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Preferences for shared autonomous vehicles

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ABSTRACT

Shared autonomous vehicles (SAVs) could provide inexpensive mobility on-demand services. In addition, the autonomous vehicle technology could facilitate the implementation of dynamic ride-sharing (DRS). The widespread adoption of SAVs could provide benefits to society, but also entail risks. For the design of effective policies aiming to realize the advantages of SAVs, a better understanding of how SAVs may be adopted is necessary. This article intends to advance future research about the travel behavior impacts of SAVs, by identifying the characteristics of users who are likely to adopt SAV services and by eliciting willingness to pay measures for service attributes. For this purpose, a stated choice survey was conducted and analyzed, using a mixed logit model. The results show that service attributes including travel cost, travel time and waiting time may be critical determinants of the use of SAVs and the acceptance of DRS. Differences in willingness to pay for service attributes indicate that SAVs with DRS and SAVs without DRS are perceived as two distinct mobility options. The results imply that the adoption of SAVs may differ across cohorts, whereby young individuals and individuals with multimodal travel patterns may be more likely to adopt SAVs. The methodological limitations of the study are also acknowledged. Despite a potential hypothetical bias, the results capture the directionality and relative importance of the attributes of interest.

1. Introduction

In recent years, car manufacturers and software companies have presented prototypes of self-driving vehicles and have announced that the autonomous vehicle (AV) technology will be available to the market in the near future (Fagnant and Kockelman, 2015a; Wadud et al., 2016). The most striking characteristic of AVs is that in their most advanced stage, the navigation of the vehicle will be fully automated, making driver input obsolete (National Highway Traffic Safety Administration, 2013). The disruptive potential of the AV technology is undeniable; as drivers will not need to pay attention to traffic anymore, the overall driving experience will be altered considerably. Drivers, who in effect may be considered passengers for most of the journey, will be able to pursue activities such as reading, working or sleeping, while traveling in their cars (Le Vine et al., 2015).

Furthermore, the advent of the AV technology may allow for the emergence of novel business models such as shared autonomous vehicles (SAVs), which could provide inexpensive mobility on-demand services and could play a vital role in sustainable transportation systems, by providing convenient last-mile solutions, which could facilitate multimodality. System-wide coordination of SAVs could mitigate congestion and could facilitate the integration of advanced propulsion

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systems (Burns, 2013). Furthermore, SAVs could reduce private car ownership levels substantially (Fagnant et al., 2015; Fagnant and Kockelman, 2014) and dynamic-ride sharing (DRS) schemes could be implemented (Fagnant and Kockelman, 2015b).

However, there are potential downsides to the ubiquity of this low-cost mobility option. The modal shift could be altered in a way so that more kilometers are traveled in small, possibly less energy-efficient vehicles. Inexpensive mobility on-demand services could erode public transit (PT) services, which rely on a sufficiently large number of users to be operated efficiently. Moreover, travelers could walk considerably less due to the convenience of the mobility on-demand services, which could have adverse effects on individuals' health.

The literature suggests that SAVs may be an attractive mobility option for elderly travelers (Fagnant and Kockelman, 2015a) and for individuals, who currently do not have access to private transportation (Anderson et al., 2014). A review of the literature dealing with the mobility behavior of these groups reveals the shortcoming of these presumptions, since there is strong evidence that these groups are in fact highly heterogeneous, which suggests that age and the availability of private transportation are insufficient discriminators of potential SAV use.

The design of effective transport policies, which aim to realize the potential benefits of SAVs, requires an understanding of how users will adopt SAVs. Yet, at this stage, little is known about how SAVs will be employed by travelers. This study intends to advance future research about the travel behavior impacts of SAVs, by exploring the characteristics of users who are likely to adopt SAV services and by eliciting willingness to pay measures for service attributes. For this purpose, a stated choice survey was conducted and analyzed, using a mixed logit model.

Several studies have investigated consumer perception of the AV technology (see Bansal et al. (2016) and the literature referenced therein), but to the best of the authors' knowledge, only two studies have specifically dealt with the adoption of SAVs. Haboucha et al. (2015) draw from stated preference data to investigate car owners' propensity to switch to SAVs on work-related and education-related trips. Furthermore, Bansal et al. (2016) analyze individuals' stated frequencies to use SAVs under different pricing scenarios and identify the characteristics of potential SAV adopters. This current study distinguishes itself from previous studies by explicitly addressing the acceptance of DRS in the context of SAV use.

The remainder of this contribution is structured as follows: In Section 2, the operations of SAV services are explained and existing ideas regarding potential users are discussed. The survey design and the data collection are described in Section 3. In Section 4, the collected data are analyzed both descriptively and inferentially. In Section 5, the results are critically discussed, policy implications are derived, the methodological limitations of the study are acknowledged and a conclusion is drawn.

2. Shared autonomous vehicles

2.1. Overview

The concept of SAVs combines elements of conventional carsharing and taxi services with AVs (Fagnant et al., 2015). SAVs could provide inexpensive and convenient mobility-on demand services (Burns, 2013; Burns et al., 2013), which have been described as driverless taxis (Fagnant et al., 2015).

Carsharing is generally considered to be a flexible mobility option, which complements public and slow modes, by offering the flexibility of the private car without the obligations associated with private car ownership (Shaheen and Cohen, 2012). As such, carsharing could potentially foster more sustainable mobility, by facilitating multi-modal travel behavior (Nobis, 2006) and in the longer run, carsharing could potentially reduce private car ownership levels (Firnkorn and Müller, 2012; Martin et al., 2011).

