Autonomous Vehicles: Ownership Behavior and Adaptive In-vehicle Time Use

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Recent years have observed rapid developments of Autonomous Vehicles (AVs), which are capable of sensing their environment and navigating without human interventions. AVs could not only improve driving safety dramatically, but also be developed as a “moving home/office/hotel”, allowing drivers to make more efficient use of time with better feelings, in comparison to traditional vehicles. This study investigates future ownership behavior of AVs and in-vehicle time use changes adapted to different levels of AVs and their diffusion rates in the market, etc., based on an ASP-off-RP survey approach (ASP: adaptive stated preference; RP revealed preference). We conducted this survey in September 2016 and collected valid data from 1,002 respondents across the whole Japan. Each respondent answered three SP profiles.

It is found that about 48% of respondents answered to prefer an AV as their future purchase, and respondents’ willingness to pay (WTP) for additional 442,762 to 869,379 Yen to buy a AV. Estimation results based on a mixed logit model indicate that additional cost and future expectation significantly influence individuals’ AVs choices. It is also revealed that respondents being elderly, with higher education level, and with an atttidue toward improving driving safety, are more likely to choose an AV compared to the conventional cars. Respondents’ preference for different levels of AVs are significantly influenced, especially by the penetration rate, additional cost, parking cost reduction, as well as the gaps between WTP and additional costs. Related to the adaptive in-vehicle time use, it is confirmed that important factors to time use for short-distance travel are WTP, gap between WTP and additional cost, attitudes toward car driving, and driving frequency and purpose; for long-distance travel, WTP, affective experience, sudden braking/handling experience and attitudes toward car driving are influential.

Key Words : *autonomous vehicles, vehicle ownership, in-vehicle time-use, Japan, ASP-off-RP survey*

1. INTRODUCTION

Thanks to the development of advanced technologies, recent years, autonomous vehicles (AVs) (or self-driving cars) have gradually jumped into our realistic life. AVs are expected to save 69 lives per year in U.S. alone, according to the National Highway Traffic Safety Association (Grand View Research, 2016). However, the public acceptance is still unclear in terms of the tradeoff between their advantage (e.g., relieved time, improved safety, and expended catchment areas) and disadvantages (e.g., security, privacy, and reliability) as well as additional costs, etc.

Nowadays, a series of AVs on-site experiments have been launched to testify the performance of AVs developed by research organizations and manufactories, such as Alphabet Inc., Tesla Motors Inc., Ford Motors Corporation, and General Motors of Audi, Google, Nissan, etc. Especially within the recent decade, a bunch of these AVs inventory companies have tried to testify the performance of their AVs through continuous driving experiment.

By the end of 2016, the Google-car has been self-driven for more than 2 million miles on city streets mostly, since they started their Google self-driving car project in 2009 (Dolgov, 2016). Meanwhile, another active AVs experiment tester, Tesla Moters, Inc., announced that their Tesla autopilot has been driving actively for 300 million miles by November, 2016 (Lambert, 2016). Even though the value of the current miles driven are still considerably far away from the 5 billion miles, the estimated number of miles that must be driven to demonstrate the lower fatality rate of AVs than human driver failure rate within the 95% of confidential level significantly (Kalra and Paddock, 2016), and the predicted time point of when the AVs at level 4 will be available in the market has been announced feasible in 2020 by the CEO of Nvidia and the head of Audi of America on a keynote address at CES conference (Ross 2017). It is mentioned by the Alto(2016) in the analysis of Canalys shown that only 1.3% of cars sold in 2016 (about 1.16 million) will offer partial autonomy (level2) and the only cars with conditional or fully autonomy in 2016 are for research and development purpose, on the meanwhile the market share of AVs have also been highly expected by an explosive growth from the current limited share in 2016 to 15% (about 15.4 million) vehicles on conditional/full autonomy (L3/L4) will be sold globally by 2025.

Summarized from 24 accident reports of the traffic accidents with AVs involved, 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-end and slide-scrap by adjacent vehicles at a relative low driving speed. This is consistent with an analysis conducted by the Schoettle and Sivak (2015), about the self-driving vehicle crashes involvement in the real-word driving. Two highlights shown in the study Schoettle and Sivak (2015) are 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 for conventional vehicles. In Japan, in the target year of the 2020 Tokyo Olympics, thousands of driverless robot taxis are planned to run on selected road sections. In August 2016, Nissan Motor Company have started to sell a small Van equipped with partially autonomous driving functions for the first time into the domestic market.

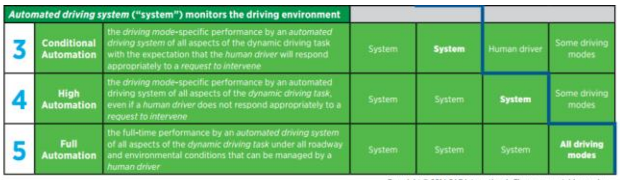
Recognizing that conditional AVs have been provided in the motor vehicle market supplement and AVs accidents have occurred in the on-road experiments, this study aims to clarify factors affecting the deployment of AVs by investigating AVs ownership and usage via an adaptive SP-off-RP survey approach, called ASP-off-RP (SP: stated preference; RP revealed preference), where SP attributes are derived from RP data at the personal level and each respondent's willingness-to-pay for additional purchase costs. Choice alternatives are a conventional vehicle reported by each respondent and several types of AVs. Several critical diffusion rates of AVs are introduced to reflect the influence of social interaction, together with the above information and parking cost reduction. As a result, a set of SP profiles are derived based on a typical experimental design. In addition to the stated ownership of AVs, each respondent was further asked to report their possible changes in in-vehicle time use behavior (i.e., multitasking) adapting to different AV functions, based on the reported actual in-vehicle time use behavior. Furthermore, changes in people's daily lives under the AVs with full-automation were also investigated, together with experience of risky driving, affective experience during driving, driving liking, and individual attributes. In the survey, both long- and short-distance trips made by not only current car users but also public transport users are targeted.

In the reminder of this paper, Section 2 describes why the ASP-RP approach is applied and the survey contents, followed by some typical aggregation analyses in Section 3. Section 4 explains the model structures employed in this paper. Section 5 estimates the stated AVs ownership and in-vehicle time use behaviors. Finally, this study is concluded in Section 6.

