and willing to pay (WTP)

Schoettle and Sivak (2014) examined public opinions in the US, the UK, and Australia via an online survey conducted on 1,533 respondents, and revealed that a majority were willing to pay (WTP) (455 USD at 75th percentile) relatively less for AV technologies equipped in their vehicles, and a general desire about technologies of connected vehicles when they become available, even though there were concerns about AV security and performance issues. In the context of the US, Bansal and Kockelman

(2016) showed that Texans were WTP 2,910, 4,607, and 7,589 USD for Level 2, Level 3, and Level 4 automation, respectively. Using data from a nationwide online panel of 1,260 respondents, Daziano et al. (2017) confirmed that a significant share of the respondents was WTP 10,000 USD or more for full automation technologies, while many were not WTP for any automation technologies. The average WTP was about 3,500 USD for partial automation and 4,900 USD for full automation. More generally, Kyriakidis et al. (2015) explored 5,000 respondents' opinions on AVs from 109 countries through an online survey. They summarized that 69% of the respondents believed that fully AVs would reach 50% market share between now and 2050. However, respondents' WTP values are diverse: about 5% are larger than 30,000 USD for full automation, and 22% people are reluctant and refuse to pay any money for AV techniques on their vehicles. It is also shown that those with a higher WTP are males who have higher income, more driving mileage, and use a car with adaptive cruise control functions.

As for factors affecting WTP and public acceptance, Shina et al. (2015) highlighted that WTP for advanced vehicle technologies are quite sensitive to the price, and that customers' preferences are highly heterogeneous for various advanced vehicle options, such as a wireless connection, voice control, and autonomous driving. Shina et al. also confirmed respondents' basic knowledge and subjective attitudes towards AVs to be potential influencing factors. Bansal and Kockelman (2016) found that affordability and equipment failure are Texans' top two concerns regarding AVs, and people who are more safety-cautious are more likely to show a higher WTP value. More generally, Becker and Axhausen (2017) presented the most comprehensive picture about research on the acceptance of AVs. They revealed that existing studies have mainly examined the effects of the following factors: sociodemographic variables (e.g., gender, age, income, education, and the presence of children), attitudinal variables (e.g., technology awareness, locus of control, sensation seeking, personality, passion for driving, and data privacy concerns), trip characteristics (e.g., population density, trip purpose, trip distance, driving on highways and in congested traffic, and special lanes for AVs), and current behavior (e.g., mileage, car sharing, autonomy level of current vehicle, car availability, use of other travel modes, and experience of traffic accidents).

2.3 Usage

In the Netherlands, as a new type of the last-mile travel mode for multimodal train trips, Yap et al. (2016) found that travelers using first-class train carriages showed a higher preference for AVs compared with other modes, such as bicycles, buses, trams, or the metro, and that the WTP for AVs is higher than that for private cars from the viewpoint of travel time savings. Harper et al. (2016) estimated potential increases in travel with AVs for the non-driving elderly and people with travel-restrictive medical conditions. Focusing on commuting mode choices between conventional vehicles, privately owned AVs, and shared AVs, Haboucha et al. (2017) conducted an SP survey on 721 individuals in Israel and North America. They found that early AV adopters are young, students, and more educated, and spend more time in vehicles. They further revealed that a large share (44%) of the respondents hesitated to adopt an AV, and even in the case of the shared AV service being completely free, only 75% would be willing to use it.

2.4 Impacts

As for the effects of AVs, Wu et al. (2011) developed a new fuel-economy optimization system (FEOS) and found that drivers aided by FEOS could save 22–31% of overall gasoline consumption in all acceleration conditions, and 12–26% in the majority of deceleration conditions. Wadud et al. (2016) further examined the energy and environmental impacts of AVs. Fagnant and Kockelman (2015) revealed that the major effects of deploying AVs in the market would be crash savings, travel time reduction, fuel efficiency, and parking benefits. Meyer et al. (2017) revealed the impacts of AVs on the accessibility of the Swiss municipalities, and found that they encouraged more urban sprawl and rendered public transport superfluous, except for in dense urban areas. Clements and Kockelman (2017) evaluated the economic effects of connected and fully AVs in the US across 13 industries and the overall economy, where the time savings derived from reduced traffic congestion and the added productivity from the hands-free driving environment of AVs are on top of the effects on specific industries. Note that all the above effects depend on how many people will own and use an AV, which needs more exploration.

2.5 Modeling approaches

This study deals with choices of different types of AVs, together with a conventional vehicle. For such a choice behavior, existing studies have mainly applied a mixed logit (MXL) model, which will also be adopted in this study. Based on an SP survey conducted in South Korea (675 respondents), Shin et al. (2015) applied a multinomial probit model for describing choices of four smart vehicle options, where autonomous and connected driving were treated as two SP attributes, together with four other attributes (price of smart car option, voice command [control vehicle by voice command], wireless Internet [3G or 4G Internet service provided], and a smart application providing real-time information about parking, traffic conditions, and incidents). They found that the functions of wireless Internet and connectivity are relatively more important than autonomous driving. Using data from a nationwide online panel of 1,260 individuals who were asked to participate in a vehicle-purchase discrete choice experiment focused on energy efficiency and autonomous features, Daziano et al. (2017) estimated a conditional logit with deterministic consumer heterogeneity, a parametric random parameter logit, and a semiparametric random parameter logit by treating purchase price, fuel cost expenses, driving range, recharging time, and levels of hybridization and automation as the SP attributes. They revealed that WTP for automation functions differs across models, but highlighted the importance of modeling flexible preferences for emerging vehicle technology. Krueger et al. (2016), Yap et al. (2016), and Haboucha et al. (2017) all applied a MXL model in line with the point highlighted by Daziano et al. (2017). Krueger et al. (2016) applied a MXL model with panel data to describe choices of shared AVs with/without ride-sharing and public transit using SP data from 435 respondents in Australia, where the SP attributes were trip distance/cost/time and waiting time. Yap et al. (2016) analyzed choices between private cars (conventional) and public transit linked with four egress modes (walking, bicycling, AV car-sharing and fully AVs) by making use of SP data collected from 1,053 respondents in the Netherlands (SP attributes: travel time/cost, parking cost, waiting time, walking time to destination, sharing vehicle or not). Differently, Haboucha et al. (2017) built a joint ownership and usage model of privately owned and shared AVs, together with commuting mode choices, using a MXL model without panel data. The data used by Haboucha et al. (2017) were also SP data, collected from 721 respondents in Israel, the US, and Canada, where purchase cost, yearly membership cost for a shared AV, trip cost, and parking cost were selected as SP attributes.