The AV technology could make carsharing more accessible and affordable. As for conventional carsharing, the walking distance to access shared vehicles is considered to be a key determinant of carsharing usage. Since SAVs will collect their passengers directly at their origin, walking times to access shared vehicles will be reduced to zero. Moreover, the AV technology could resolve the relocation issues of one-way carsharing and reduce the costs of providing one-way carsharing services (Firnkorn and Müller, 2015). In addition, carsharing with AVs could mitigate the availability concerns of users, i.e., users of one-way carsharing fear that a vehicle will not be available nearby after completing the activity at the destination (Fagnant and Kockelman, 2014). The AV technology will also dramatically lower the likelihood of accidents so that the insurance primes contained in current carsharing rates could be reduced.

Moreover, the AV technology could facilitate the implementation of DRS schemes, under which travelers, who travel from a similar origin to a similar destination, are allocated to the same vehicle to travel together for some part of their trip. DRS would allow for better capital utilization and would reduce the environmental impact of mobility on-demand services. In a simulation-based study of an SAV fleet in Austin, USA, it was determined that the excess vehicle kilometers traveled due to empty vehicle relocation could approximately be halved under DRS (Fagnant and Kockelman, 2015b). Ride-sharing with conventional vehicles requires users to incur high transaction costs for searching for ride opportunities, for arranging pick-ups and for cost-sharing agreements. In many cases, transaction costs may offset the benefits of ride-sharing. Even if ride-sharing was supported by information and communication technology (ICT), drivers would still need to navigate to the origin and the destination of the passenger for whom a ride opportunity is provided. Furthermore, the applicability of ride-sharing is restricted to cases, where the route between the driver's origin and destination roughly coincide with the ride-receiving person's origin and destination. In conjunction with a comprehensive ICT integration, the AV technology and SAVs could resolve the barriers, which currently hinder a greater uptake of ride-sharing. However, DRS heavily relies on user acceptance, as users must be willing to spend some time with a stranger in the confined space of an SAV.

2.2. Relation of SAVs to other modes

SAVs could potentially complement PT networks, by offering convenient last-mile solutions and by providing services on less frequently used routes. However, SAV systems could also pose a threat to PT systems, because SAVs could provide a more convenient user experience at a competitive rate. The overall ride experience of SAVs without DRS would be much smoother, as no transfers would be necessary and the vehicle would not have to stop to let passengers board or egress the vehicle. SAVs would offer more privacy and intimacy, seating availability would be guaranteed and walking times would be significantly reduced. As a consequence, travelers could make more efficient use of their travel time than on PT.

Moreover, SAVs could compete with private transportation. SAVs could provide a similar level of flexibility as private cars, but users would not have to interact with the vehicle, which would allow users to pursue relaxing or productive activities while traveling. In addition, SAVs could be established as an inexpensive alternative to taxis. SAVs would offer similar advantages as conventional carsharing, but at a greater convenience. Yet, SAVs will also have similar restrictions as conventional carsharing – most importantly, high travel costs for high-frequency users and no private storage space in the vehicle.

Empirical evidence suggests that the use of the private car is not only influenced by utilitarian considerations, but also by symbolic-affective motives such as the use of the car as symbol of social status and self-expression as well as feelings of autonomy, freedom and flexibility (Anable and Gatersleben, 2005; Steg, 2005). The impersonal or collective nature of SAVs suggests that for some individuals, SAV services may not be able to satisfy symbolic-effective ends to the same degree as the private car can. Therefore, it can be assumed that individuals, who put a high-value on the non-utilitarian motives of mobility, might not choose to use SAVs, even though configurations of an SAV service may be objectively superior to the mobility offered by a private car.

2.3. Potential user groups

Little is known about the potential users of SAVs. It has been argued that the AV technology could attract those without current access to private transportation or those, who were previously unwilling or unable to drive a private car (Anderson et al., 2014). Moreover, SAVs could constitute an attractive mobility option for the elderly or individuals too young to drive (Fagnant and Kockelman, 2015a). In the following paragraphs, these presumptions will be discussed in more detail. However, due to the extensive legal implications, the use of SAVs by individuals aged younger than the legal age of driving will not be investigated in this study.

Elderly travelers are most commonly characterized as individuals aged 65 years old and older. At this age, a considerable number of individuals have retired from work or have reduced their working hours. As a consequence, a significant shift of travel behavior can be observed, as individuals are not required to do work-related trips anymore and generally do fewer and shorter trips than before retirement (Rosenbloom, 2001). Alsnih and Hensher (2003) provide evidence that elderly travelers are generally more dependent on the private car than younger travelers. It is reported that license holding and car availability drop significantly at the age of 75 years due to health effects. Consequently, seniors may have to rely on social networks of relatives and friends to be mobile (see Alsnih and Hensher (2003) and the literature referenced therein). Car availability and the ability to drive are widely considered to impact well-being and health (see Haustein and Siren (2014) and the literature referenced therein). Nonetheless, the cause-and-effect relationship between driving cessation and health is ambiguous and disputable (Haustein, 2012; Scheiner, 2006).

Based on the above characterization of senior travelers, it could be argued that SAVs may be an age-appropriate mobility option for elderly travelers, as SAVs could provide convenient and flexible mobility at a low cost without the burden of having to drive by oneself. Yet, empirical evidence suggests that the cohort of elderly travelers is in fact highly heterogeneous and motives of the use of different modes vary considerably across cohort subgroups (Haustein, 2012). The same argument can be put forward for travelers who do not have access to private transportation, regardless of their age: Individuals may deliberately choose to limit the number of mobility options in their choice sets due to practical or hedonic considerations (Jacques et al., 2013).

It can be concluded that the characteristics of potential users of SAVs are vague at best, as there is little to no theoretical of empirical evidence, which can be considered to arrive at an a-priori segmentation of potential SAV users.

3. Method

This research draws from an online survey, which was completed by 435 residents of major metropolitan areas of Australia. The survey comprised two parts. In the first part, a questionnaire was presented to survey takers to collect information about socio-demographic characteristics as well as about mobility-related characteristics and behavior. Furthermore, Haustein's (2012) Likert type attitudinal indicators aimed to obtain measurements for modal preferences. The second stage of the survey featured a stated choice experiment, in which the respondents were asked to indicate whether they would switch to an SAV on a trip they recently undertook.