2. DATA COLLECTION

The SP approach has been widely applied to capture consumers' preferences for not-yet-existing alternatives (AVs are such an example). However, it suffers from various biases due to unrealistic scenarios assumed in the survey. To enhance the survey reliability, an SP-off-RP approach (Train and Wilson, 2008) has been developed, where SP alternatives and their levels of attributes are constructed based on the information in an actual market setting reported by respondents. In this study, AVs are treated as a vehicle updated from respondents' current vehicles. It is considered that respondents' AVs choices may vary with individual's actual travel behavior and experience, such as short or long distance driving, experiences of unsafe driving behaviors, and so on. Respondents' self-cognition on subjective safety stage, in terms of whether and how much the driver wants to improve his/her current driving safety level, may also affect the AVs choices. Furthermore, social interactions may play a critical role in encouraging or discouraging respondents to purchase an AV.

Vehicle types in the SP part include conditional AVs, high AV, Full AVs, and current vehicle type owned by respondent himself/herself. The above three types of AVs (see figure 1) are defined based on SAE International's levels of driving automation for on-road vehicles (SAE International, 2014). For capturing respondents' stated preference for AVs properly, each respondent was asked to report a change (increase, decrease, or no change) of respondent's income in the past five years. Such a change is assumed to continue in the future when they have to make a choice of buying a new car or not, and what types. Such income changes are expected to allow respondents to report their stated preference in a more realistic way.



Automated driving system ("system") monitors the driving environment						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Figure 1: summaru of SAE international's levels of driving automations level 3 to level 5

As a result, five types of attributes were selected for the SP survey, each of which has two or three levels.

(1) Penetration rates of different types of AVs (3 attributes): Penetration rates of conditional AVs, high AVs, and full AVs have been introduced with 3 levels for each. Considering the technological advantages and the resulting cost, there should be an increasing trend from the conditional AVs to full AVs. Therefore, first, the penetration rate of fully AVs is fixed to have three levels: 5%, 10%, and 20%, and then, the levels for the rest two AVs are determined based on the additional increase at the three different levels of full AVs, separately.
(2) Additional cost for AVs (3 attributes): Following the concept of penetration rate definition of different types of AVs, additional costs for vehicle types of conditional AVs and full AVs were also calculated based on the full AVs, by fixing additional cost of full AVs to be three levels: 700,000, 850,000, and 1000,000 Yen, corresponding to its penetration rates of 20%, 10%, and 5%. Levels of the additional costs for the rest two AVs are calculated based on the additional reductions corresponding to the above three levels, separately.
(3) Insurance reduction for AVs (2 attributes): Since there was no insurance reduction policies released by any insurance companies at the timing of the survey, the insurance reduction rate of conditional and high AVs are assumed to follow the same rate, and full AVs are expected to enjoy a higher reduction rate, considering its highest safety level.
(4) Parking cost for AVs (1 attribute): With the self-driving/self-parking function, it is expected that the AVs could contribute to the parking cost reduction by parking itself to a cheaper parking lot, a little far from users' homes. Here, two levels of parking cost are introduced, 50% reduction and no reduction. The 50% parking cost reduction is assumed based on the calculation of Litman (2012) for comprehensive annual parking cost reduction for moving a parking space to outside central business district (CBD) or suburbs.
(5) Timing of AVs release in the market (1 attribute): Respondents' AVs choices are made under the assumption that all types of the AVs are available in market. Because the timing of AVs release in the actual market may be important to some respondents, it is introduced as an additional SP attribute with three levels: 5, 10, and 15 years from the present.

In total, 18 SP profiles were obtained by employing an orthogonal fractional factorial design. In the survey, they are equally divided into 6 groups, each of which has three SP profiles.

3. Data Aggregation

The survey was conducted in Japan, respondents were recruited by considering the distributions of age, gender, and population size of the whole population in the whole Japan. Concretely speaking, 1,002 respondents were recruited with the assistance of a major Internet survey company: 400 from three megacity areas (Tokyo, Nagoya and Osaka), 300 respondents from governmental ordinance cities, and 302 from other areas in Japan. Respondents were 15~70 years old. The number of male respondents (507) was nearly equal to that of female (498). Each of the 1,002 respondents answered to three SP profiles and as a result, the total sample size is 3,006 SP responses.

Among all the SP responses, 52% chose to buy their traditional vehicle they have had, while conditional AVs are preferred by 19%, high AVs by 15%, and the rest least 14% share goes to full AVs. SP responses for all the 18 assumed SP scenarios (profiles) are shown in Figure 2. Across the 18 scenarios assumed, shares of respondents' current traditional vehicle selection vary from 44% to 52%.

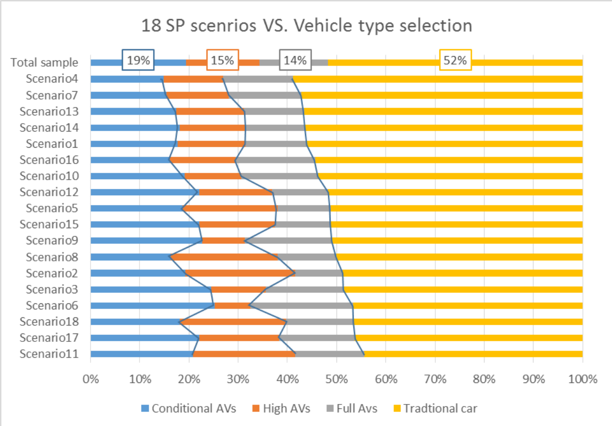


Figure 2. Respondents' vehicle preferences aggregate at scenarios

As for respondents' WTP towards three types of AVs (Table 1), it is calculated that on average, respondents would like to pay for additional 442,762 Yen, about 23.2% increase from the original price of their current owned conventional car, for getting a conditional AVs. The WTP for high AVs and full AVs are 627,572 Yen (33.1% increase) and 869,379 Yen (46.1% increase), respectively.