The above literature review revealed limited studies in the context of the US, Europe, and Australia. Little has been done in the context of Asia. Especially, in Japan, as a developed country, automakers have invested a lot on the development of AV technologies and made various efforts to deploy them in the market. However, scientific insights are limited. To fill this research gap, the present study tries to investigate the Japanese public’s preferences and the shift in vehicle ownership behaviors from current conventional vehicles to AVs with different levels based on individuals’ heterogeneous WTP and future expectations.

3. Survey Design

The SP approach has been widely applied to capture consumers’ preferences for not-yet-existing alternatives (Hensher, 1994; Train and Wilson, 2008), and AVs are such an example. However, SP responses suffer from various biases due to hypothetical choice scenarios assumed in the survey. To enhance the reliability of survey data, this study specified SP attributes of AVs by referring to RP information reported by respondents, which is in line with the ideas of the SP-off-RP and pivoting approaches (Train and Wilson, 2008). The pivoting approach defines the SP alternatives that are similar to (pivoted off) an alternative that an individual chooses in an actual situation. The chosen alternative (RP) is either included in or excluded from the choice set. In the SP-off-RP survey, the respondent is asked which of the RP alternatives he/she would choose if the attributes of the chosen alternative were made worse and/or the attributes of any of the unchosen alternatives were made better, i.e., the SP choice set is the same as the RP choice set. SAE International (2014) defined six levels of automation, ranging from Level 0 (no automation) to Level 5 (full unrestricted automation), as shown in Table 1. This study focuses on the last three levels, Level 3 (*Conditional* AV), Level 4 (*High* AV), and Level 5 (*Full* AV), and treats conventional vehicles (Levels 0–2) as a reference. In other words, the SP choice set in the survey includes four alternatives.

Table 1: Levels of driving automation

Vehicle type	SAE level	Name	Execution of Steering and Acceleration/ Deceleration	Monitoring of Driving Environment	Fallback Performance of Dynamic Driving Task	System Capability (Driving Modes)
Conventional vehicle	0	No Automation	Human driver	Human driver	Human driver	N/A
	1	Driver Assistance	Human driver and system	Human driver	Human driver	Some driving modes
	2	Partial Automation	System	Human driver	Human driver	Some driving modes
Autonomous vehicle (AV)	3	Conditional Automation	System	System	Human driver	Some driving modes
	4	High Automation	System	System	System	Some driving modes
	5	Full Automation	System	System	System	All driving modes

The following five types of attributes were selected for the SP survey, each of which has two or three levels. These attributes were selected based on a literature review in terms of either ignorance or ill-representation in existing studies.

(1) Penetration rates of AVs (three attributes): Usually, social interactions play a critical role in encouraging or discouraging customers' choice decisions (Manski, 1993) and vehicle ownership (Kuwano et al., 2011). To reflect such a phenomenon, penetration rates of *Conditional* AV, *High* AV, and *Full* AV are assumed, each of which has three levels, defined based on the diffusion of innovation theory (Rogers, 2003). Considering the technological advantages and the resulting cost, there should be an increasing trend from *Conditional* AV to *Full* AV. Therefore, first, the penetration rate of *Full* AV is fixed to the following three levels: 5%, 10%, and 20%, and then the levels for the other two AVs are determined based on the additional increase in the rate corresponding to the above three levels, separately. The three levels roughly correspond to the shares of innovators, early adopters, and early majority in the conventional diffusion curve.

(2) Additional purchase cost for AVs (three attributes): This attribute is associated with the amount people are WTP. Becker and Axhausen (2017) presented a comprehensive review on WTP in the context of AVs, mainly in US and Europe. Unfortunately, no studies on Japanese peoples' WTP for AVs at the national level can be found. In this study, additional purchase costs for *Conditional* and *High* AVs were calculated based on *Full* AV, and additional purchase costs were fixed to three levels: 700,000, 850,000, and 1000,000 JPY, corresponding to the penetration rates of 20%, 10%, and 5%, respectively, in the future market. Levels of the additional purchase costs for the other two AVs were calculated based on the additional reductions corresponding to the above three levels, separately. Here, the effects of operational cost of AVs are excluded because of its future uncertainty, which is associated with the progress of technological development and legal requirements (e.g., presence of driver, driving license requirements, responsibility in the case of accidents).

(3) Insurance discount rate for AVs (two attributes): Because AVs can operate in a much safer way than conventional vehicles, relevant insurance premiums are expected to shrink. There was no insurance discount policy released by any insurance company in Japan at the time of the survey. Here, the

insurance discount rate of *Conditional* and *High* AVs is assumed to be the same with three levels of 10%, 30%, and 50%, and *Full* AV is expected to enjoy a higher discount rate (from 15% to 70%), considering that it has the highest safety level. Insurance has not been examined in the context of AVs, as reviewed by Becker and Axhausen (2017).

(4) Parking cost for AVs (one attribute): With self-driving/self-parking functions, it is expected that AVs could contribute to the parking cost reduction by parking itself in a cheaper parking lot, a little bit farther from users' homes. Here, two levels of parking cost reduction are introduced, 50% and 0% (i.e., no reduction). The 50% reduction is assumed based on the calculation by Litman (2012), who compared parking costs for moving parking spaces to an outside central business districts or the suburbs. Studies on the impacts of parking cost reduction on AV ownership are missing in the literature (see Becker and Axhausen [2017]).

(5) Release timing of AVs to the market (one attribute): Respondents' choices of AVs are made by assuming that all types of the AVs will be available in the future market. However, when the AVs will be released in the future may matter to the choices of AVs. To this end, the release timing of AVs in the future market is further introduced into the SP survey. Three levels are assumed: 5, 10, and 15 years from the present time. No studies can be found in the literature with respect to the effects of the release timing of AVs as described above.

For car users, the conventional vehicle refers to their current car. In this sense, the survey method follows the pivoting approach. Additional AV purchase costs are constructed by a comparison with the purchase costs (only vehicle body price) of their current vehicles. In this sense, the survey method is in line with the SP-off-RP survey. The SP survey targeted both car and public transport users, even though data from the latter are not used in this study (public transport users were told that the conventional vehicle refers to a conventional vehicle in the current market).

To reflect properly the influence of income in the future, each respondent was asked to report a change (increase, decrease, or no change) in his/her income in the past 5 years, and then this change was assumed to continue in the future when they would have to make a choice about buying a new car or not, and if so, what type, based on the above-mentioned SP attributes. Such treatment is expected to allow respondents to answer SP questions in a more realistic way. An example of an SP profile is shown in Table 2.