3.1. Stated choice experiment

The stated choice experiment consisted of three stages.

3.1.1. Stage 1: Specification of a reference trip

The first stage of the experiment aimed to elicit a revealed preference from the subjects. Subjects were asked to provide details about a trip they had recently made. Prior to the collection of the trip details, subjects were made aware of the definition of a trip and the difference between a trip and a tour was highlighted. Subjects were required to state the purpose of the trip, the means of transportation they used, the approximate distance between the origin and the destination, the travel time and waiting time if applicable as well as the approximate monetary cost of the trip. To check the plausibility of the trip details, subjects were asked to provide addresses of the origin and the destination of their trip, where known, or crude approximations, where unknown.

3.1.2. Stage 2: Instructions

To introduce subjects to SAVs, a Prezi-based presentation was integrated into the survey. Prezi software allows for a more engaging display of information, which was deemed necessary due to the amount of text-based information contained in the survey. The information presented was inspired by Burn's vision of SAV services (Burns, 2013): It was highlighted that SAVs would be self-driving vehicles, which would not require any driver input. Therefore, it would not be necessary to hold a driving license to use an SAV. In addition, vehicle occupants would not need to pay attention to traffic and could thus dedicate their in-vehicle-time to relaxing or productive activities. It was emphasized, that SAVs would be part of a fleet of shared vehicles, which would be easily available upon request. It was also highlighted that SAVs could be imagined as driverless taxi services. Furthermore, subjects were presented how the concrete use of an SAV for a trip could look like. Subjects were told that they could use their smartphone to request a vehicle and that the vehicle would arrive after a specified waiting time. Upon arrival at their destination, there would be no need to park the vehicle or to incur parking fees, as the vehicle would continue on to pick up the next passenger. Subjects were also informed about DRS and it was stressed that DRS would involve riding inside the same vehicle for some portion of the trip.

3.1.3. Stage 3: Choice tasks

In the last stage of the experiment, subjects were confronted with five choice tasks, which required subjects to select one out of three mobility options for the trip they had specified. The choice tasks were presented in a conjoint format (Fig. 1).

3.1.3.1. Alternatives. Two of the three alternatives were hypothetical and involved the use of SAVs. The first hypothetical option allowed subjects to travel in an SAV by themselves, while the second hypothetical option involved DRS. SAV with and without DRS were separated into two distinct alternatives to account for other systematic influences on utility, which

Suppose the following three alternatives were available to you. Which alternative would you choose for the trip you have specified before?

	Alternative 1: Shared autonomous vehicle (without ride-sharing)	**Alternative 2: Shared autonomous vehicle (with ride-sharing)**	**Alternative 3: Your current option Public transit only**
travel cost [AUD]	9.6	4.8	3.50
travel time (including waiting time) [minutes]	21	26	30
waiting time [minutes]	5	10	5

○ Alternative 1: Shared autonomous vehicle

○ Alternative 2: Shared autonomous vehicle with ride-sharing

○ Alternative 3: Your current option (Public transit only)

Fig. 1. Conjoint format of the choice tasks.

cannot be captured by the attributes of the alternatives. The third option constituted an opt-out alternative and was equivalent to the mobility option the subjects had specified. This third option thus represents a respondent-specific reference alternative in each of the choice tasks.

3.1.3.2. Attributes of the alternatives. The attributes of the hypothetical alternatives were pivoted around the attributes levels of the revealed preference to increase the realism of the choice task (Hess and Rose, 2009). Three attributes were provided to specify the three alternatives: travel cost, travel time and waiting time. The travel cost of an option denoted the monetary cost subjects would have to incur when using this option for their trip. Travel time was defined as the door-to-door travel time including waiting time. Waiting time denoted the time subjects would spend not moving and waiting outside a vehicle. The attribute levels of the opt-out alternative were not changed across choices and were equal to the details the subject had specified before, but the attribute levels of the two hypothetical alternatives were varied across choice scenarios. For the travel cost, three attribute levels (0.2 AUD/min, 0.4 AUD/min, 0.6 AUD/min) were established. This parametrization is consistent with the presumption that SAVs will constitute a low-cost mobility option, which is to compete with PT and the private car. At the same time, it was intended to avoid that the SAV alternatives would strictly dominate the revealed preference. The travel time was the sum of the in-vehicle travel and the waiting time. The in-vehicle travel time featured one attribute level and was calculated based on the distance subjects had input for the trip they had recently made and an average speed of 30 km/h. This speed is reasonable for road transport in an urban environment and is consistent with Burns' (2013) vision that SAVs are specifically designed for traveling at relatively low speeds. Three levels (0 min, 5 min, 10 min) were established for the attribute waiting time. From a user perspective, waiting time can be assumed to be an important service attribute. Moreover, waiting time is critical for the determination of SAV fleet sizes and ultimately affects the operating cost of the service (Fagnant and Kockelman, 2015b).

3.1.3.3. Choice sets. Given two attributes with three levels and a one-level attribute, a complete factorial experimental design features nine profiles for each alternative. Applying the minimal overlap principle (Huber and Zwerina, 1996), nine choice sets were created for the two hypothetical alternatives. For each respondent, five choice sets were randomly selected from the set of nine.

3.2. Data collection

The survey was implemented, using software by Qualtrics and completed by an Australian online panel administered by Qualtrics in April 2015. The participants were systematically sampled from the panel. Firstly, the participants were required to live in a major metropolitan area of Australia (Adelaide, Brisbane, Melbourne, Perth, Sydney). In addition, age and income quotas were imposed. To improve the quality of the data, three attention filters were included into the survey. Two of which required respondents to select a specific response for a Likert item and one of which asked respondents to input a word into a text box. Only complete and valid responses were included into the analysis.