Table 1: Average WTP Values and Percentage towards AVs

	WTP (WTP>=0)		
	JPY	USD	Increase
Conditional AVs	442,762	3,916	23.2%
High AVs	627,572	5,550	33.1%
Full AVs	869,379	7,689	46.1%

Currency: 1 JPY=0.008844 USD;
Increase: increase from original price of current conventional car

Concerning respondents' adaptive in-vehicle time use behaviors, various types were reported, which are further divided into five types, including mind_focus, hand_focus, eye-focus, mix_focus, as well as drive focus behaviors. As shown in Figure 3, the mixed_focus time-use behavior, such as sleep and personal care inside the car show an average 10% share. For other three types of driving unrelated behaviors (Figure 4), mind-distraction behavior takes a predominate role. Moreover, as high as 3 times of times use on mind-distraction behaviors are identified on driver's planed time use behaviors, adopting to various levels of AVs.

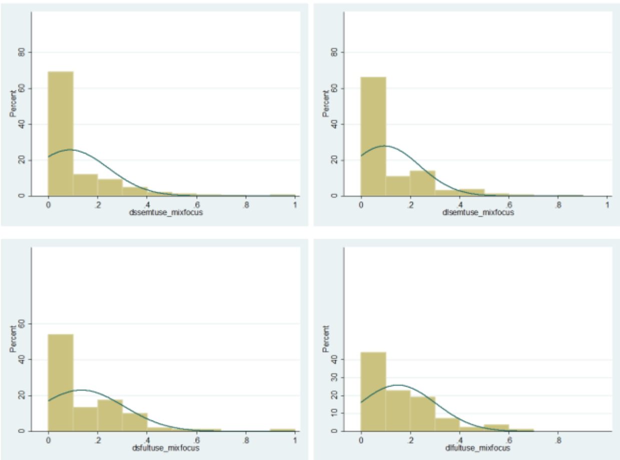


Figure 3. Additional mixed time use distribution on car-based behavior

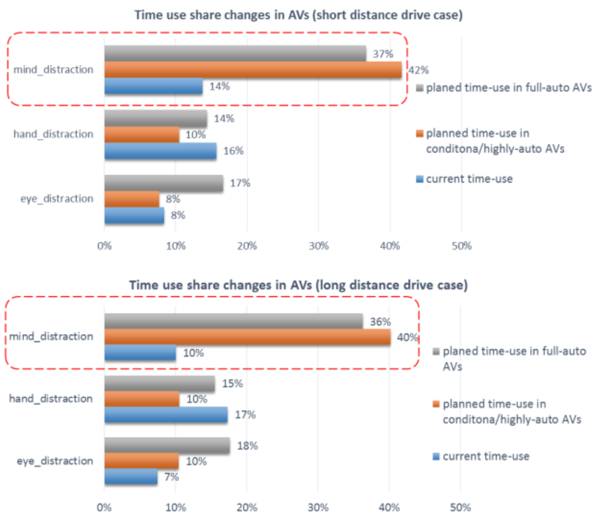


Figure 4. In-vehicle time use changes in AVs

4. METHODOLOGY

4.1 Mixed Logit (MXL) model

Here, a mixed logit (MXL) model with panel data (Hole, 2007, 2013) is employed to represent each respondent's stated choice behaviors of AVs ownership, repeated under three SP profiles. The utility that individual n chooses j choice alternative on choice occasion t (refers to an SP profile in this study) is given as follows:

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

where, β'_n is a vector of individual specific coefficient; x_{njt} is a vector of observed variables; ε_{njt} is a random term distributed under IID extreme value. The density for β is denoted as $\int(\beta|\theta)$ where θ are parameters of the distribution. The probability that an individual n makes choices at different time point t from J choice alternatives can be given by:

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

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

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

4.2 Seemingly Unrelated Regression Model

The Seemingly Unrelated Regression (SUR) model model is used to estimate adaptive in-vehicle time use behavior under different AVs deployment scenarios (i.e., SP profiles). It is a set of separate regression equations allowing for the contemporaneous cross-equation error correlations. Such correlated error terms reduce standard errors of the estimated parameters, consequently improve the reliability level of estimations, by comparing with those from separate regressions (Zellner, 1962; Anastasopoulos and Mannering, 2016). Here, in this analysis, four regression equations are estimated simultaneously to capture the percentage of each individual's time use on eye-focus, hand-focus, mind-focus, and mix-focus behaviors, influenced by a list of explanatory variables.

5. MODEL ESTIMATION RESULT

5.1 AVs ownership behavior

The MXL model with panel data is estimated by employing the STATA software (Version 13). Estimation results arre shown in Table 2. McFadden's Rho-squared was calculated to check model goodness of fit. Rho-squared value (0.21) and adjusted Rho-squared value (0.19) indicate that the model fit the data well. Detail discussions of the results are given below with respect to to different explanatory variables.

5.1.1 SP factors with random effects

To capture the preference heterogeneity across individuals' panel decision making behaviors, the SP factors shown in the stated preference scenario design are added into the model by imposing random distributions on the coefficients. In compliance with our expectation, statistical significance of the random coefficients indicates that significant mixing occurs in these variables. In line with this consideration, the importance of heterogeneity, which are ignored by the conventional MNL model structure, in SP survey result interpretation was re-confirmed.

It can be summarized from the MXL results that on average respondents are more sensitive to the additional cost of the AVs compared to their current traditional vehicles. Penetration rate and insurance reduction do impose a random effect on individuals' preference on AVs, however, the average impact is not significant, statistically. Significant position influencing impact of realize time that imply that respondents are more likely to select AVs when comparatively longer realize time period have been assumed. Potential explanation is that respondents are still reluctant to the AVs vehicles, and expected longer technical development. On the other hand, respondents are expected to have higher affordability for the AVs, longer time periods later.

Parking cost also significantly influence on respondents' AV preference, however, parking cost reduction property of fully-automatic vehicle played a negative impact on drivers AV vehicle selection behavior compare with traditional vehicles, which is contradictory to our general assumption. One potential explanation on this arbitration analysis result might be that the realization of the fully-automatic vehicle is still less reliable for the current people and additional cost on fuel consumption of gasoline or electricity for the additional travel distance caused by the self-parking behavior of the full-auto AV is not clearly investigated. Aggregation analysis of the parking cost reduction and respondents' AVs vehicle preference result is show in Figure 5.