Table 2: An example of SP profile

<table>
<tr><td colspan="5">Assuming that your future income will increase by 30%, please select your most preferred vehicle from the following four types.</td></tr>
<tr><td>SP attributes</td><td>Conditional AVs</td><td>High-AVs</td><td>Full-AVs</td><td rowspan="6">Conventional vehicle</td></tr>
<tr><td>Penetration rates of AVs</td><td>25%</td><td>20%</td><td>20%</td></tr>
<tr><td>Release timing of AVs to the market</td><td colspan="3">10 years later simultaneously</td></tr>
<tr><td>Additional cost for AVs (JPY)</td><td>200,000</td><td>350,000</td><td>700,000</td></tr>
<tr><td>Insurance discount rate for AVs</td><td colspan="2">50%</td><td>55%</td></tr>
<tr><td>Parking cost for AVs</td><td colspan="3">50%</td></tr>
<tr><td>Choice</td><td>❑</td><td>❑</td><td>❑</td><td>❑</td></tr>
</table>

In total, 18 SP profiles were obtained by employing an orthogonal fractional factorial design, which attempts to examine the main effect of each SP attribute on vehicle choice. In the survey, these are divided into six groups, each of which has three SP profiles.

The respondents of this survey consisted of not only car users, but also public transport users. Here, we only focus on car users. In addition to the above SP part, each car user respondent was further asked to report: his/her actual travel behavior and driving experience for short- and/or long-distance driving; occurrence of unsafe driving incidents during driving; and self-cognition about behavioral changes toward safe driving measured in terms of whether and how much he/she wants to improve his/her current driving safety level. The respondents were further asked to report their WTP for additional purchase costs above the three types of AVs, after reading a brief explanation about each type. Finally, individual attributes were investigated.

4. Survey Implementation and Aggregate Analysis

The survey was conducted in Japan in December 2016, and data were collected from 1,002 respondents by following the distributions of age, gender, and population size by region across the whole population in Japan, with the assistance of a major Internet survey company. The regions were divided as follows: three megacity areas (Tokyo, Nagoya, and Osaka) (400 respondents), governmental ordinance cities (excluding those in the above three megacity regions: 300 respondents), and other regions (302). Respondents were 15–70 years old. The number of male respondents (507) was nearly equal to that of female respondents (498). Each of the 1,002 respondents answered three SP profiles, and as a result, the total sample size was 3,006 SP responses.

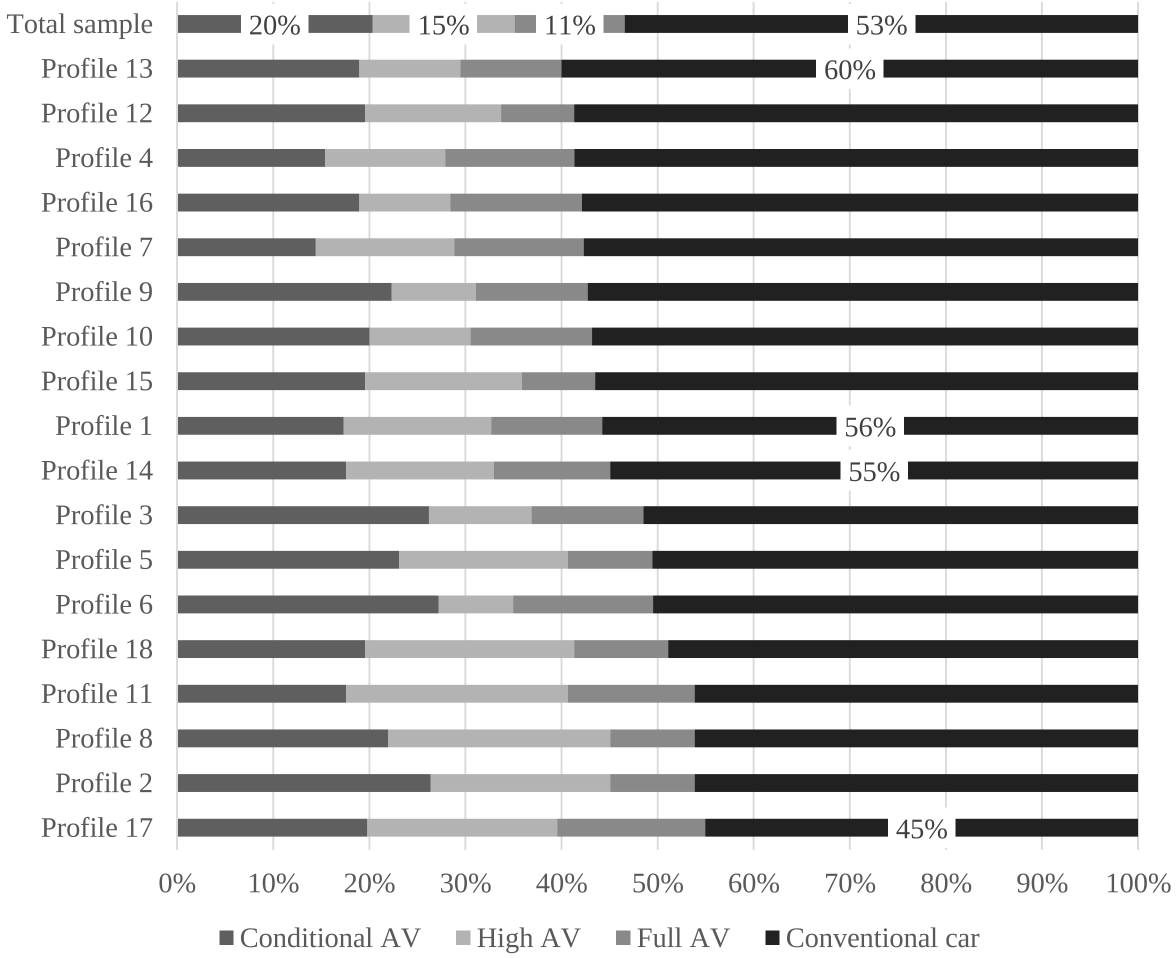


Figure 1. Vehicle preferences by SP profile

This study focuses on car users (576 persons), who provided 1,728 SP responses. Among all the SP responses, 53% chose to buy a conventional car, while 20% preferred *Conditional* AVs, 15% selected *High* AVs, and the rest (11%) *Full* AVs. SP responses for all 18 assumed SP profiles are shown in Figure 1. Shares of stated AV choices varied between 40% and 55%. In an existing study using 4,260 SP responses collected from 721 individuals living in Israel and North America, Haboucha et al. (2017) found that 65% of the respondents in Israel and 46% in North America preferred to own an AV (privately-owned or shared). Thus, the stated AV shares between Japan and North America are not significantly different, even though they cannot be compared precisely because of different survey conditions.

Respondents' WTP for additional costs when purchasing the three types of AVs (Table 3), on average, are 402,233 JPY for a *Conditional* AV, which is about a 22.3% increase from the original price of a conventional car. The WTP for *High* and *Full* AVs are 563,847 JPY (31.9% increase) and 793,611

JPY (45.7% increase), respectively. In the case of the WTP being positive, these values range between 499,324 and 934,518 JPY.