4. Data analysis and discussion

4.1. Sample composition

The sample comprised 435 individuals. Marginal distributions of the variables gender, age, income and labor force status are reported in Table 1 for the sample and the population. Based on the population margins, a weighted sample was generated.

Table 1
Sample and population frequencies of selected variables.

Variable (values)	Sample distribution[a]	Population distribution[b]
Gender (female, male)	(51.7%, 48.3%)[c]	(51.4%, 48.6%)
Age [years] (18–29, 30–49, 50–64, 65–74, ⩾75)	(27.8%, 20.0%, 21.4%, 26.4%, 4.4%)	(22.9%, 37.7%, 22.6%, 8.9%, 7.9%)
Weekly income [AUD] (0–599, 600–1249, ⩾1250)	(38.6%, 39.5%, 21.8%)	(49.4%, 29.0%, 21.6%)[d]
In labor force (yes, no)	(58.8%, 41.2%)	(66.3%, 33.7%)[d]

Data source of population frequencies: Australian Bureau of Statistics (2013).
[a] $N = 435$.
[b] Population includes adult residents of Greater Capital City Statistical Areas of Adelaide, Brisbane, Melbourne, Perth and Sydney. The population size is 10.4 million.
[c] One respondent indicated to be of other gender. This observation was assigned to the female category.
[d] Includes individuals aged 15 years and older.

For the original sample, 24.8% of the respondents lived in a household, where some of the household members were younger than 18 years old. Moreover, 89.2% of the respondents indicated that they held a driving license. 92.0% of those who held a driving license owned a car and 64.5% of those who held a driving license, but did not own a car, indicated that they had access to a car on a regular basis. Therefore, 86.3% of the respondents owned a car or had regular access to one as driver. 4.6% of the respondents did not hold a driving license and did not have access to a car as a passenger on a regular basis. 84.6% of the respondents indicated that they knew what carsharing is. 8.7% of the respondents indicated that they used carsharing. 55.3% of the carsharing users traveled by carsharing at least once a week.

4.2. Modality styles

Modality styles (e.g. Vij et al., 2013) were identified by clustering respondents' self-reported frequencies of use of the four transport modes car, PT, walking and bicycling, using the *k*-means algorithm (Hartigan and Wong, 1979). The response options (daily, two to three times per week, once per week, two to three times per month, once per month, less than once per month, never) were coded from one (daily) to seven (never). It was found that the gain of additional explained variance diminished, as the number of clusters exceeded five. Thus, a five-cluster solution was selected based on the proportion of explained variance (71.8%) and the interpretability of the solution. Based on their cluster means, the clusters are labeled and characterized as follows:

- *Uni-modal car users (UMC):* Individuals assigned to this cluster travel almost exclusively by car. The average reported frequency of car use is between daily and two to three times per week. By contrasts, the average reported use frequencies of all other modes are within the interval of less than once a month and never (25.3% of the original sample; 25.8% of the weighted sample).
- *Pedestrial car users (PCU):* Individuals assigned to this cluster travel by car and walk relatively frequently, while other modes are rarely used. The average reported frequencies of car use and walking fall between daily and two to three times per week and respectively between one and two times per week. By contrast, the average frequency of PT use is between once and less than once per month. Bicycling is reported with an average frequency that falls close to never (26.4% of the original sample; 24.7% of the weighted sample).
- *Passive bi-modals (PBM):* Individuals who belong to this cluster mostly travel by car and by PT, but rarely walk or bicycle. The average reported frequencies of car use and PT use fall between daily and two to three times per week and respectively between once and thrice per week. The average reported frequency of walking is close to less than once a month and the average reported frequency of bicycling is close to never (12.2% of the original sample; 11.2% of the weighted sample).
- *Pedestrial tri-modals (PTM):* Individuals assigned to this cluster bicycle rarely, but use all other modes relatively frequently. Traveling by car is reported with an average frequency between once and thrice per week. PT use and walking are reported with an average frequency of two to three times per week (23.7% of the original sample; 25.7% of the weighted sample).
- *True multi-modals (TMM):* Individuals belonging to this cluster use all four modes relatively frequently, as the average reported frequencies of all four modes are located within the interval of daily and weekly use (12.4% of the original sample; 12.6% of the weighted sample).

4.3. Reference trip specification

The summary statistics of the trip characteristics, around which the attributes of the hypothetical alternatives were pivoted, are enumerated in Table 2. Furthermore, Table 3 reports the joint frequencies of the variables trip purpose and the means of transportation for the reference trip. Table 3 shows that the majority of the trips were made for the purposes of working or shopping and 74.3% of the trips were made by car and 18.6% of the trips involved PT.

4.4. Stated choice analysis

Each of the 435 respondents completed faced five choice scenarios. Consequently, 2175 choices were observed. The alternative SAV without DRS was chosen 342 times and the choice SAV with DRS was observed 277 times. The opt-out option was selected 1556 times. The stated choice data were analyzed within the framework of the Mixed Logit Model (MXL) (e.g. Train, 2003).

Table 2
Reference trip characteristics.

Statistics	Distance (km)	Cost (AUD)	Travel time (min)	Waiting time (min)
1st quartile	4.0	1.4	12.0	0.0
Median	10.0	3.0	25.0	2.0
Mean	16.3	5.1	34.7	4.4
3rd quartile	20.0	5.0	45.0	5.0
Std. dev.	19.6	6.3	30.0	7.0

Table 3
Joint distribution of trip purposes and means of transport for the reference trip.