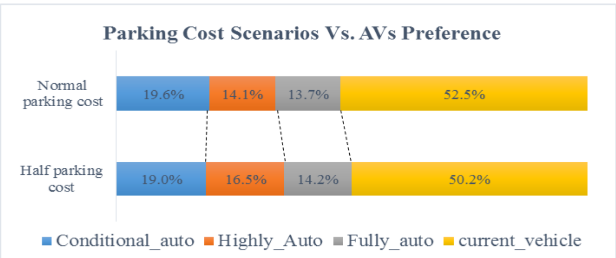


Figure 5. cross-aggregation of parking costand AV preference

At the aggregation level, parking cost reduction of the fully automatic vehicle will contribute to slightly increase of respondents' highly and fully automatic vehicles preference rate, therefore, lower conditional automatic vehicle as well as current traditional vehicles preference rate could also be observed.

5.1.2 Willingness to pay (WTP)

To further investigate public's acceptance of three types of AVs, individual's WTP among three types of AVs have been measured in responding to their specific additional cost designed in each scenario. Difference of additional cost and respondents' WTP have been calculated and re-defined into two indicators of low_WTP (addition cost value is higher than WTP) and high_WTP (addition cost value is lower than WTP) to capture the people's different responses to gain and lose in decision making behaviors. Lose aversion property is measured by taking logarithm form of low_WTP, and gain property is measured by taking exponential form of high_WTP to better represent individuals' different heterogeneous responses through control of variance dispersion of parameters.

Model estimation result of the MXL result shown that respondents' preference of AVs are more sensitive to the gain property. Concretely speaking, significant negative sign of the low_WTP indicate that the larger amount of the addition cost value less that the WTP, respondents are more likely to select the AVs. On the other side, significant mixing impact of the high_WTP could also be identified, but the impact is insignificant.

5.1.3 Individual attributes

One of the big breakthrough of the AVs is expected that the self-driving property of AVs could help to improve non-drivers' travel mobility, such as young, elderly, and disabled people. Therefore, in this model structure respondents' age attribute is re-defined into 5 dummy factors, by measuring respondents' age falling in to age band of 20s (15~29), 30s (30~39), 40s (40~49), 50s (50~59), and 60s (60~69). Age band of 30s was set as reference age band by considering the high vehicle ownership (White Paper on Land, Infrastructure and Transport in Japan, 2013) and low vehicle purchase tendency than other age bands (http://reposen.jp/2361/14/48.html). Model estimation result of the MXL result shown that among 5 age band, elderly person including of 50s and 60s are more interested in select AVs than their current traditional vehicles. There is no significant difference between male and female respondents' AVs preference, which is different from the case study conducted by Schoetle and Sivak (2014) in U.S., U.K, and Australia. In the meanwhile, respondents with higher level education background (university level or higher) are more interested to choose AVs. Moreover, individuals who have household more member of elderlies, who are older than 65 years old, also responded with significant AVs preference. However, number of household's youth member, including primary and middle school child, shows no significant preference between AVs and traditional vehicle. Individual's current driving safety improve propensity also impose no significant influencing impact on their AVs selection behaviors.

5.1.4 Future income expectation

Similar to the WTP factor, influences of individual's future (5 years later) income expectation on their vehicle type selection behaviors are measured by two separate indicators, expected income increase rate treated as gain and expected income decreased rate as lose, based on their current income value.

Regarding to individual's future income expectation, model estimation results show that respondents who have reported a smaller future income decrease rates are more likely to choose AVs than their traditional vehicles. Even though there is no significant influencing impact on respondents' future income increasing rate on their vehicle preferences, the lose aversion property reflect from income decrease trends and AVs preference is in compliance with the lose aversion phenomenon from prospect theory.

5.1.5 Driving experience

Considering impacts of driver's travel demand on individual vehicle type preferences, drivers' previous driving properties have also been involved into the explanatory structure to interpret their future vehicle selection behaviors. Here, two types of driving experience, including short distance and long distance driving experience have been discussed, separately. Trip properties of sudden brake/handling experience, trip frequency, and trip purpose have been inspected in the model.

Surprisingly, no significant influencing impact could be identified from drivers' experience of short trip driving experience on their AVs selection behavior. However, different from short trip driving experience, drivers' long trip driving experience of sudden brake/handling behavior during long trip driving impose an significant positive impact on their AVs selection behavior, it can be interpreted at the AVs are highly expected by the respondents in relieving them from monotonous and long term driving tasks, and therefore reduce the potential risks they have experience in sudden brake/handling behaviors previously. Moreover, the AVs are preferred by respondents with driving purposes of visit friend, and business for long trip driving experiences.

5.2 Adaptive in-vehicle time use behavior

Considering of different driving characteristics, two types of driving behaviors have been investigated separately, including short-distance driving and long-distance driving. Definitions of the short and long distance here are generalized toward respondents, where the short-distance driving refers to driving behaviors within individual's daily activity circle. Then, long-distance driving is relatively longer than the short distance drive. Besides variables employed in vehicle ownership study in section 5.1, individual's affective experience (e.g. happy, irritable, and unhappy) while previous driving and attitudes level towards car driving, e.g. like driving, good at driving, feel driving is dangerous, try to avoid driving, and want to driving more, have also been considered to explain individual's perceived time use behavior.

Model estimation results are shown in Table 3, where two separated SUR model results were integrated into one table. Significant positive sign of "time use of fully_automatic vehicle" indicates that respondents who intent to buy a fully-automatic AV are more likely to spent more time use on eye-focus and hand-focus behaviors corresponding to their short-distance and long-distance driving behaviors, separately. The usage of AVs are more likely to relief elderly drivers, here ageing from 60~69, from conventional driving tasks by conducting more eye and hand focus behaviors during their in-vehicle time. Expected increasing in personal income will significantly contribute to more driving unrelated time use, e.g. hand-focus and mix-focus in short-distance drive, as well as hand-focus in long-distance drive. On the other hand, losses from income decreasing will leading to respondents less time use on mind-focus and mix focus behavior while driving.

To further clarify the contributing of the explanatory variables, the variance proportion of each equations have been calculation for all the explanatory variables, shown in Figure 6 and Figure 7.

