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Consumer preferences for different CAV technologies and service models

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Abstract

Transport technologies and service providers are moving towards a significant revolution in shifting travel habits, with the rise of alternative fuel vehicle technologies, autonomous vehicles and shared mobility services (Vij, 2020). It is imperative to consider different factors influencing individual travel behaviour in order for the transport system to fulfil the needs of various sub-populations as well as the short and long term social, economic and environmental objectives. This study explores how consumers will engage with connected and automated vehicles (CAVs) and will likely adopt this technology as a service. A quantitative exploration of citizen/consumer attitudes and preferences towards CAV technology is provided to understand which factors are likely to impact CAV uptake in Australia, and how do these factors vary across different sub-population groups. Data for our analysis comes from a nationwide online stated preference survey of 2,993 demographically and geographically representative Australians, administered in 2022. A latent class model was employed, and seven segments were identified that varied in their taste and preferences for CAV services.

Keywords: Connected and autonomous vehicles, latent class model, consumer preferences

1. Introduction

It is anticipated that CAV technologies will enable on-demand, door-to-door transport services as a new form of micro public transport, which combines the benefits of existing mass public transport services and private modes of motorized transport but does not suffer from the same drawbacks (Vij, 2020). Compared to mass public transport services that require high densities and large catchment areas in order to be feasible, and consequently suffer from first and last-mile connectivity problems, micro public transport can offer door-to-door services. Compared to private modes of motorized transport, where high running and parking costs and frequent congestion can limit access and use, micro public transport is expected to be cheaper, faster and more convenient (Acheampong et al., 2021).

In addition to the characteristics of CAVs and the new mobility services that they enable, the characteristics of different consumer groups may influence the adoption of CAVs. For example, previous studies have shown that male respondents are more positive about the potential benefits of driverless vehicles than females (Cunningham et al., 2019). Differences in people's propensity to innovate, risk perceptions and personal goals have all been shown to affect whether consumers are more likely to adopt technological innovations more generally. Further, contextual factors such as social influence and institutional distrust (e.g., towards the government, vehicle manufacturers, technology companies) may prove critical to achieving potential benefits offered by CAVs (Lazanyi and Maraczi, 2017). Finally, demographic characteristics such as income and education are also likely to have an influence (Bansal et al., 2016).

Governments will play a crucial role in managing the introduction and diffusion of CAVs in society. They will develop the regulatory environment in which CAVs are commercialised, provide the infrastructure on which they operate, and potentially offer information and support to the general population on the use and uptake of the technology. In general, while greater adoption of CAVs could potentially offer significant benefits to the transport system and society more broadly, unlocking these benefits requires a better understanding of the Australian society's views on the technology.

This study aims to provide a quantitative exploration of citizen/consumers attitudes and preferences towards CAV technology and understand which factors are likely to impact CAV uptake by Australian consumers, and how do these factors vary across different sub-population groups.

Our study contributes to the large and rapidly growing body of work on consumer preferences for CAV technologies and service models in three notable ways. First, our study examines consumer preferences for different levels of automation in greater detail than previous studies. To the best of our knowledge, previous studies have examined consumer preferences for partial and full automation separately (e.g. Ulahannan et al., 2020, Rodrigues et al., 2021, Souka et al., 2020, Jiang et al., 2019, Wali et al., 2021), but they haven't distinguished between other intermediate levels of automation. We explicitly measure preferences for each of the six levels of vehicle automation, as defined by the Society of Automotive Engineers (Society of Automotive Engineers, 2021). Given that many stakeholders have raised safety concerns with regards to intermediate levels of automation (e.g. Tabone et al., 2021, Kaber, 2018, Dolgov, 2016), it is important to understand how consumers perceive them.

Second, our study examines consumer preferences for vehicle and service attributes that have not received as much attention from previous studies. For example, we examine preferences for different interior design features. Many studies have argued that CAVs could enable greater productivity, by allowing individuals to use time ordinarily spent driving in pursuit of other activities, but this would require a change in existing vehicle interior designs. Similarly, we examine preferences for having a standby driver and/or chaperone in the vehicle, as early trials and commercial implementations of CAV technologies are likely to include them.