	Means of transport						
	Car as driver incl. Motorbike/ scooter, carsharing (%)	Car as passenger incl. taxi (%)	Bicycle (%)	PT (%)	PT and car combined (%)	Walking (%)	*Margin (%)*
Trip purpose							
Work	18.6	1.6	0.0	4.4	3.2	0.7	*28.5*
Education	1.1	1.1	0.5	1.6	1.1	0.5	*6.0*
Shopping	23.9	5.5	0.0	3.0	0.0	3.2	*35.6*
Leisure	10.1	3.9	0.2	1.6	1.8	0.7	*18.4*
Medical or dental appointment	5.7	1.8	0.0	1.4	0.0	1.4	*10.3*
Own residence	0.5	0.2	0.0	0.2	0.2	0.0	*1.1*
Margin	*60.0*	*14.3*	*0.7*	*12.2*	*6.4*	*6.4*	*100.0 (N = 435)*

4.4.1. Model formulation

The choice model is established as follows: In choice scenario $t \in \{1, \ldots, T_n\}$, individual n derives utility $U_{in,t}$ from alternative i with $U_{in,t} = V(\boldsymbol{X_{in,t}}, \xi_{in,t}; \boldsymbol{\beta}) + \epsilon_{in,t}$. Individual n is assumed to choose alternative i over j, if $U_{in,t} > U_{jn,t}$, where $i, j \in C_n$. V is the systematic utility, which is linear in parameters $V = \boldsymbol{\beta}'\boldsymbol{X_{in,t}}$, where $\boldsymbol{X_{in,t}}$ denotes a vector of observed explanatory variables, including service attributes, socio-demographic characteristics, reference trip attributes and the individual's modality style. $\boldsymbol{\beta}$ is a vector of coefficients on the explanatory variables. The disturbances $\epsilon_{in,t}, \xi_{in,t}$ capture the unobserved part of the utility. $\xi_{in,t} \sim D(\boldsymbol{\Theta_\xi})$, $\boldsymbol{\Theta_\xi}$ being a set of parameters, is a flexible disturbance, which allows one to impose distributional assumptions on random parameters. $\epsilon_{in,t}$ is assumed to be independent and identically distributed (iid) Extreme Value across observations. Hence, conditional on $\xi_{in,t}$, the probability of the choice model takes on the logit form: $P_t(i|\boldsymbol{X_{n,t}}, \boldsymbol{\xi_{n,t}}; \boldsymbol{\beta}, \mu) = \frac{e^{\mu V(\boldsymbol{X_{in,t}}, \xi_{in,t}; \boldsymbol{\beta})}}{\sum_{j \in C_n} e^{\mu V(\boldsymbol{X_{jn,t}}, \xi_{jn,t}; \boldsymbol{\beta})}}$, whereby μ denotes the scale parameter, which is set to one. The conditional probability is combined across individual n's T_n choice scenarios to obtain the conditional probability of observing individual n's vector of choices $\boldsymbol{y_n}$: $P(\boldsymbol{y_n}|\boldsymbol{X_n}, \boldsymbol{\xi_n}; \boldsymbol{\beta}, \mu) = \prod_{t=1}^{T_n} \prod_{i \in C_n} P_t(y_{nti} = 1|\boldsymbol{X_{n,t}}, \boldsymbol{\xi_{n,t}}; \boldsymbol{\beta}, \mu)^{y_{nti}}$. y_{nti} is a binary variable, which is one, if alternative i was chosen by individual n in choice scenario t and zero otherwise. To obtain the unconditional probability of the choice model, the conditional choice probability must be integrated over the joint density $f(\xi|\theta_\xi)$ of the flexible disturbances $\xi_{n,t}$: $P(\boldsymbol{y_n}|\boldsymbol{X_{n,t}}; \boldsymbol{\beta}, \boldsymbol{\Theta_\epsilon}, \boldsymbol{\Theta_\xi}, \mu) = \int P(\boldsymbol{y_n}|\boldsymbol{X_n}, \boldsymbol{\xi_n}; \boldsymbol{\beta}, \mu) f(\xi|\theta_\xi) d\xi$. This unconditional probability is summed across individuals to obtain the likelihood of the sample $\mathcal{L}(\boldsymbol{\beta}, \boldsymbol{\Theta_\xi}|\boldsymbol{y}, \boldsymbol{X}) = \prod_{n=1}^{N} P(\boldsymbol{y_n}|\boldsymbol{X_{n,t}}; \boldsymbol{\beta}, \boldsymbol{\Theta_\epsilon}, \boldsymbol{\Theta_\xi}, \mu)$. Since the integral does not have a closed-form solution, the likelihood must be maximized, using maximum simulated likelihood methods, such as implemented in Python Biogeme (Bierlaire, 2003).

4.4.2. Modeling procedure

To arrive at the final model specification, an iterative procedure, comprising five stages, was employed. A summary of the different model specifications developed for each stage is reported in Table 4. For all model specifications, coefficients on service attributes were estimated in willingness-to-pay WTP space instead of preference space (e.g. Gaker et al., 2011) to directly obtain measures for the value of in-vehicle time (VoIVT) and the value of waiting time (VoWT), as this non-linear transformation of the utility function bypasses the computational challenges associated with obtaining WTP estimates in

Table 4
Summary of different model specifications.

	Model #				
	1	2	3	4	5
Distinguishing features of the model specification					
– Piece-wise definition of the coefficients on VoIVT for the hypothetical alternatives	x	✓	✓	✓	✓
– Distribution of the coefficients on VoIVT	N/A	Fixed	Fixed	Random: log-normal	Random: triangular
– Log-transformation of cost attribute	x	x	✓	✓	✓
Number of estimated parameters	57	57	57	60	57
Log-likelihood	−1487.9	−1466.4	−1388.8	−1380.8	−1387.0
Akaike Information Criterion	3089.9	3046.7	2891.6	2881.7	2888.0
Bayesian Information Criterion	3322.2	3279.0	3123.9	3126.2	3120.3

random-coefficient models (Hensher et al., 2005). The estimates of the coefficients on value of time (VoT) measures and alternative-specific constants, which were obtained for each of the five model specifications, are enumerated in Table 5. In the interest of brevity, Table 6 reports the estimates for coefficients on individual-specific variables only for the final model specification.