For driver's short-distance travel behavior in AVs, take the variance proportion into consideration, the figure shows that time use rate of respondents' eye-focus are donimately influenced by the gap between the additional cost require and their WTP towards the AVs. Then, factors contribute mostly to driver variance proportion of hand-focus behaviors are attitudes towards driving and trip purpose. In the meanwhile, related to respondents' time use for mind-focus, the variance are widely contributed by the attitude factors, trip purpose factors, and also gap attributes between additional cost and WTP for selected AVs. On the other hand, factors contribute to the higher proportion of time use variance in mix-focus behaviors are occupation of company workers, income changing rate, current vehicle ownership of both individual and household, as well as attitude towards driving.

On the other hand, for driver's long-distance travel behavior in AVs, factors contributing to variance proportion of four type of time-use behaviors are different from short-distance travel situation. Influencing factors contributing to the higher proportion of variance are concentrated to factors of attitude toward driving, gap between additional cost and WTP. Moreover, contribution effects of individuals' previous sudden brake/handling experiences (both long and short distance driving) on variance proportion of people's time use of eye-focus should not be ignored.

6. CONCLUSION

As a new type of travel mode, AVs are expected to relieve drivers from driving tasks, which may further influence road users' potential driving habits. However, without strong evidence of the potential changes that might be induced by the AVs, it is very difficult to make comprehensive transportation planning adapted to the deployment of AVs in the market. Even though the social dilemma about the autonomous vehicles still exist, the ambivalence responses among the people towards the AVs still catch our big concerns, especially for AVs development and promotion industries.

In this study, an ASP-off-RP survey was conducted to investigate the Japanese people's responses to the future AVs deployments, where conditional AVs, high AVs, and full AVs are targeted. As a result of an Internet survey, 3,006 SP responses were collected from 1,002 respondents across the whole Japan. Respondents were selected based on the distributions of age, gender property of three different administration areas to represent the whole population, including the megacity area, government ordinance cities, and others. Heterogeneous decision making behaviors, especially, individuals' WTP and future expectation have also been considered based on the prospect theory. Together with the consideration of additional cost influences, reliability and safety concerns towards the AVs have also been considered in the SP scenario designs by introducing the various timings of releasing full AVs in market, penetration rates of AVs in the market and rate of insurance fee reductions. Different from simply ask about respondents' WTP and selection opinion towards the still under developing technologies, scenarios in this survey takes respondents' future income expectation and relative prospection property into consideration.

Revealed from the data aggregation, it is found that almost half (48%) of the respondents have expressed their preference for the various types of AVs compared to their current conventional cars, even though law registration and AVs related policy making in Japan are still unclear. On average, the respondents are likely to pay additional 23.2% to 46.1%, corresponding to about 442,762 to 869,379 Yen (about 3,918 to 7,693 US dollars), from the original price of current conventional cars to buy an AV. Comparing with the WTP value calculated by Bansal et al. (2016) in their Austin case study, where on average additional 3,300 and 7,253 USD could be paid for Level 3 and Level 4 automation vehicles, higher WTP for Level 3 and lower WTP for Level 4 could be observed. Japanese respondents' WTP values are lower than Americans. The large WTP gap between two automation levels observed in the study of Bansal et al. (2016) is not inconsistence with the Japanese case.

Analyses based on the MXL model with panel data found that respondents' AVs shifting behavior is significantly influenced by the additional cost required, where lower additional cost is preferred, a natural response. In addition, the significantly influencing impact of the gap between individuals WTP and additional cost required is also emphasized. Concretely speaking, the larger the gap betwee the reported WTP and the additional cost required, the more likely AVs would be selected. This result makes sense. Meanwhile, a significant AVs preference has been identified from respondents who are older than 50 years old, or with a university education background. Lose aversion property of respondents who imposed with less future income decrease also show significant AVs preference behaviors. Last but not least, significant influencing impact could also be identified from respondents' previous driving experience, e.g., sudden brake and/or handling behavior and various driving purposes.

Important factors affecting short-distance drivers' adaptive in-vehicle time use behaviors are WTP, gap between WTP and additional cost, attitudes toward car driving, and drivers' previous driving experience, i.e. driving frequency and purpose. For long-distance travel, impact of WTP, affective experience, sudden braking/handling experience and attitudes toward car driving become influential.

It is expected that findings in this study provide useful insights into the future development of law legislation, policy making, as well as shared autonomous vehicles (SAV). As a new type of travel mode option, the modification, realization, and adaption to the AVs in the new transportation system is quite essential. It is also important to check different responses from various regions and countries, to further perusing a more reliable and high efficient transportation system. Needless to say, more efforts should be made together with technology development and law legislation.