Table 3: Average WTP Values of Additional Purchase Costs of AVs

	WTP (WTP>=0)			WTP (WTP>0)		
	JPY	US$	Increase rate	JPY	US$	Increase rate
Conditional AVs	402,233	3,557	22.3%	499,324	4,416	27.7%
High AVs	563,847	4,987	31.9%	666,679	5,896	37.7%
Full AVs	793,611	7,019	45.7%	934,518	8,265	53.8%

Currency: 1 JPY = 0.008844 US$; Increase rate: from the original price of the current conventional car

5. Methodology

Here, a MXL model with panel data (McFadden and Train, 2000; Train, 2009; Hole, 2007, 2013) is employed to represent each respondent's stated choices of AVs ownership, which are repeated for three SP profiles in the survey of this study, like three waves in a panel survey. The utility that individual *n* chooses *j* alternative at choice occasion *t* (refers to an SP profile in this study) is given below.

$$U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt} \tag{1}$$

Here, β_n' is a vector of individual-specific coefficients of explanatory variable vector (x_{njt}), and ε_{njt} is an error term following an IID extreme value distribution. The density function for β is denoted as $f(\beta|\theta)$, where θ are parameters of the distribution. The probability that individual *n* makes sequential *t* choices from *J* alternatives can be given by the following equation.

$$S_n = \int \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta_n' x_{njt})}{\sum_{j=1}^{J} \exp(\beta_n' x_{njt})}\right]^{y_{njt}} f(\beta|\theta) d\beta \tag{2}$$

In equation (2), y_{njt} is a dummy variable that equals 1 when alternative j is chosen by individual *n* at choice occasion t, and to 0, otherwise. Then, the simulated log-likelihood (SLL) function can be obtained by maximizing the simulation under r draws (Halon draws) for each individual *n* from the distribution of β, where $\beta_n^{[r]}$ is *r-th* draw of individual *n* from the distribution of β as follows.

$$\mathrm{SLL} = \sum_{n=1}^{N} \ln\left\{\frac{1}{R}\sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta_n^{[r]} x_{njt})}{\sum_{j=1}^{J} \exp(\beta_n^{[r]} x_{njt})}\right]^{y_{njt}}\right\} \tag{3}$$

In the SP survey, we presented respondents with the release timing of AVs to the market (5, 10 or 15 years later). Even though we did not ask respondents when they would buy or would not buy, it can be interpreted that respondents made choices for the future, which refers to a period longer than 5, 10 or 15 years. In this sense, the above modeling approach assumes that people's choice behavior will not change over the above period and their responses to SP attributes are not time-sensitive. In other words, the discounting effects of money over the period are ignored. This is because the release timing is just an SP attribute and the resulting SP choices are not inter-temporal choices in nature. To avoid any misleading understanding, the above model is called MXL model with repeated choices in this study.

6. Model Results and Discussion

To estimate the MXL model, we introduced two types of explanatory variables: alternative-specific and alternative-generic variables. Here, the conventional vehicle is treated as a reference in model estimation.

During the model estimation, the parameters of the alternative-specific variables (the five SP attributes, and WTP for additional purchase cost reported by respondents) are assumed to be the same across the three AV alternatives, while the alternative-generic variables (individual attributes, future income expectation, behavioral change toward safe driving, and driving experience) are only introduced into the utility functions of the three types of AVs, and their corresponding parameters are also assumed to be the same across the three AVs. Introducing the WTP for additional purchase cost in the model complements the role of the additional purchase cost set in the SP experiment.

To accommodate the random effects, this study tried two types of distributions: an unbounded distribution (i.e., normal distribution) and a bounded distribution (i.e., lognormal distribution). The good feature of adopting an unbounded distribution is that it allows the existence of both positive and negative responses to a specific factor. However, this may also be a shortcoming of such an unbounded distribution because it may wrongly accept unrealistic responses. And Hess et al. (2005) further showed that a model using unbounded distribution (e.g., the normal distribution) always has better fit than the true model with a bounded distribution. Because there are probably correlations between the random-effect parameters, this study further incorporate such correlations into the model. The MXL models were estimated by employing STATA software (Version 14), with 500 Halton draws and 50 burnings. Unfortunately, we cannot obtain any converged results from models with the lognormal distribution, even by changing the numbers of draws and burnings. As a result, we chose the model shown in Table 4, which assumes a normal distribution to random-effect parameters and incorporates correlations between random-effect parameters. The McFadden Rho-squared value (0.492) and adjusted Rho-squared value (0.477) indicate that the model fits the data well. The likelihood ratio test against multinomial logit (MNL) model is 1526.69 (degree of freedom: 21), suggesting that the MXL model performs better than MNL model (i.e., without standard deviations of and correlations between the random-effect parameters). We estimated alternative-specific constant terms, which are however all insignificant. Detailed explanations about parameter estimation and relevant discussions are given below.

6.1 Attributes with random effects

Examining the effects of SP attributes is one of the main purposes in this study. To capture the influence of unobserved heterogeneity across individuals, both the mean and standard deviation parameters of each SP attribute are estimated by assuming a normal distribution, which can accommodate the existence of both positive and negative responses to each SP attribute. In other words, the unobserved heterogeneity with respect to each SP attribute is captured by the standard deviation parameter, which is also called the random-effect parameter. Considering the importance of WTP, its random effect is also incorporated in the same way. Table 4 shows not only the mean and standard deviation parameters, but also the interval values (mean $\pm$ 1.96*standard deviation) under 95% confidence level. One can see that all interval values range from negative to positive values, even though there are four negative mean values and two positive mean values. And as shown in Figure 2, the six random-effect distributions can be represented by the normal distribution, to some extent, even though, especially, additional purchase cost seems to follow a left-skewed distribution. Fortunately, the parameter values ranges from negative to positive, suggesting that the unbounded distribution is more suitable than the bounded distribution. This supports the use of the normal distribution.

Concerning the random effects, except for the mean parameter of release timing of AVs to the market, all the others are statistically significant at 5% or 1% level. Even though the release timing imposes no significant influence on respondents' choices of AVs, on average, such influence is not applicable to all samples because the standard deviation parameter is statistically significant at the 1% level. All the above results support the design of the SP survey by including the above SP attributes in this study. All the six significant standard deviations suggest the existence of respondents' heterogeneous responses to the six attributes. This reconfirms the importance of unobserved heterogeneity in representing travel choice behavior.