In the first three stages, flexible disturbances were not introduced into the model structure so that the choice models collapsed to the well-known multinomial logit model. First, a basic multinomial logit model (MNL) including alternative-specific and individual-specific variables was estimated. However, this model specification produced relatively large p-values for the coefficients on the VoIVT for the hypothetical alternatives. An analysis of the responses to the choice tasks revealed that when respondents had specified a relatively long reference trip in terms of the covered distance, respondents rarely chose any of the hypothetical alternatives, because the opt-out alternative dominated the hypothetical alternative. As a consequence, the VoIVT approached zero for these respondents and the coefficients estimated on VoIVT were distorted for the hypothetical alternatives. Thus, the second modeling step aimed to control this anomaly. It was found that smaller p-values for the coefficients on the VoIVTs for the hypothetical alternatives could be produced by specifying the coefficients in question in a piece-wise fashion, i.e. β_i was defined as $\beta_{i,\text{base}} + m \cdot \beta_{i,\text{modifier}}$, with m denoting a dummy variable equal to either zero or one. $\beta_{i,\text{base}}$ is a generic coefficient, to which a modifying $\beta_{i,\text{modifier}}$ is added, depending on the value of m. An exploration of different specifications revealed that the anomaly could be most effectively controlled by constraining the base coefficient to zero and by estimating the modifying coefficient, only if the in-vehicle time of the hypothetical alternatives was less than 2.5 times the in-vehicle time of the reference trip. This condition was fulfilled by 92.0% of the observations.

Moreover, the fit of the model could be considerably improved, by adding one AUD to the cost attributes of all alternatives and by taking the natural logarithm of the sums. This log-transformation was incorporated in the third and the following model specifications. As a consequence of the log-transformation of the cost-attribute, the coefficients estimated in WTP

Table 5
Estimates of coefficients on VoT and alternative-specific constants.

Coefficient	Model 1		Model 2		Model 3		Model 4		Model 5	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
SAV without DRS										
Constant	−2.02	0.00	−2.03	0.00	−0.28	0.54	−0.13	0.81	−0.27	0.57
VoT: In-vehicle time										
Base	23.90	0.12	0.00[a]		0.00[a]		0.00[a]		0.00[a]	
Modifier										
Fixed coefficient			60.90	0.00	0.66	0.00				
Random coefficient										
Location							0.17	0.00	0.78	0.00
Scale							−0.04	0.91	0.78	
VoT: Waiting time	2.03	0.01	2.22	0.00	0.05	0.00	0.05	0.00	0.05	0.00
Travel cost	−0.02	0.00	−0.02	0.00	−1.20	0.00	−1.37	0.00	−1.22	0.00
SAV with DRS										
Constant	−2.30	0.00	−2.38	0.00	−0.77	0.14	−0.66	0.26	−0.76	0.14
VoT: In-vehicle time										
Base	48.50	0.11	0.00[a]		0.00[a]		0.00[a]		0.00[a]	
Modifier										
Fixed coefficient			64.20	0.00	0.82	0.00				
Random coefficient										
Location							0.40	0.00	1.06	0.00
Scale							0.13	0.80	1.06	
VoT: Waiting time	6.32	0.00	5.61	0.00	0.10	0.00	0.08	0.00	0.10	0.00
Travel cost	−0.02	0.00	−0.02	0.00	−1.04	0.00	−1.20	0.00	−1.05	0.00
RP										
VoT: In-vehicle time										
Base										
Fixed coefficient	5.71	0.04	7.45	0.01	0.93	0.00	−0.26			
Random coefficient										
Location								0.00	1.16	0.00
Scale							1.33	0.00	1.16	
Modifier (Means of transport: car as driver)	7.65	0.04	7.51	0.04	0.73	0.05	0.32	0.44	0.52	0.18
Modifier (Means of transport: PT)	−2.12	0.66	1.82	0.70	0.06	0.89	0.22	0.73	−0.13	0.80
VoT: Waiting time										
Base	0.82	0.01	0.98	0.00	0.10	0.00	0.08	0.07	0.09	0.00
Modifier (Means of transport: car as driver)	−0.26	0.42	−0.43	0.20	−0.04	0.19	−0.01	0.77	−0.03	0.28
Modifier (Means of transport: PT)	−0.51	0.25	−0.63	0.17	−0.06	0.13	−0.06	0.28	−0.06	0.17
Travel cost	−0.08	0.00	−0.09	0.00	−0.89	0.00	−0.09	0.00	−0.90	0.00

[a] Constrained by specification.

Table 6
Individual-specific coefficients as estimated for model specification 5.

Coefficient	SAV without DRS		SAV with DRS	
	Estimate	*p*-value	Estimate	*p*-value
Gender (reference = female and other)				
Male	0.21	0.16	0.01	0.93
Age (reference = 30 to 49 years old)				
18–23 years old	0.08	0.78	0.30	0.33
24–29 years old	0.26	0.28	0.63	0.01
50–64 years old	0.13	0.59	−0.02	0.95
65–84 years old	−0.43	0.10	0.01	0.98
Income (reference = 599 AUD/week or less)				
600–1249 AUD/week	0.01	0.97	−0.20	0.26
1250 AUD/week or more	−0.33	0.12	−0.30	0.21
Presence of children (persons aged 17 years old or younger) in the household (reference = no)				
Yes	−0.11	0.52	−0.31	0.12
Car availability (reference = yes)				
No	−0.21	0.42	0.13	0.61
Means of transportation (reference = bicycling or walking)				
Car as driver incl. motorbike/scooter, carsharing	0.69	0.05	0.24	0.53
Car as passenger incl. taxi	0.35	0.36	0.68	0.07
PT incl. PT only and PT and car combined	0.91	0.04	0.49	0.27
Trip purpose (reference = education or own residence)				
Work	0.15	0.63	0.40	0.23
Shopping	−0.70	0.03	−0.48	0.15
Leisure	−0.33	0.12	−0.36	0.32
Medical or dental appointment	−0.81	0.03	−0.70	0.08
Carsharing user (reference = no)				
Yes	0.19	0.47	1.05	0.00
Modality (reference = PCU)				
UMC	−0.29	0.16	−0.18	0.45
PBM	0.44	0.08	0.04	0.90
PTM	0.51	0.02	0.75	0.00
TMM	0.51	0.03	0.89	0.00