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REFERENCES

1) Alto, P. (2016) 15% of new cars sold worldwide in 2025 will be autonomous vehicles. Shanghai, Singapore and Reading (UK) – Wednesday, 7 December 2016. Available at: https://www.canalys.com/newsroom/15-new-cars-sold-worldwide-2025-will-be-autonomous-vehicles (aceess on 2017/04/05)
2) Bansal, P., Kockelman, K.M., Singh, A. (2016) Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. Transportation Research Part C: Emerging Technologies, 67, 1-14.
3) California Department of Motor Vehicles (2016) Report of traffic accident involving an autonomous vehicle (OL316) Available at: https://www.dmv.ca.gov/portal/dmv/detail/vr/autonomous/autonomousveh_ol316+ (access on 2017/02/17)
4) Casley, S.V., Jardim, A.S., and Quartulli, A.M. (2013) A study of public acceptance of autonomous cars, Interactive Qualifying Project, submitted to the faculty of the Worcester Polytechnic Institute, April 30th, 2013.
5) Chen, Z., He, F., Yin, Y., Du, Y. (2017) Optimal design of autonomous vehicle zones in transportation networks. Transportation Research Part B: Methodological, 99, 44-61.
6) Dolgov, D. (2016) Two million miles closer to a fully autonomous future, Waymo Team, (access on 17/02/2017: https://medium.com/waymo/two-million-miles-closer-to-a-fully-autonomous-future-14eb74064e7#.t17s90gmi), December 14.
7) Fagnant, D.J., Kockelman, K. (2015) Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transportation Research Part A: Policy and Practice, 77 (2015), pp. 167–181
8) Grand View Research (2016) Autonomous cars/driverless cars market analysis and segment forecasts to 2024. Market Research Report. (Accessed by: http://www.grandviewresearch.com/industry-analysis/driverless-cars-market)
9) Hole, A.R. (2007) Estimating mixed logit models using maximum simulated likelihood. The Stata Journal, 7(3), 388-401.
10) Hole, A.R. (2013) Mixed logit modelling in Stata-An overview [PowerPoint slides] Retrieved from http://www.stata.com/meeting/uk13/abstracts/materials/uk13_hole.pdf (accessed by 2017/02/12)
11) James, A., Nidhi, K., Karlyn, S., Paul, S., Constantine, S., Oluwatobi, O. (2014) Autonomous Vehicle Technology: A Guide for Policymakers. Washington, DC: RAND Corporation.
12) Kalra, N., Paddock, S.M. (2016) Driving to safety: how many miles of driving would it take to demonstrate autonomous vehicle reliability? Transportation Research Part A: Policy and Practice, 94, 182-193.
13) Lambert, F. (2016) Tesla has now 1.3 billion miles of Autopilot data going into its new self-driving program, accessed by: https://electrek.co/2016/11/13/tesla-autopilot-billion-miles-data-self-driving-program/ (accessed on 2017/02/18).
14) Lamotte, R., Palma, A.D., Gerokiminis, N. (2017) On the use of reservation-based autonomous vehicles for demand management, Transportation Research Part B: Methodological, 99, 205-227.
15) Levin, M., Boyles, S. (2016) A multiclass cell transmission model for shared human and autonomous vehicle roads, Transportation Research Part C: Emerging Technologies, 62,103–116.
16) Litman, T. (2012) Parking Management: Strategies, Evaluation and Planning. Victoria Transport Policy Institute. Victoria, B.C.
17) Market report (2016) The Future of Autonomous Vehicles and the Impact on Tire Markets to 2026. (Accessed by: http://www.smithersrapra.com/market-reports/tire-industry-market-reports/the-future-of-autonomous-vehicles-and-the-impact-o on 2017/02/17)
18) Ross, P.E. (2017) CES 2017: Nvidia and Audi Say They'll Field a Level 4 Autonomous Car in Three Years, access by http://spectrum.ieee.org/cars-that-think/transportation/self-driving/nvidia-ceo-announces (accessed on 2017/02/18)
19) Schoettle, B., Sivak, M. (2014) A survey of public opinion about autonomous and self-driving vehicles in the U.S., the U.K., and Australia.
20) Shina, J., Bhatb, C. R., Youd, D., Garikapatid, V. M., Pendyalad, R. M. (2015) Consumer preferences and willingness to pay for advanced vehicle technology options and fuel types, Transportation Research Part C: Emerging Technologies, 60, 511-524.
21) Society of Automotive Engineers International (2014) automated driving levels of driving automation are defined in new SAE international standard J3016 (access on 2016/08/01 http://cyberlaw.stanford.edu/files/blogimages/LevelsofDrivingAutomation.pdf).
22) Train, K., Wilson, W.W., 2008. Estimation on stated-preference experiments constructed from revealed-preference choices. Transportation Research Part B 42, 191-203.
23) Wadud, Z., MacKenzie, D., Leiby, P. (2016) Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles, Transportation Research Part A: Policy and Practice, 86 (2016), pp. 1–18
24) Yap, M.D., Correlia, G., Areme, B.V. (2016) Preferences of travellers for using automated vehicles at last mile public transport of multimodal train trips. Transportation Research Part A: Policy and Practice, 94, 1-16.

25) Zhang, W., Guhathakurta, S., Fang, J., Zhang, G. (2015) Exploring the impact of shared autonomous vehicles on Urban parking demand: An agent-based simulation approach.

Table 2. Model Estimation results of mixed logit model with panel data for AVs ownership

	Parameter	T-value	Sig.
SP factors with Mixed effect			
Penetration rate of AVs (%): Mean	-6.85	-2.71	***
Variance	14.57	4.48	***
Additional purchase cost for AVs (10,000 Yen): Mean	-0.06	-5.54	***
Variance	0.10	7.86	***
Insurance reduction rate for AVs (%): Mean	-0.50	-0.40	
Variance	6.38	3.37	***
Permanent-parking cost reduction rate (%): Mean	1.63	2.07	**
Variance	1.03	0.56	
Timing of AVs sale release (years): Mean	0.02	0.27	
Variance	1.38	5.71	***
Gap between additional purchase cost and WTP			
Ln (Positive gap value + 1): Mean	-1.41	-4.51	***
Variance	2.36	6.03	***
Exp (Negative gap value): Mean	0.56	0.69	
Variance	5.33	6.12	***
Individual Attributes			
Aged under 30s [15-29 years old] (Yes: 1; No: 0)	-1.2	-0.86	
Aged 40s [40-49 years old] (Yes: 1; No: 0)	0.33	0.26	
Aged 50s [50-59 years old] (Yes: 1; No: 0)	1.68	1.11	
Aged 60s [60-69 years old] (Yes: 1; No: 0)	2.72	1.75	*
Gender (Male: 1; Female: 0)	-0.58	-0.58	
High-education (University level or above: 1; otherwise: 0)	2.6	2.55	**
Number of elderly members (aged 65 years old or above) in household	-1.26	-1.66	*
Number of primary & middle school students in household	0.92	1.53	
Safety behavioral change			
Stage of Driving Safety Improvement (Try to improve: 1; otherwise: 0)	1.04	1.12	
Future expectation of income			
Exp (absolute value of income decrease)	-3.22	-2.44	**
Ln (absolute value of income increase + 1)	3.26	0.6	
Short-distance driving experience			
Sudden braking/handling (Yes: 1; No: 0)	-1.3	-1.17	
Frequency (times/week)	0.26	0.79	
Driving time (minutes)	-0.98	-0.55	
Commuting purpose (Yes: 1; No: 0)	0.93	0.88	
Shopping purpose (Yes: 1; No: 0)	-1.3	-1.17	
Long-distance driving experience			
Sudden braking/handling (Yes: 1; No: 0)	7.2	4.13	***
Frequency (??)	2.03	1.53	
Driving time (minutes)	0.54	0.41	
Tourism (Yes: 1; No: 0)	-0.78	-0.47	
Going back to hometown (Yes: 1; No: 0)	-3.95	-2.01	**
Visiting friends (Yes: 1; No: 0)	3.28	1.78	*
Business (Yes: 1; No: 0)	7.2	4.13	***
Initial Log likelihood	-1667.56		
Converged Log likelihood	-1312.66		
McFadden Rho-squared	0.21		
Adjusted McFadden Rho-squared	0.19		