Third, our study offers novel insights on the demographic determinants of CAV uptake. For example, we find that individuals living in metropolitan areas are more likely to desire greater vehicle automation, while those living in regional areas are more likely to prefer lesser vehicle automation. Other demographic variables, such as age, gender, education, and employment status also appear to have some influence on preferences, but the patterns are not always clear. For example, in general, young adults seem more inclined to prefer highly autonomous vehicles, but our findings also identify a segment of young adults that display a strong preference for driver assistance features, but do not want any higher levels of automation.

2. Literature review

This section explores consumer perceptions, attitudes and willingness-to pay for access to CAVs for passenger transport. This body of literature is vast and rapidly growing. There are multiple review papers that have tried to summarise the key findings that have emerged from this collective body of work. For example, Becker and Axhausen (2017) provide an early review of 16 studies that have examined consumer preferences for CAV technologies. Gkartzonikas and Gkritza (2019) build on their review, summarising findings from 43 studies "that have conducted stated preference/choice experiments to examine potential user preferences/behaviours towards AVs". Other relevant reviews of public acceptance and intention to use CAVs include Golbabaei et al. (2020), and Nordhoff et al. (2019).

We begin by reviewing studies that have specifically examined willingness-to-pay for having access to CAVs technologies through shared mobility services. Krueger et al. (2016), in their survey of 435 Australians nationwide, find that service attributes such as travel time, waiting time and fares will be significant determinants of consumer adoption of shared CAV services, and young travellers will likely be early adopters. Bansal et al. (2016), in their survey of 347 residents of Austin, Texas in the United States, find that only 13 per cent of survey participants would be willing to give up personal vehicles and rely exclusively on shared CAVs costed at roughly $1/mile, and at least 35 per cent of survey participants would be unwilling to use shared CAV services at all, regardless of their costs. Haboucha et al. (2017), in their survey of 721 individuals living across Israel and North America, find that consumers are still hesitant to embrace CAV technology, and that even if shared CAV services were completely free, 25 per cent of their sample would still be unwilling to use the service. Hao and Yamamoto (2017), in their case study on Meito Ward, Nagoya in Japan, predict that up to 30 per cent of total trips conducted in the region could be served by shared CAVs in the future. Finally, based on their analysis of survey data from 3,985 geographically and demographically representative Australians nationwide, Vij et al. (2020) predict that roughly one-third of the Australian population can be expected to frequently use shared CAV services that cost roughly $0.30 per km, and roughly half of the population will use these services rarely or never. In summary, studies estimate that roughly 25-50 per cent of the population are still unwilling to use shared CAV services, roughly 30 per cent are expected to use these services frequently if they were available today, and remaining individuals fall somewhere between these two extremes.

Studies that have examined the geographic and demographic determinants of CAV uptake have typically found that age and gender are strongly correlated with consumer acceptance and intention to use CAVs, such that young men are most likely to adopt these new technologies, and older women are least likely (see, for example,Vij et al., 2020, Shabanpour et al., 2018, Lavieri et al., 2017, Krueger et al., 2016, Kyriakidis et al., 2015). Studies have additionally reported some patterns of correlation with other variables, such as income, employment and place of residence, but these relationships are not as consistent across studies. In general, studies find that while incomes are positively correlated with willingness to pay for access to CAV technology, there is usually no statistically significant relationship between income and intention to use the technology. For example, Cunningham et al. (2019) find that "individuals with a higher reported salary were willing to pay a relatively greater amount for a fully-automated vehicle than their current vehicle… [However,] respondents' salary generally showed weak correlations across the [other] survey items". Their findings are consistent with the international review of Becker and Axhausen (2017), Bansal et al. (2016) as well as Kyriakidis et al. (2015) where they observed a significant positive relationship between willingness to pay for an automated feature and income of the respondents, as would be expected. Because people with higher incomes have more money available with which to experiment, the idea that those people buy the technology at an earlier time is also plausible (Bansal et al., 2016). Respondents with lower incomes could also be accustomed to waiting for new technology to spread and become cheaper. However, none of the studies showed that income had a significant effect on intentions to use the new technology."

Similarly, the relationship between education and attitudes towards CAV technology is unclear. In their survey of 1,355 respondents from two Chinese cities, Liu et al. (2019) find that education has a positive and statistically significant impact on willingness to pay for automation. However, in their survey of respondents in Austin, Texas, Zmud et al. (2016) did not find any statistically significant relationship between education and intention to use AVs.