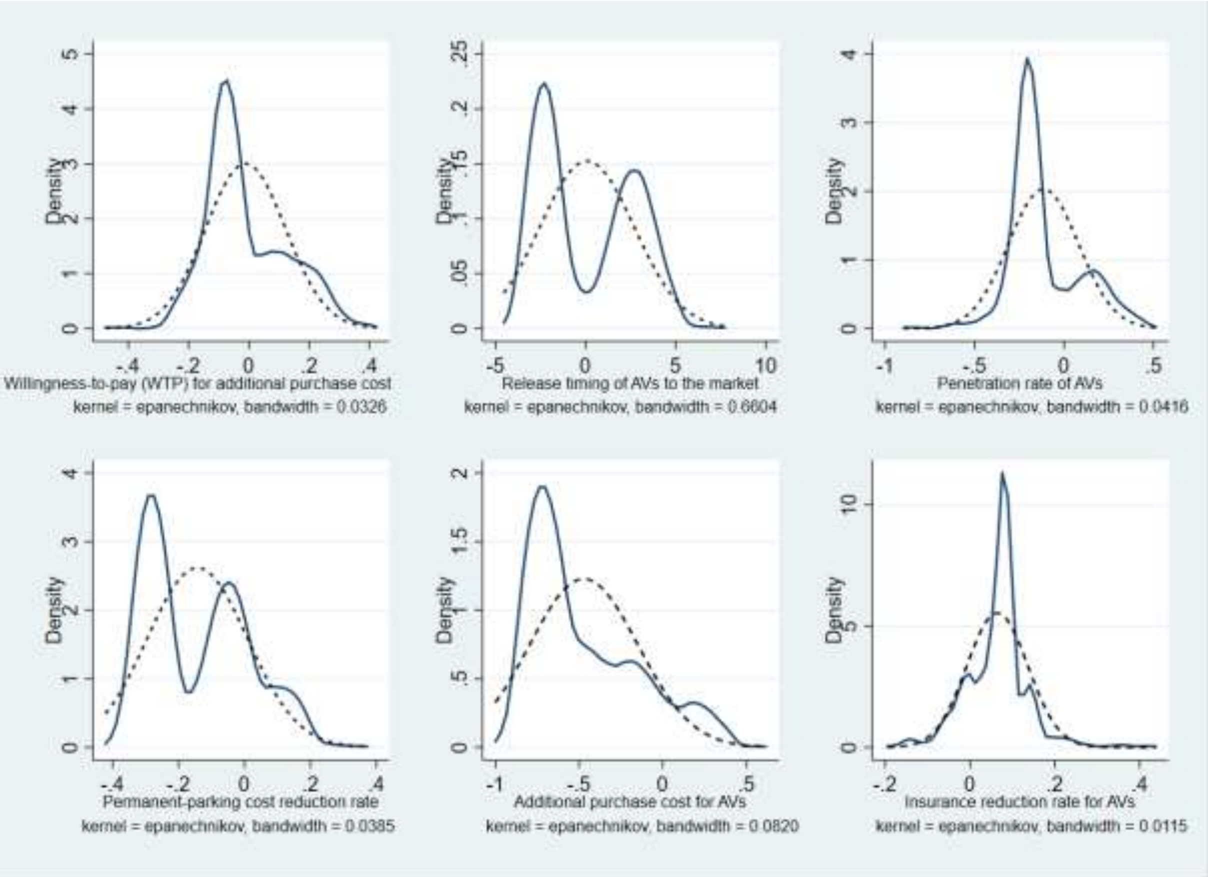
Especially, as shown in Table 5, most of correlation parameters are statistically significant. Among all the correlations, permanent-parking cost reduction rate and additional purchase cost for AVs show the highest value (0.790), followed by that (0.770) between release timing of AVs to the market and permanent-parking cost reduction rate, and that (0.720) between release time of AVs to the market and

Table 4: Estimation results of the mixed logit model with repeated choices

Explanatory variables		Parameter	t-score	sig.
Random-effect variables				
Willingness-to-pay (WTP) for additional purchase cost (10,000 Yen)	mean	-0.02	-1.83	**
	standard deviation	0.27	5.15	***
	interval estimate	[-0.55, 0.51]		
SP factors with random effects				
Additional purchase cost for AVs (10,000 Yen)	mean	-0.46	-4.72	***
	standard deviation	0.43	5.59	***
	interval estimate	[-1.31, 0.39]		
Insurance reduction rate for AVs (%)	mean	0.07	2.45	**
	standard deviation	0.17	3.75	***
	interval estimate	[-0.27, 0.40]		
Permanent-parking cost reduction rate (%)	mean	-0.14	-1.95	**
	standard deviation	0.20	3.09	***
	interval estimate	[-0.54, 0.26]		
Penetration rate of AVs (%)	mean	-0.13	-2.14	**
	standard deviation	0.39	4.12	***
	interval estimate	[-0.88, 0.63]		
Release timing of AVs to the market (years)	mean	0.13	0.88	
	standard deviation	3.43	4.91	***
	interval estimate	[-6.59, 6.84]		
Individual attributes				
Aged under 30s [15-29 years old] (Yes: 1; No: 0)		-11.38	-3.59	***
Aged 30s [30-39 years old] (Yes: 1; No: 0): reference				
Aged 40s [40-49 years old] (Yes: 1; No: 0)		1.25	0.73	
Aged 50s [50-59 years old] (Yes: 1; No: 0)		0.83	0.36	
Aged 60s [60-69 years old] (Yes: 1; No: 0)		5.77	2.62	***
Gender (Male: 1; Female: 0)		-3.04	-1.94	*
High-education (University level or above: 1; otherwise: 0)		5.10	3.27	***
Number of elderly members (aged 65+ years old) in household		-5.60	-3.5	***
Number of primary & secondary school students in household		-0.68	-0.81	
Behavioral change toward safe driving				
Stage of driving safety improvement (Try to improve: 1; otherwise: 0)		0.54	0.37	
Future expectation of income				
exp (absolute value of income decrease)		-5.49	-2.19	**
ln (absolute value of income increase + 1)		-2.44	-0.23	
Short-distance driving experience				
Sudden braking/handling (Yes: 1; No: 0)		-5.44	-2.89	***
Driving time per trip (minutes)		0.11	3.96	***
Driving frequency (times/week)		1.81	3.03	***
Driving purpose 1: commuting purpose (Yes: 1; No: 0)		-2.71	-1.25	
Driving purpose 2: shopping purpose (Yes: 1; No: 0)		3.90	2.09	**
Long-distance driving experience				
Sudden braking/handling (Yes: 1; No: 0)		13.17	4.49	***
Driving time per trip (minutes)		0.001	0.33	
Driving frequency (times/week)		3.98	2.49	**
Driving purpose 1: tourism (Yes: 1; No: 0)		4.14	2.40	**
Driving purpose 2: going back to hometown (Yes: 1; No: 0)		0.68	0.35	
Constant terms	Conditional AV	-1.22	-0.3	
	High AV	2.79	0.61	
	Full AV	-1.08	-0.19	

Initial log-likelihood: -2395.52; Converged log-likelihood: -1217.22;
McFadden Rho-squared: 0.492; Adjusted McFadden Rho-squared: 0.477;
Likelihood ratio test against MNL model: Chi2(21) = 1526.69, p =0.0000

sig.: Significant level (*: 10%; **: 5%; ***; 1%)



(dotted line: theoretical distribution; solid line: empirical distribution)

Figure 2. Plots of random-effect parameters

additional purchase cost for AVs. Furthermore, a correlation higher than 0.5 is observed with respect to penetration rate of AVs and WTP for additional purchase cost for AVs, and release timing of AVs to the market and permanent-parking cost reduction rate. Because the release timing affects the price of AVs and relevant costs of owning/using AVs, the above results indicate that cost factors affect the ownership of AVs in a complicated way. Reflecting such correlations in both survey and modeling processes is important.