Table 3. Model Estimation results of SUR model for adaptive in-vehicle time use behavior

8	short distance driving in-vehicle time use behavior								long-distance driving in-vehicle time use behavior							
	Eyefocus		Handfocus		Mindfocus		Mixfocus		Eyefocus		Handfocus		Mindfocus		Mixfocus	
	Coef.	sig	Coef.	sig	Coef.	sig	Coef.	sig	Coef.	sig	Coef.	sig	Coef.	sig	Coef.	sig
timeuse of fully_automatic vehicle	0.07	***	0.02		0.01		-0.04		0.00		0.04	*	-0.01		0.03	
age20s [15-29 years old] (Yes: 1; No: 0)	0.04		-0.03		0.09		-0.02		-0.04		0.03		0.07		-0.04	
age40s [40-49 years old] (Yes: 1; No: 0)	0.05		0.06		-0.07		-0.03		-0.01		0.02		-0.10		0.04	
age50s [50-59 years old] (Yes: 1; No: 0)	0.07		-0.01		-0.12		-0.06		-0.09	**	-0.01		0.00		-0.10	
age60s [60-69 years old] (Yes: 1; No: 0)	0.09	*	0.08	*	-0.15		-0.01		-0.07		0.03		0.05		-0.08	
Highedu	0.03		0.08	***	0.07		-0.01		0.03		0.03		0.04		-0.10	***
gender	0.02		-0.05	*	-0.01		-0.18	***	0.04		-0.02		-0.03		-0.01	
companywk	-0.04	*	0.01		-0.01		0.08	**	-0.04		0.04		0.00		-0.01	
housewife	0.02		-0.02		-0.17		-0.12	*	0.06		0.07	*	-0.07		-0.01	
houshod_income	0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00	***
ln_incomeincrease	0.10		0.40	***	-0.23		0.62	***	0.12		0.20	*	0.31		0.27	
exp_incomedec	0.17	*	-0.12		-0.41	*	-0.28	**	0.06		0.01		-0.45	**	-0.12	
expwtpdeccon	-0.02		0.01		-0.15		-0.01		0.03		-0.17	***	-0.02		0.11	
expwtpdec_high	0.35	***	0.09		-0.28		0.01		0.02		0.06		-0.01		-0.15	
expwtpdec_ful	0.03		-0.05		-0.16		-0.20	*	0.16	*	-0.01		-0.30		-0.29	**
lnwtpinc_con	0.05	**	0.00		-0.06		-0.03		-0.01		0.03		-0.09	*	-0.07	**
lnwtpinc_high	-0.06	**	-0.01		0.08		0.02		0.00		-0.01		0.04		-0.02	
lnwtpinc_ful	-0.07	***	0.00		0.07		0.04		-0.01		0.02		0.09		0.09	**
premidschoolno	0.04	***	0.05	***	-0.03		0.04	*	0.02	*	0.02		-0.04		0.01	
elderly65no	-0.01		0.01		-0.03		-0.01		0.01		0.00		0.00		0.01	
couple	0.06		0.00		-0.20	*	0.00		0.05		0.00		-0.33	***	0.00	
couplewithchild	0.04		-0.02		-0.06		-0.07		-0.04		-0.03		-0.05		0.03	
livealone	0.06		0.04		-0.03		-0.16	**	-0.04		0.07		-0.07		0.07	
hlshod_vel_ownship	0.02		-0.02		-0.15	***	-0.06	**	0.01		0.00		-0.16	***	-0.01	
self_vel_ownship	-0.03		-0.01		0.08		0.19	***	-0.03		-0.02		0.17	**	-0.03	
vehi_price	0.00		0.00	**	0.00		0.00	*	0.00		0.00	**	0.00		0.00	**
shortdis_brak	-0.01		-0.05		0.07		-0.07		-0.13	***	-0.04		0.04		-0.07	
longdis_brak	-0.01		0.05		0.09		0.07		0.14	***	-0.01		-0.12		0.09	
saffunction_price	0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00	
Affective experience1	0.00		0.00		-0.01	**	0.00		0.00		0.00		-0.01	*	0.00	*
Affective experience2	0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00	
Affective experience3	0.00		0.00		0.00		0.00	**	0.00		0.00		0.00		0.00	
ds_freq	0.03	**	0.04	***	-0.01		-0.03		-0.05		-0.06		-0.14		0.10	*
driving purpose(s:commute;l:business)	0.15	*	-0.17	**	-0.50	**	-0.06		0.06		0.02		-0.07		-0.04	
driving purpose(s:pickup;l:tourism)	-0.03		-0.30	***	-0.03		0.02		-0.03		0.01		0.07		-0.02	
driving purpose(s:shopping;l:hometown)	0.02		-0.23	***	-0.40	**	-0.03		-0.09	*	0.01		0.03		-0.03	
driving purpose(s:restaurant;l:visit)	-0.12		-0.17		-0.42		-0.05		-0.09		-0.03		-0.04		-0.15	*
ds_entertainment	0.04		-0.21	**	-0.31		-0.18										
ds_hobby	-0.06		-0.47	***	0.14		-0.15										
likedrive	0.01		0.01		-0.03		-0.03		0.04	**	0.00		-0.09	**	0.04	
gooddrive	-0.01		-0.01		0.10	***	-0.03		-0.06	***	0.00		0.17	***	-0.05	*
dangrdrive	-0.06	***	-0.07	***	0.09	*	-0.07	***	-0.03		-0.01		0.01		0.01	
avoiddrive	0.03	*	0.07	***	0.04		0.01		0.04	**	0.00		0.03		0.02	
drivemore	-0.01		-0.01		-0.01		0.00		0.02		-0.02		-0.01		-0.01	
_cons	-0.16		0.28	*	0.91	**	0.98	***	-0.07		0.14		0.70	*	0.48	*