Studies do not find any significant differences across geographic and demographic characteristics in terms of preferences for CAV ownership and shared use. The same segments that are predicted to be early owners of CAVs are also predicted to be early adopters of shared CAV services. In general, the diffusion of CAV technology is predicted to follow the pattern of other recent disruptions to the transport system, such as the emergence of ridesharing, carsharing and micro-mobility services, which have appealed to similar segments of the population (Vij, 2020).

Based on our review, we did not find any Australian studies that have explicitly examined patterns of correlation between place of residence (e.g. metropolitan, regional, remote) and willingness to use CAV technology. However, Vij et al. (2020) examine general consumer preferences for different on-demand transport (ODT) services in Australia, where shared autonomous vehicles could offer one such ODT service. In general, they find that residents living in regional and remote areas are most likely to adopt these technologies last. Their findings are supported by the international review of Becker and Axhausen (2017) where they concluded that residents of urban areas are more inclined to use self-driving cars. Bansal et al. (2016) investigated the adoption time for SAVs. With residents of rural areas expecting long waiting times and high travel costs for long distance trips, it is plausible that a taxi service is more appealing to urban dwellers. Furthermore, Bansal et al. (2016) found that respondents prefer to use the technology in monotonous driving situations, such as on highways and in congested traffic. While Cunningham et al. (2019) did not explicitly examine impacts of place of residence, they found that weekly driving hours is highly correlated with willingness to pay. This shows that commuters with longer weekly travels have a higher monetary value for AV technology and services since they can do multitasking when using this service. Supporting this position, they reported that respondents that drove more hours per week, if riding in an AV, they are more likely to engage in all but one of the activities studied, particularly to 'do work', 'eat/drink' and 'engage with a personal device (Cunningham et al., 2019). Their findings offer a useful counterpoint to other studies. Individuals living in regional and remote areas frequently undertake trips over longer distances and relatively monotonous driving conditions that could more readily be substituted with CAV technology. Therefore, while the individuals themselves living in these areas might be less enthusiastic about autonomous cars, the nature of the driving environment might offset their reluctance, and potentially facilitate more rapid diffusion in regional and remote areas.

3. Data & Method

Data for our analysis came from a sample of Australians aged 18 years and over. In all, 3022 respondents were drawn from a major national market research company. After cleaning the data for 2993 respondents remained for analysis purposes. The survey was tested and piloted in December 2021 and administered online in January 2022, using a web-based interface. Respondents were asked to think about a recent short-distance trip they made that took longer than 5 minutes to complete and that was completed using some form of motorized transport. Subsequently, respondents were presented scenarios, such as the example shown in Figure 1, where they could make this trip using one of three hypothetical transport options that vary in terms of vehicle automation level and other attributes. Each respondent was presented 8 different scenarios. The attributes of the alternatives were varied systematically across scenarios, based on the potential range of values listed in Table 1, based on a statistically robust experiment design.

Table 1: Attributes and the values they can take across different SP scenarios

Attribute		Potential value
1	**Vehicle automation level**	No automation (zero autonomy, the driver performs all driving tasks)
		Driver assistance (vehicle is controlled by the driver; but some driving assist features may be included in the vehicle design)
		Partial Automation (vehicle has combined automated functions, like acceleration and steering, but the driver must remain engaged with the driving task and monitor the environment at all times)
		Conditional Automation (driver is a necessity, but is not required to monitor the environment; the driver must be ready to take control of the vehicle at all times with notice)
		High Automation (vehicle is capable of performing all driving functions under certain conditions; but the driver has the option to take control)
		Full Automation (vehicle is capable of performing all driving functions under all conditions; the driver/passenger has no control)
2	**Driver or chaperone**	You will need to be the (standby) driver
		The vehicle comes with a (standby) driver
		The vehicle comes with a chaperone, but no standby driver
		The vehicle does not have a chaperone nor a standby driver
3	**Interior design & functionality**	Car with regular seats
		Car with airplane style seats with a front table, power outlets, etc.
		Shuttle bus with both seating and standing room for passengers
4	**Shared use**	You will NOT have to share the vehicle with other passengers
		You may need to share the vehicle with up to 2 other passengers
		You may need to share the vehicle with up to 5 other passengers
		You may need to share the vehicle with up to 10 other passengers
5	**Maximum vehicle speed**	20 km/h; 40 km/h; 50 km/h; 60 km/h; 70 km/h; 90 km/h; 100 km/h; 110 km/h;
6	**Cost of use**	\$0.20 per km; \$0.50 per km; \$0.80 per km; \$1.00 per km; \$1.20 per km; \$1.50 per km