For insurance reduction rate, the mean parameters are positive, suggesting that more respondents are likely to own an AV if insurance reduction rate is higher. The mean parameter of additional purchase cost is negative. These results look logical. However, different from our expectations, respondents are more likely to own an AV if WTP for additional purchase cost is lower, permanent-parking cost reduction rate is lower, and penetration rate is lower, as suggested by the mean parameters. Because all interval estimates have both negative and positive values, interpreting the meaning of each attribute needs to pay attention to different respondents' heterogeneous responses. For example, as for the penetration rate of AVs in the market, the higher the rate, the lower the choice probability of AVs, as suggested by the mean parameter (–0.13) of the penetration rate. This seems counterintuitive. Actually, the standard deviation parameter of the penetration rate is 0.39, indicating that the 95% confidence interval value of the penetration rate parameter is [-0.88, 0.63], as seen in Table 4. Thus, some respondents show a negative preference for the penetration rate, and others a positive preference. The use of the MXL model allows for such heterogeneous responses across individuals. To illustrate such heterogeneity more clearly, Table 6 shows the magnitudes of standard deviations relative to mean parameters. The value "Φ ($-\beta_k/s_k$)" is used to judge respondents' preference patterns (depending on the sign of β_k/s_k), where Φ is the cumulative standard normal distribution, and β_k and s_k are the mean and standard deviation of the kth parameter. It is found that only 14.5% of respondents prefer a higher additional cost, 47.2% prefer a lower WTP, 35.3% prefer a higher insurance reduction rate, 24.4% prefer a higher permanent parking cost reduction rate, 37.1% prefer a higher penetration rate, and 48.5% prefer an earlier release timing of all types of AVs in the market.

Table 5: Variance and covariance as well as correlations between random-effect parameters

	v1	v2	v3	v4	v5	v6
v1	0.148 **	-0.007	0.099 **	0.056 **	0.026 *	-0.038 ***
	1.000 **	-0.100	0.080 **	0.540 **	0.330 *	-0.230 ***
v2		0.030 *	-0.225 **	0.013 *	0.001	0.011 *
		1.000 *	-0.380 **	0.280 *	0.040	0.140 *
v3			11.732 ***	0.058	0.531 **	1.071 ***
			1.000 ***	0.060	0.770 **	0.720 ***
v4				0.073 ***	0.016	0.006
				1.000 ***	0.290	0.050
v5					0.041	0.069 **
					1.000	0.790 **
v6						0.188 ***
						1.000 ***

(1) v1: penetration rate of AVs, v2: insurance reduction rate for AVs, v3: release timing of AVs to the market, v4: willingness to pay for additional purchase cost for AVs, v5: permanent-parking cost reduction rate, v6: additional purchase cost for AVs

(2) Significant level [*: 10%; **: 5%; ***; 1%]

(3) value in upper tier: variance/covariance; value in lower tier: correlation

Table 6: Interpretation of preference for attributes with random effects

Attributes	β_k/s_k	$\Phi(-\beta_k/s_k)$	y=1- Φ, if β_k/s_k <0; y=Φ, otherwise	Interpretation
Willingness-to-Pay for additional purchase cost (10,000 JPY)	-0.069	52.8%	47.2%	prefer lower WTP
Additional purchase cost for AVs (10,000 JPY)	-1.058	85.4%	14.5%	prefer higher additional cost
Insurance reduction rate for AVs (%)	0.376	64.7%	35.3%	prefer higher insurance reduction rate
Permanent parking cost reduction rate (%)	-0.695	75.6%	24.4%	prefer higher parking cost reduction rate
Penetration rate of AVs (%)	-0.328	62.9%	37.1%	prefer higher penetration rate
Release timing of AVs to the market (years)	0.037	51.5%	48.5%	prefer shorter earlier release

Then, how to understand those counterintuitive results? Actually, there are two types of counterintuitive results: the first type is that the mean parameters are counterintuitive, and the second is that the interval estimates are counterintuitive. For the first type, for example, this case study estimates that a higher penetration rate leads to a lower ownership level of AVs. This suggests that people tend to less own an AV if its share in the market becomes high. If this is true, one may expect that the market share of AVs will not be as high as expected. In case of permanent-parking cost reduction rate, we compared the SP choice shares of the four types of vehicles with respect to the two cases of normal parking cost (i.e., the reduction rate is 0%) and half parking cost (i.e., the reduction rate is 50%) (see Figure 3), and found that taking the three types of AVs as a whole, the share of choosing an AV is slightly higher than that of a conventional vehicle. Thus, the aggregate analysis results are consistent with our expectation. However, Figure 3 further shows that parking cost reduction owing to the introduction of AVs decreases the choice of *Conditional* AV from 21.3% to 18.2%. It can be said that the counterintuitive sign of parking cost reduction is mainly because of the decision on *Conditional* AV. Probably, respondents suspected the possibility of a larger reduction rate for permanent-parking cost. For the second type of counterintuitive results, for example, there are some respondents showing that higher reduction rate of insurance leads to a lower probability of owning an AV, as shown by negative values of the interval estimate. There are probably misperceptions about the influence of insurance reduction because of inexperience with *High* AV and *Full* AV. As described in Section 1, Nissan Motor Company has released a small van equipped with partially autonomous driving functions on expressways since August 2016. Since then, news about how Japanese insurance companies would prepare for AVs reported that some companies would use the current insurance scheme to support the introduction of Nissan's van, i.e., no reduction in insurance, but policies of other companies were unclear. Such news may affect the respondents' decisions.

AV is a fully new type of vehicle. It is still difficult to say that it will show a similar ownership pattern as those traditional vehicles. In other words, for example, it is not sure to say that the negative sign of the penetration rate is wrong. What we can surely say is that empirical studies should be accumulated in the future.