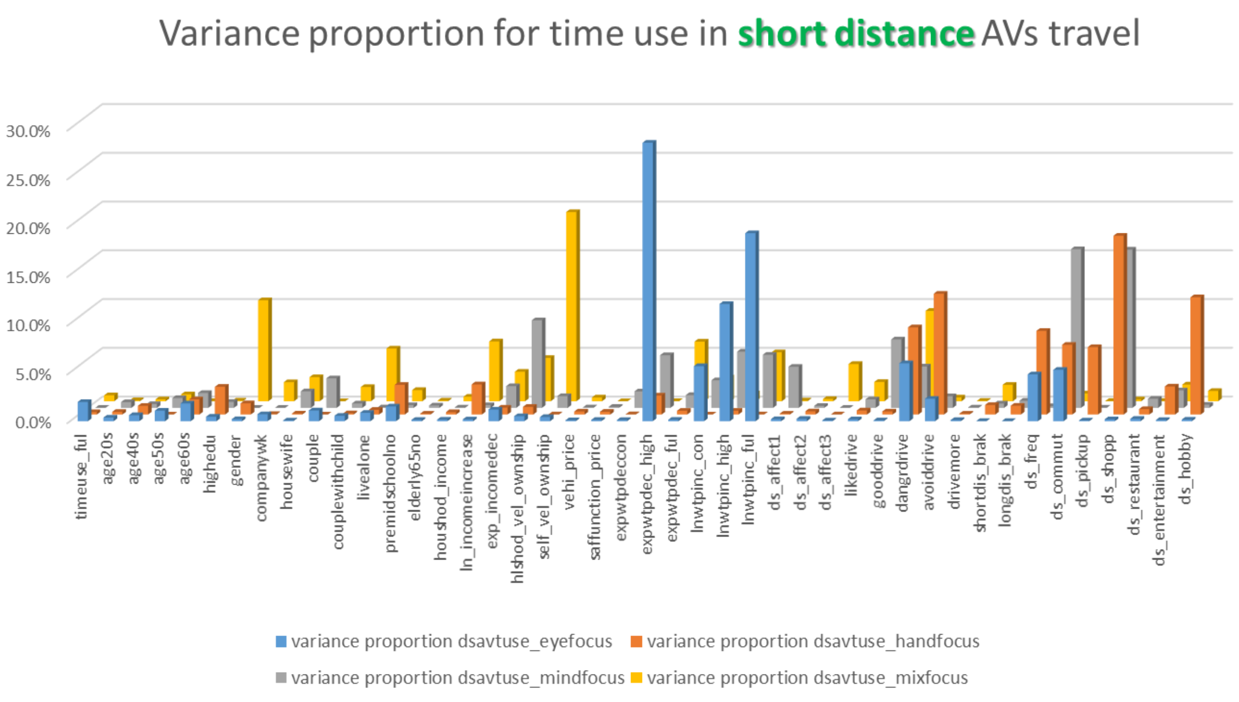

Figure 6. Variance proportions of explanatory variables on AVs adaptive in-vehicle time use behavior (short distance)

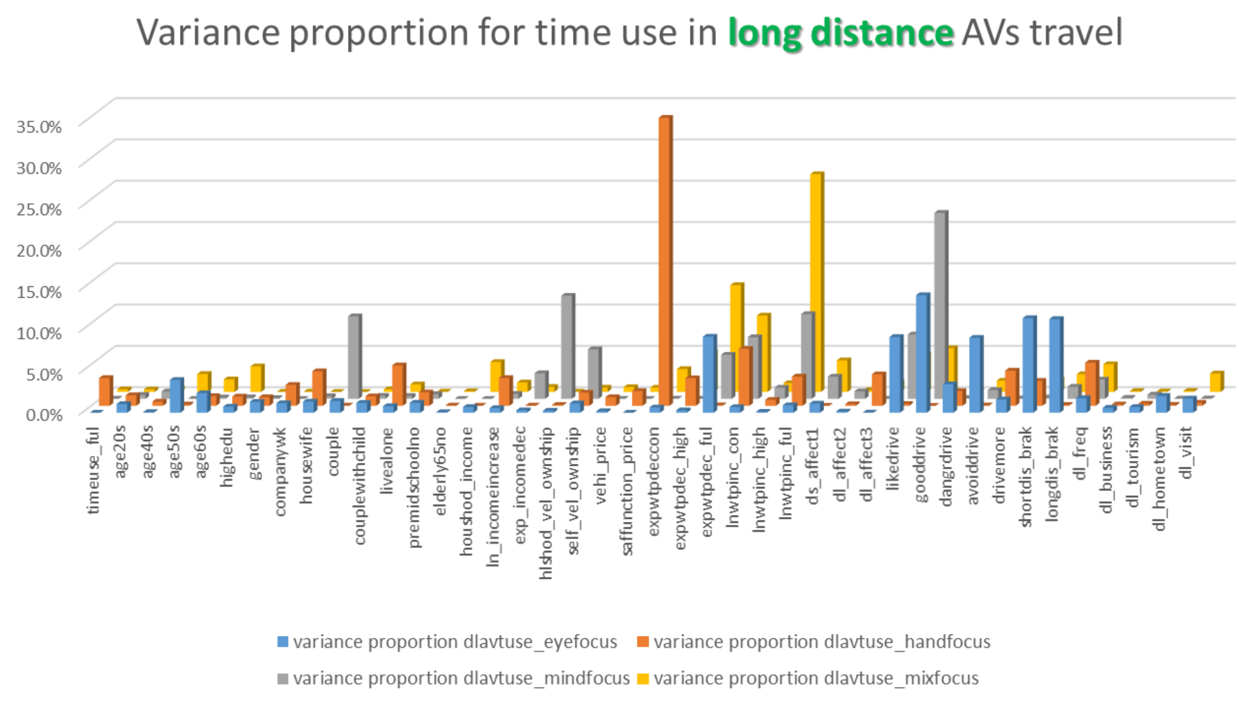

Figure 7. Variance proportions of explanatory variables for AVs adaptige in-vehicle time use behavior (long distance)