4. Econometric Framework

We use a latent class choice model (LCCM) (Vij and Walker, 2014) to study taste heterogeneity in preferences towards different CAV technologies and service models. LCCMs are finite mixtures of discrete choice models. They were first developed in the field of marketing sciences as tools to identify relatively homogenous consumer segments that differ substantially from each other in terms of their behaviour in the marketplace (Kamakura and Russell, 1989). They have since emerged as a very popular form of discrete choice model, finding application in a wide variety of disciplines, including but not limited to transportation. In our case, LCCMs allow us to identify segments in the population that differ in terms of their preferences for different CAV technologies and service models.

LCCMs comprise two components: a class membership model and a class-specific choice model. The class membership model formulates the probability that a decision-maker belongs to a particular segment, or class, as some function of the characteristics of the decision-maker.

Figure 1: Example SP task to elicit public preferences for different CAV technologies and service models

University of South Australia

In this section of the survey, we would like to understand your willingness to use automated vehicles. We would like you to consider the same recent trip you mentioned in the previous question. Below we have summarised your answers.

<u>**Recent trip**</u>

Purpose: Shopping
Mode used: Light rail
Time spent on travelling: 5 minutes
Distance travelled: 5 km
Approximate cost of latest use of taxi or rideshare: $1.00 per km

In the screens that follow, we will show you <u>**eight**</u> hypothetical scenarios. For each scenario, you will be presented three different transport options that you could use for this trip. The options vary in terms of the level of vehicle automation, cost of use, and other attributes, such as the example shown below. You will be asked to indicate the option that you would most prefer to use for this trip.

Please think about each scenario independently of the previous scenarios.

EXAMPLE SCENARIO

Think of the same recent trip you mentioned previously.

Now imagine that only the following transport options were available to you. Which would you most likely choose?

	Option 1	Option 2	Option 3
Vehicle automation level	High Automation (vehicle is capable of performing all driving functions under certain conditions; but the driver has the option to take control)	Full Automation (vehicle is capable of performing all driving functions under all conditions; the driver/passenger has no control)	Conditional Automation (driver is a necessity, but is not required to monitor the environment; the driver must be ready to take control of the vehicle at all times with notice)
Driver or chaperone?	The vehicle comes with a standby driver	The vehicle comes with a chaperone?, but no standby driver	You will need to be the standby driver
Interior design and functionality	Shuttle bus with both seating and standing room for passengers	Car with airplane style seats with a front table, power outlets, etc	Car with regular seats
Shared use	You may need to share the vehicle with up to 10 other passengers	You may need to share the vehicle with up to 2 other passengers	You will NOT have to share the vehicle with other passengers
Maximum vehicle speed	20 km/h	50 km/h	100 km/h
Cost of use	50 cents per km	$1 per km	80 cents per km
Preferred option	○	◉	○

Conditioned on the class that the decision-maker belongs to, the class-specific choice model formulates the probability that the decision-maker chooses a particular alternative as some function of the attributes of all of the alternatives in the choice set. We begin with a description of the class membership model, formulated in our case as the familiar multinomial logit function:

$$\mathrm{P}(\mathrm{q}_{ns} = 1) = \frac{\exp(\mathbf{z}_\mathbf{n}' \boldsymbol{\gamma}_s)}{\sum_{\mathbf{s}'=\mathbf{1}}^{\mathrm{S}} \exp(\mathbf{z}_n' \boldsymbol{\gamma}_{\mathbf{s}'})} \tag{1}$$

, where q_{ns} equals one if household h belongs to class s, and zero otherwise; $\mathbf{z}_n$ is a vector of decision maker characteristics, such as age, gender, income and household structure; $\boldsymbol{\gamma}_s$ is a vector of class specific parameters denoting sensitivity to the decision-maker characteristics; and S is the total number of classes.

Next, we describe the class-specific choice model. In each task each decision-maker is shown several different scenarios, where each scenario presents a choice between three different CAV technologies and service options. The decision-maker is asked to indicate which option they prefer. Therefore, for a given decision-maker n and scenario t, the class-specific choice model predicts the probability that option j is preferred.