space become marginal VoT measures, which must be evaluated at a certain level of the travel cost to obtain an absolute measure of the VoT. More specifically, provided a level of travel cost measured in AUD, the corresponding value of the WTP is generated by adding unity and by subsequently multiplying the sum by the coefficient estimate of the marginal VoT measure.

As the MNL framework restricts substitution patterns and does not adequately account for preference heterogeneity among across respondents, two MXL specifications were explored, in which random distributions were imposed on the coefficients on VoIVT. From a behavioral standpoint, VoT measures should be non-negative (Hensher and Greene, 2003). This constraint is satisfied by the log-normal distribution and the triangular distribution. A log-normal distribution for the coefficients on the WTP for a reduction in in-vehicle time was implemented in the fourth modeling step. However, insignificance of the scale coefficients indicates that the log-normal distribution does not provide an adequate fit to the data. In the fifth and final step, a symmetric triangular distribution with mean = spread and support on the interval $[0; 2\beta]$ was implemented (see Hensher and Greene, 2003). As discussed by Hensher and Greene (2003), this distribution has desirable properties, because it assures that the coefficient in question is strictly positive, but also constrained, as opposed to the fat-tailed log-normal distribution.

4.4.3. Discussion of results

4.4.3.1. Value of time. For the final model specification, the estimated coefficients on VoT measures are statistically significant and have the expected signs. Statistical significance of the random coefficients indicates that significant mixing occurs in these variables. Moreover, positive and statistically significant estimates for the coefficients on VoWT corroborate the hypothesis that waiting time is a critical service attribute of SAV operations (Fagnant and Kockelman, 2015b). Fig. 2 shows an evaluation of the marginal VoT measures, as function of the travel cost on the interval [0 AUD; 20 AUD]. Fig. 2 highlights the variation in the VoT estimates across the hypothetical alternatives and shows that the two options are perceived as two distinct mobility options. The marginal WTP estimates of the SAV alternative involving DRS are greater than those of the alternative SAV without DRS, which suggests that service configurations and fares are critical determinants of DRS acceptance, particularly if SAVs with DRS were to compete with SAVs without DRS.

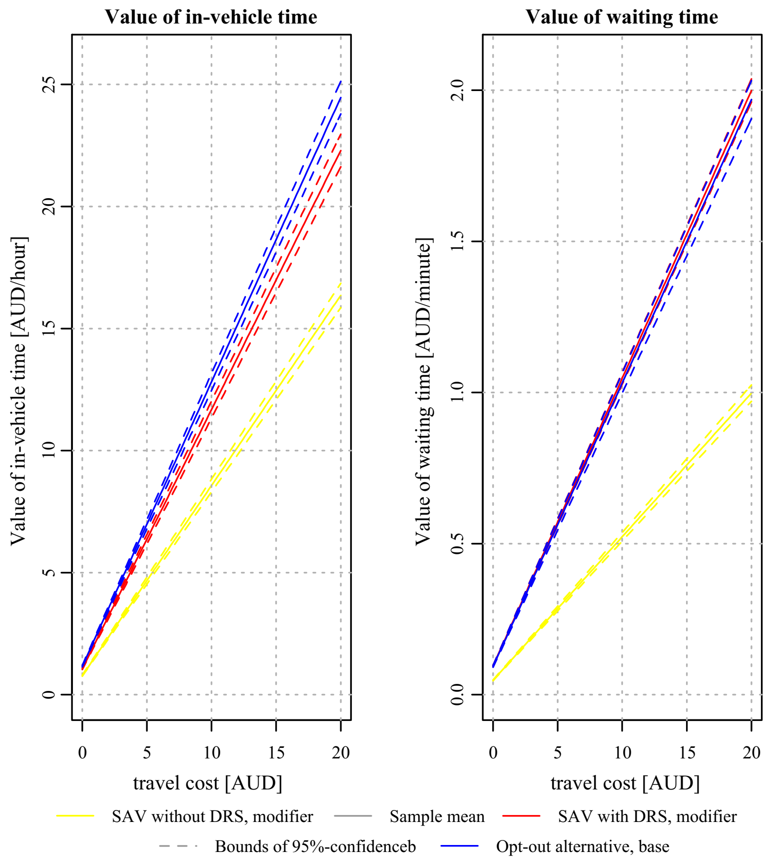

Fig. 2. Evaluation of mean estimates of VoIVT and VoWT including 95%-confidence bands as for model specification 5 (for hypothetical alternatives, only the mean estimates of the VoT modifiers are plotted; for the opt-out alternative, only the base VoT estimates are plotted).

4.4.3.2. Individual-specific coefficients. Table 6 reports the estimates of the individual-specific coefficients for the final model specification. The results do not indicate a strong relationship between age and the propensity to use any of the hypothetical alternatives. A statistically significant relationship is only revealed for individuals aged between 24 and 29 years old, who are relatively more likely to select the option SAV with DRS. While it has been hypothesized that SAVs may be an attractive mobility option for the elderly (Fagnant and Kockelman, 2015a), respondents aged between 65 and 84 years old are not relatively more likely to select any of the SAV options in the experimental setting of this study.