6.2 Individual attributes

Here, age, gender, education, and household structure are selected. As for age, four dummy variables are estimated, where the variable "aged 30s [30–39 years old]" is treated as a reference. Model estimation results show that two out of the four age dummy variables are significant at 1% level, i.e., aged under 30 [15–29 years]: less likely to own an AV (parameter: –11.38), and aged in the 60s [60–69 years]: more likely to own an AV (parameter: 5.77). Especially, the degree of preference for the lower ownership by those aged under 30 (i.e., young people) is much higher than that for higher ownership by those aged in the 60s. In other words, young people are more likely to own conventional vehicles than AVs. One potential reason for this bigger negative response might be because of their lower level of income. Since the late 1990s, a decline in young people's car ownership in Japan has been observed (Zhang et al., 2016). If this trend continues in the future, it may be difficult to expect more ownership of AVs by young people. Intuitively, this may be true, considering that young drivers may prefer controlling their cars by themselves, rather allowing the car to control itself, because of their shorter driving history compared with older drivers. As reviewed by Becker and Axhausen (2017), most existing studies on the acceptance of AVs treat age as a continuous variable. In this sense, the above findings are all new.

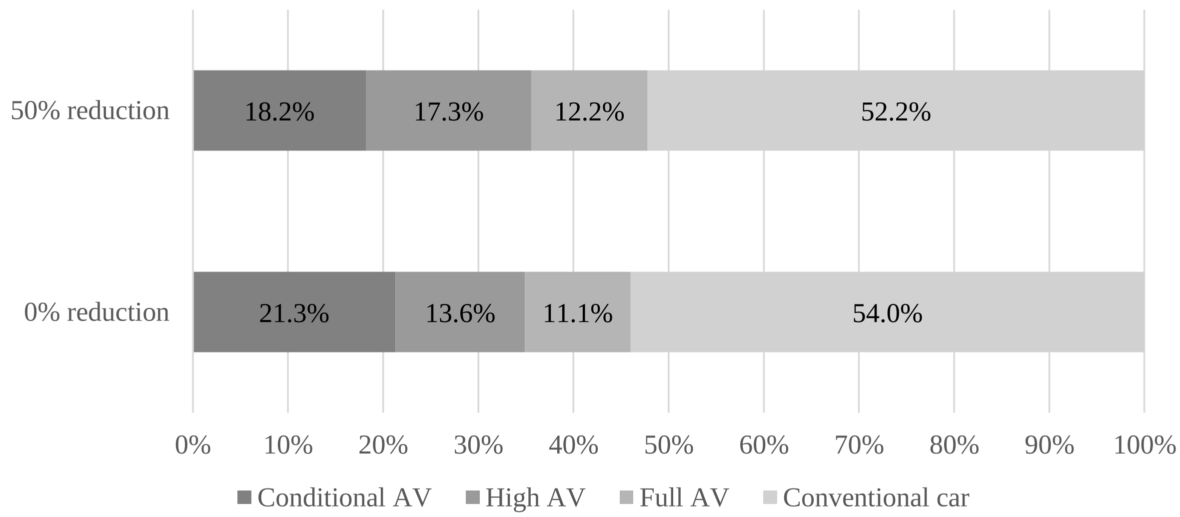


Figure 3. Reduction rate of permanent parking cost and shares of vehicle choices

There is significant difference between male and female respondents' preferences for AVs because the gender parameter is significant. Such significance is reflected by the fact that the share of AVs chosen by males is 47.8%, and that chosen by females is 44.5%. This finding is consistent with the case study conducted by Schoettle and Sivak (2014) in the US, the UK, and Australia, but differ from that reported by Bansal et al. (2016) in the context of the US (the Austin region). Different from existing studies, in this study, we balanced the distributions of age and gender between the whole population and the samples. The only way to further confirm whether our findings are correct may be to increase the sample size.

Respondents with a higher education background (university level or higher) are more interested in choosing an AV. We found one study looking at the influence of education on intention to use an AV in the context of the US (Zmud et al., 2016); however, that study showed no significant influence of education.

The presence of primary and middle school children in a household does not affect the choice of an AV. Differently, the above study by Zmud et al. (2016) showed a negative influence of the presence of children on the intention to use an AV. However, the number of household members aged 65 years and older is negatively associated with AV ownership, which is contrary to our expectation, because we thought that those aged 65 years and older would care more about their safety and consequently choose an AV, in comparison with younger drivers.

6.3 Future income expectation

Influences of individual future income on vehicle type choices are measured by two separate variables: expected income decrease (%) and expected income increase (%) from the current income level. Such treatment is because people may be more sensitive to a decrease than to an increase in income. To this end, expected income decrease is expressed by transforming the absolute value of income decrease into an exponential form, and expected income increase is described by transforming the absolute value into a logarithm form. As a result, it is found that an income increase is insignificant, but an income decrease is significant. The parameter of expected income decrease is estimated to be negative, meaning that respondents who are expected to have lower income in the future are less likely to choose AVs compared with conventional vehicles; this is straightforward. By contrast, an increase in future income does not affect vehicle choice. This indicates that the additional costs of purchasing an AV assumed in the survey are acceptable, considering increases in the future, and as a result, such respondents become less sensitive to income. Unfortunately, we could not find any study examining the effects of future income.

6.4 Behavioral change toward safe driving

The parameter of this variable is estimated to be positive (0.54), indicating that respondents who are willing to improve their current safety status more frequently prefer an AV. Unfortunately, this parameter is statistically insignificant, different from our expectation. The automobile industry has demonstrated the safety performance of AVs in various ways. If this analysis result can be generalized, then why people like to own an AV is not because of its safety performance; rather, it may be because people can be relieved from driving a car. This implies that to increase the share of AVs in the market, it is necessary to make a better advertisement of AVs in terms of comfort without human interventions to driving. A literature review suggests that no study has examined the effects of the above behavioral change.

6.5 Driving experience

Here, driving experience is captured by two variables, one for short-distance driving and the other for long-distance driving, in terms of sudden braking/handling experience (indicating safety concern), driving frequency (i.e., familiarity with driving), previous driving time per trip (i.e., driving intensity), and main driving purpose. No studies can be found that examine the effects of the above factors.