Let $\mathrm{u}_{\mathrm{ntj|s}}$ be the utility of alternative $\boldsymbol{j}$ for scenario $\boldsymbol{t}$ and decision-maker $\boldsymbol{n}$, conditional on the decision-maker belonging to class $\boldsymbol{s}$, specified as follows:

$$\mathrm{u}_{\mathrm{ntj|s}} = \mathbf{x}_{\mathbf{ntj}}' \boldsymbol{\beta}_s + \varepsilon_{\mathrm{ntj|s}} \tag{2}$$

,where X_{ntj} is a vector of attributes specific to the option; $\boldsymbol{\beta}_\mathbf{s}$ is the vector of class-specific parameters denoting sensitivities to these attributes; and $\varepsilon_{\mathrm{ntj|s}}$ is the stochastic component of the utility specification, assumed for the sake of mathematical convenience to be i.i.d. Gumbel with location zero and scale one across schemes, scenarios and decision-makers. Assuming the decisionmakers are utility-maximizers, the class-specific probability that alternative $\boldsymbol{j}$ is preferred over the other alternatives is given by the logit expression:

$$\mathrm{P}\big(\mathrm{y}_{\mathrm{ntj}} = 1 | \mathrm{q}_{\mathrm{ns}} = 1\big) = \mathrm{P}\big(\mathrm{u}_{\mathrm{ntj|s}} \geq \mathrm{u}_{\mathrm{nt}j'\mathrm{|s}}\ \forall j' = 1, \dots, \mathrm{J}\big) = \frac{\exp\big(\mathrm{x}_{\mathrm{ntj}}' \beta_s\big)}{\sum_{j'}^{J} exp\big(X'_{\mathrm{nt}j'} \beta_s\big)} \tag{3}$$

, where $\mathrm{y}_{\mathrm{ntj}}$ equals one if arrangement $\boldsymbol{j}$ is preferred, and zero otherwise; and $\boldsymbol{J}$ is the number of alternatives shown to the decision-maker for any scenario. The reader should note that heterogeneity in the decision-making process is captured by allowing the taste parameters $\boldsymbol{\beta}_\mathbf{s}$ to vary across classes.

Equation (3) may be combined iteratively over alternatives and scenarios to yield the following class specific probability of observing the vectors of choices y_n.:

$$\mathrm{P}(\mathbf{y}_\mathbf{n} | \mathrm{q}_{\mathrm{ns}} = 1) = \prod_{t=1}^{T} \prod_{j=1}^{J} \big[\mathrm{P}\big(\mathrm{y}_{\mathrm{ntj}} = 1 | \mathrm{q}_{ns} = 1\big)\big]^{\mathrm{y}_{\mathrm{ntj}}} \tag{4}$$

, where $\mathbf{y}_\mathbf{n} = \langle \boldsymbol{y}_{\boldsymbol{n}\mathbf{11}}, \dots, \boldsymbol{y}_{\boldsymbol{nTJ}} \rangle$; and $\boldsymbol{T}$ is the number of scenarios shown to a single decision-maker. Equation (1) and (4) may be combined and marginalized over classes, to yield the unconditional probability of observing the vectors of choices $\mathbf{y}_\mathbf{n}$, which in turn may be combined iteratively over decision-makers to yield the following likelihood function for the data:

$$\mathrm{L}(\boldsymbol{\beta}, \boldsymbol{\gamma} | \mathbf{y}, \mathbf{w}, \mathbf{x}, \mathbf{z}) = \prod_{\mathrm{n}=1}^{\mathrm{N}} \sum_{\mathrm{s}=1}^{\mathrm{S}} \mathrm{P}(\mathbf{y}_\mathbf{n} | \mathrm{q}_{\mathrm{ns}} = 1) \mathrm{P}(\mathrm{q}_{\mathrm{ns}} = 1) \tag{5}$$

The unknown model parameters $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ may be estimated by maximizing the likelihood function. All models for this study were estimated using the software package PandasBiogeme (Bierlaire, 2020). As our sample was stratified exogenously based on demographic and geographic variables, we do not reweight the sample during model estimation (Ben-Akiva and Lerman, 1985).