The coefficients on the attributes of the reference trip allow for inferences about how SAVs may be used by travelers. Both SAV options are relatively less likely to be selected on trips for the purpose a medical or dental appointment. Moreover, the propensity to choose the option SAV without DRS is adversely affected, when the reference trip was undertaken for the purpose of shopping. Furthermore, respondents, who traveled by car as driver on the reference trip, are relatively more likely to choose the option SAV without DRS, while selecting the option SAV with DRS is more likely if the reference trip was undertaken by car as passenger. Respondents who traveled by PT on the reference trip, are relatively more likely to switch to the option SAV without DRS, while switching to SAV with DRS is not relatively more likely.

A strong relationship between an individual's modality style and an individual's propensity to switch to SAVs is suggested by the results. More specifically, membership in the PTM and TMM clusters significantly increases the propensity to select one of the SAV options. A possible explanation is that individuals with multi-modal travel patterns frequently re-evaluate mobility-related decisions (Kuhnimhof et al., 2006) and are therefore relatively more open to explore novel mobility options. In addition, individuals, who use PT on a regular basis, may be less hesitant to use shared mobility options. The relationship between the propensity to switch to SAVs and an individual's modality styles highlights that SAVs may facilitate multi-modal travel behavior. Nonetheless, the availability of SAVs may not incentivize almost exclusively car-oriented individuals to engage in more multi-modal travel patterns.

Moreover, the results indicate that travelers, who currently use carsharing, are more inclined to choose the option SAV with DRS. Several studies have investigated the characteristics of carsharing users: Pro-environmental attitudes and innovativeness have been recognized as commonly shared characteristics among carsharing users (Burkhardt and Millard-Ball, 2006). Schaefers (2013) identified four motivational patterns, which underlie carsharing use, including thriftiness, convenience, social innovativeness and pro-environmental considerations. Furthermore, carsharing users are likely to exhibit multi-modal travel patterns (Kopp et al., 2015), which corroborates that carsharing may be used as a flexible facilitator of multi-modality (Schaefers, 2013). This prior research suggests a possible relationship between higher-order orientations and the propensity to use SAVs with DRS.

5. General discussion and conclusion

5.1. Main results

The results of this survey contribute to a growing body of literature on SAV adoption, by substantiating knowledge about the potential users of SAVs. More specifically, the results suggest that service attributes including travel time, waiting time and fares are significant determinants of SAV use and DRS acceptance. Considerable variation of VoT estimates across the alternatives SAVs without DRS and with DRS indicates that the two alternatives are regarded as two distinct mobility options. SAV with DRS are more likely to be selected by young travelers and a strong relationship between an individual's modality style and the propensity to choose SAVs is revealed. In addition, current carsharing users are relatively more likely to use SAVs with DRS. Respondents, who traveled by car as driver on the reference trip, are relatively more likely to choose the option SAV without DRS, while selecting the option SAV with DRS is more likely if the reference trip was undertaken by car as passenger. Interestingly, switching to any of the hypothetical options is not relatively more likely, if respondents traveled by PT on the reference trip.

5.2. Policy implications

Several policy implications can be derived. Overall, the results suggest that the adoption of SAV services will most likely differ across sub-groups and modality may be a major discriminator of sub-group membership. While multi-modal travelers may adopt SAVs to facilitate their multimodality, individuals whose modality is mostly and almost exclusively centered around the use of the private car may be reluctant to use SAVs. Furthermore, market penetration rates may be greater among young travelers. The derived policy implications are complementary to the existing literature, which deals with the policy implications of the AV technology in general (Anderson et al., 2014; Fagnant and Kockelman, 2015a, 2014; Wadud et al., 2016).

5.3. Methodological limitations

Two caveats related to the methodology employed in this study should be pointed out. First, a hypothetical bias may be present in the data due to the hypothetical nature of the stated choice experiment, i.e. the results obtained in this study might be of limited value in realistic settings. Nevertheless, it is worthwhile noting that regardless of the importance of hypothetical bias as a topic of interest, there currently exist only a handful of such studies that do so in relation to discrete choice experiments, with the majority of such studies relating to other forms of stated preference methods, in particular contingent valuation studies (Beck et al., 2016). Whilst the general consensus from these studies is that choice experiments may, just as with contingent valuation methods, be prone to the phenomenon (Broadbent, 2014), choice experiments are still of use, particularly with regards to matters of policy focus. That is, whilst the results may not reflect precisely the preferences of decision makers, they can be useful in identifying directionality and relative importance with regard to attributes of interest. Second, the results of this study may be subject to a status quo bias, i.e. due to the not only hypothetical, but also highly futuristic nature of the choice alternatives, the preferences elicited from the respondents of the stated choice survey may not accurately reflect consumers' preferences by the time the hypothetical alternatives may actually be available in the marketplace.

To predict the impacts of SAVs on travel behavior and the demand for existing mobility options in a more accurate manner, a refinement of stated choice methods is necessary, i.e. the hypothetical and the status quo biases must be adequately accounted for. Nonetheless, the results presently capture the directionality and relative importance of various attributes of interest.

5.4. Conclusion

To identify the characteristics of potential users of SAVs, a stated choice survey, in which respondents were asked to indicate whether they would switch to an SAV without DRS or an SAV with DRS on a recent trip, was conducted and analyzed, using a Mixed Logit Model. The results indicate that service attributes may be critical determinants of SAV use and DRS acceptance. A strong relationship between the set of modes, which an individual frequently uses, and the propensity to choose SAVs was revealed. Moreover, policy implications were derived. The uptake of SAV services will most likely differ across population subgroups, whereby the set modes, which an individual frequently use, may be an important determinant of subgroup membership.

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