Interestingly, for both short- and long-distance driving, experience of sudden braking/handling is influential to the choices of an AV, but in different ways. Concretely speaking, such an experience in long-distance driving increases the choice probability of an AV, because the corresponding parameter is positive (13.17), while experience in short-distance driving reduces the probability, because the corresponding parameter is negative (–5.44); the former observation for long-distance driving is intuitive. As for short-distance driving, it refers to daily driving, for which the speed is usually lower, but traffic situations are more complicated, in comparison with long-distance driving. Such features of short-distance driving may discourage respondents' ownership of AVs, or, respondents may just suspect the ability of AVs to improve driving safety under more complicated traffic conditions. Even in short-distance driving, when driving intensity increases (i.e., longer driving time), respondents prefer to own an AV because the parameter of driving time is positive (0.11) and statistically significant at 1% level. The reason why the parameter of driving time in the case of long-distance driving is insignificant may be because after driving time/distance reaches a certain level, respondents become less sensitive to it. In other words, there may exist a threshold of driving time/distance that segments respondents into owners and non-owners. Concerning driving purposes, shopping in case of short-distance driving and tourism in case of long-distance driving are estimated to be influential because their parameters are positive (3.90 and 4.14, respectively), suggesting that AVs may allow drivers to go shopping in a much easier way than using a conventional car and to enjoy tourism more during driving. Finally, driving frequency is influential in both short- and long-distance driving. Their parameters are all positive, implying that people driving more frequent tend to own an AV. This implies that if a car dealer wants to sell an AV to a customer, he/she first needs to figure out whether the customer usually drives for long times/distances. If a governmental agency wants to promote AVs, drivers who drive longer should be targeted.

7. Conclusion

Research on AVs has been actively conducted in developed countries; however, it is still unclear whether and how to deploy AVs for resolving various traffic issues. This is partially because there are still many unknowns about people's preferences for AVs in comparison with conventional vehicles, especially considering the influences of various observed and unobserved heterogeneities. More academic research should be accumulated. This study has made additional efforts in the context of Japan, focusing on the ownership behavior of AVs in the future. Future preferences are quantitatively measured based on an online SP survey, where *Conditional* AV, *High* AV, and *Full* AV are targeted. We selected 1,728 SP responses from current car users from data collected from 1,002 respondents who were recruited from the whole of Japan in 2016 considering the distributions of age and gender across different administration areas. Unobserved heterogeneities with respect to major factors were captured by using a MXL model with repeated choices.

On average, the respondents' WTP for additional purchase cost of AVs was 402,233–793,611 JPY (about 3,557–7,019 USD), in comparison with conventional vehicles. This average WTP is within the range of the WTP calculated by Bansal et al. (2016) in their Austin case study: 3,300–7,253 USD for Level 3 and Level 4 AVs. WTP for Level 4 almost doubles that for Level 3 in the study of Bansal et al. (2016), which is quite different from the Japanese case of this study (WTP for Level 4 was 40% higher than that for Level 3). With the above WTP and considering the influence of other factors, the SP survey in this study revealed that almost half (47%) of the total sample (1,728 SP responses) stated that they preferred to own an AV.

Analyses based on the MXL model with repeated choices showed that all SP attributes introduced in the survey were statistically influential to the ownership behavior of AVs in terms of mean and/or standard deviation parameters. Most of the correlations between random-effect parameters are also significant. However, both expected and unexpected results with respect to the random-effect variables are observed, suggesting the necessity of accumulating more case studies. As for the influence of expected future income, only income decrease was influential in a way to reduce the ownership of AVs. Young people tend to avoid owning AVs, which contrasts with the elderly group. Effects of the number of different household members and driving purposes on the ownership of AVs are mixed. Intention to improve driving safety seems irrelevant to the ownership of AVs. People with risky driving experience in long-distance driving and frequent driving prefer owning AVs.

The above findings have important policy implications for deploying AVs in the market to resolve various traffic issues. Even though various advantages of AVs have been emphasized by automakers and pro-AV policy makers, it seems that the respondents in this case study were honest, because there were still about half of them who did not prefer to own an AV. Such an honest response may be reflected in their honest perceptions about the disadvantages (e.g., security, privacy, and reliability) of AVs (e.g., Zmud et al., 2016). Consumers' preferences determine the market size of AVs and the strategies to deploy them in the market, as well as policy making for various public purposes. Our results suggest that: (1) policy makers and marketers should undertake more efforts to measure people's WTP for AVs when making an investment decision properly and to set a sale price by accumulating more empirical studies with respect to different population groups; (2) vehicle ownership among young people should still be a noteworthy policy issue, in the case of not only conventional vehicles, but also AVs; (3) policy makers and marketers should pay more attention to the role of household life (Zhang, 2017), as suggested by the influence of household members, in the development of AVs by properly accommodating various household needs via the use of AVs; (4) it may be more suitable to deploy AVs for long-distance trips (especially for the purpose of tourism) than for short-distance trips, as suggested by driving experience parameters; and (5) the negative sign of sudden braking/handling may indicate that future cities need to adapt to the presence of AVs if pro-AV policies have to be made.

There are some limitations to this study. First, this study adopts a normal distribution for random effects. Hess et al. (2005) pointed out that such an unbounded distribution may not reflect true behavioral mechanisms. Unfortunately, there are no theoretically sound criteria for such a choice. It is therefore important to carefully choose suitable distributions for representing random effects. For this, more empirical studies should be done for deriving more convincing insights to better represent the heterogeneous relationships between travel choices and their potential factors across decision makers. In case of continuous distributions, model estimation results may be sensitive to the shape of distribution. To tackle such issue, it may be worth exploring the use of non-parametric approaches. Second, this study ignored the effects of operation costs during the use of an AV because of the future uncertainties associated with technological development and legal requirements. Such uncertain costs may lower the ownership of AVs; however, in terms of future oil prices and the progress of low-carbon transport policies, conventional vehicles are not free of uncertainties, either. Third, the MXL model adopted in this study captured the influence of unobserved heterogeneity in terms of random effects, but ignored the possible influence of observed heterogeneity with respect to the WTP and SP attributes of AVs, i.e., responses to these attributes may differ across individuals in terms of their sociodemographics. Fourth, the SP survey assumed a future income change for respondents as a choice context; other contextual factors may be influential. For example, as suggested by the life-oriented approach (Zhang, 2017), vehicle ownership and usage is associated with various life choices. When choosing an AV, people may think about what would happen to their lives when an AV becomes available.

It is obviously necessary to conduct more research to overcome the above limitations and further confirm the effects of various factors, with respect to not only personal ownership and usage of AVs, but also shared ownership and usage, from both the behavioral and institutional perspectives. Especially, low-carbon transport needs to promote more shared mobility. AVs can be used for various purposes and in various forms and contexts by different populations. Behavioral research should focus on understanding not only the behavioral outcomes, but also the decision-making processes associated with behavioral changes over time. Institutional designs are required to support the publicly acceptable use of AVs in a sustainable way. In line with this, it is crucial to understand how different stakeholders, including customers and their families, automakers, and governmental bodies, respond to different pricing policies, responsibilities required by society, lifestyles/workstyles, and so on. Last but not least, for better institutional design, social communication among stakeholders may be crucial to make smart use of AVs in a collective way from the viewpoint of social psychology.

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