5. Results and findings

We estimated a number of LCCMs with different model specifications, where we varied the explanatory variables and the number of classes. Our dataset comprised 2993 individuals, each of whom were shown eight different choice scenarios. To facilitate comparison, Table 2 enumerates for each model the number of parameters estimated, the log-likelihood at convergence, McFadden's rho-bar-squared (ρ^2), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC). Based both on statistical measures of fit and behavioural interpretation, we select the seven-class LCCM as the preferred model specification. In terms of fit, the seven-class LCCM has the lowest BIC and the AIC value. In terms of the signs and relative magnitudes of the different model parameters and the accompanying behavioural interpretation of each of the latent classes, results for the seven-class LCCM proved to be the most satisfying.

Table 2: Summary statistics for LCCMs with varying numbers of classes

Classes	Parameters	Log-likelihood	ρ^2	AIC	BIC
2	58	-21578.8	0.177	43273.6	43621.8
3	95	-20742.1	0.208	41674.3	42244.7
4	134	-20167.3	0.228	40602.6	41407.1
5	88	-20007.4	0.236	40190.9	40719.2
6	96	-19889.7	0.240	39971.4	40547.8
7	96	-19836.9	0.242	**39865.9**	**40442.3**
8	109	-19882.8	0.240	39983.7	40638.1

Table 3, presents the estimation results for class membership model and Table 4 presents the class-specific choice models of public preferences for different CAV technologies and service models. The coefficients that were not significant with 80 per cent confidence level have been omitted from the final model. Over the following paragraphs we have placed emphasis on the behavioral differences between classes and have reviewed and summaried some of the key attributes of each of these seven classes using a sample enumeration exercise. The expected socioeconomic composition for each class has also been calculated. Furthermore, to ease comprehension, the classes have been ordered in terms of increasing enthusiasm for using CAV technology as a service. These descriptions are summarized in Table 5.

First, we find that roughly half of the sample population, comprising four of the seven classes, want low levels of automation or no automation. For example, Class 1 does not want any vehicle automation, showing a strong preference for human-driven vehicles. Individuals belonging to this class are more likely to be older, have low incomes and high car ownership rates. Similarly, Class 2 has a positive preference for driver assistance features but does not want any higher levels of automation. Compared to Class 1, individuals belonging to this class are more likely to be younger and have high incomes. However, similar to Class 1, Class 2 (as well as Class 3) have high car ownership rates. Together, these findings indicate that those with high car ownership rates do not see as much value in higher vehicle automation, likely because they are able to meet their mobility needs using their existing household vehicle(s). Conversely, the other half of the sample population, comprising three of the seven classes, shows a neutral or positive preference towards high automation levels, and are more likely to have low car ownership and license rates, and/or report difficulties in getting around. Class 7 in particular, is very enthusiastic towards CAV technology, willing to pay as much as $2 more per km to have the chance to use it. This further confirms that CAV technologies will likely appeal most to those consumers for whom they address an unmet need.

We find that those living in metropolitan areas are more likely to desire greater vehicle automation, while those living in regional areas are more likely to prefer lesser vehicle automation. Again, this is likely correlated with mobility needs. Individuals living in metropolitan areas with low car ownership and license rates, and/or difficulties in getting around are more likely to depend on public transport to fulfil their mobility needs. Given that highly autonomous vehicles could significantly improve public transport level-of-service, these individuals stand to gain from their deployment. Conversely, regional areas usually have poor public transport services, and local residents are more dependent on private vehicles. Consequently, they likely do not see significant value in having access to highly autonomous vehicles.

Other demographic variables, such as age, gender, education, and employment status also appear to have some influence on preferences, but the patterns are not always clear. For example, in general, young adults seem more inclined to prefer highly autonomous vehicles. However, individuals belonging to Class 2 are more likely to be younger, and as mentioned before, these individuals display a strong preference for driver assistance features, but do not want any higher levels of automation. Similarly, women seem less inclined to prefer highly autonomous vehicles. However, individuals belonging to Class 6 do not prefer low vehicle automation, and individuals belonging to this class are more likely to be female.

Fourth, across all classes, there is a strong aversion to sharing the vehicle with other passengers. On average, we estimate that most Australians are willing to pay roughly $0.6 - $1.2 more per km to *not* have to share a vehicle (but in some cases, this willingness to pay can be as low as $0.1 per km for Class 6, and as high as $4.8 per km for Class 5). Relatedly, our analysis also finds that most Australians would prefer not to have standby drivers or chaperones when the technology and service models become commercially available. This is likely related to the same desire to have the vehicle to themselves.

None of the classes expressed a positive preference for airplane style seating with a front table, power outlets, etc. that would allow them to work and/or engage in other activities while travelling. This is somewhat surprising, given that many industry reports have argued that CAVs could lead to productivity gains, by allowing passengers to use time ordinarily spent driving in pursuit of other activities (e.g Enam et al., 2021). However, there is significant disagreement about the nature and magnitude of these productivity benefits. Most academic studies have argued that the productivity benefits have been overstated, and passengers "most likely to engage in activities that are already quite prevalent today in manual driving conditions - observing the scenery, interacting with passengers, eating and drinking, or doing nothing at all" (Cunningham et al., 2019). These same reasons are likely at play here, and there is likely limited value to changes in interior design that support more productive time use.

There is a strong preference for using higher speed services across all classes. Only Class 7, the most enthusiastic CAV supporters in our sample, are insensitive to vehicle speeds, indicating a willingness to use any and all CAV services, including low-speed shuttles like the kind that have been extensively trialled in Australia. However, all other classes prefer higher speeds. We estimate that the average Australian is willing to pay roughly $0.1 more per km to be able to travel faster by 10 km/h, with some segments willing to pay as much as $0.3 more per km.

Table 3: Class membership model

Variables	Class I CAV sceptics (reference)		Class II		Class III		Class IV		Class V		Class VI		Class VII CAV enthusiasts	
	Est	*p-value*	*Est*	*p-value*	*Est*	*p-value*	*Est*	*p-value*	*Est*	*p-value*	*Est*	*p-value*	*Est*	*p-value*
Class-specific constant	0	-	0.421	0.3	0.705	0	-0.27	0.36	-0.596	0.02	-0.322	0.2	-1.031	0
Gender														
Male	0	-	-	-	-1.25	0	-0.364	0.11	-0.755	0	-	-	-	-
Female (reference)	0	-	-	-	-	-	-	-	-	-	-	-	-	-
Age														
18-24 years (reference)	0	-	-	-	-	-	-	-	-	-	-	-	-	-
25-34 years	0	-	-	-	-	-	-	-	-	-	-	-	0.864	0
35-44 years	0	-	-	-	-0.469	0.2	-	-	-	-	-	-	0.703	0
45-54 years	0	-	-	-	-0.408	0.18	-	-	-	-	-	-	-	-
55-64 years	0	-	-	-	-0.419	0.14	-	-	-	-	-	-	-0.963	0
65 years and plus	0	-	-	-	-	-	-	-	-	-	-	-	-	-
Age continues	0	-	-4.071	0	-	-	-	-	-	-	-	-	-	-
Number of vehicles														
No vehicle	0	-	-	-	-	-	-	-	-	-	0.697	0.01	1.023	0
One vehicle	0	-	-	-	0.391	0.07	0.683	0.04	0.942	0	0.716	0	1.078	0
Two Vehicles	0	-	0.5	0.05	-	-	0.616	0.05	0.564	0.02	0.368	0.09	0.695	0
More than two (reference)	0	-	-	-	-	-	-	-	-	-	-	-	-	-
City location														
Regional (reference)	0	-	-	-	-	-	-	-	-	-	-	-	-	-
Metro	0	-	-	-	-	-	-	-	-	-	0.273	0.08	0.374	0.03
Employment														
Employed full time	0	-	-	-	-	-	-	-	-	-	0.358	0.01	0.848	0
Employed part time	0	-	-	-	-	-	-	-	-	-	-0.444	0.01	-	-
Unemployed	0	-	-	-	-	-	-	-	-	-	-	-	1.176	0
Not in the labour force (reference)	0	-	-	-	-	-	-	-	-	-	-	-	-	-
Education														
College degree	0	-	-	-	-	-	-	-	-	-	0	0	0.24	0.19
Diploma/certificate degree	0	-	-	-	-	-	-	-	-	-	0.37	0	-	-
Year 12 or below (reference)	0	-	-	-	-	-	-	-	-	-	-	-	-	-
Difficulties in getting around														
No (reference)	0	-	-	-	-	-	-	-	0	-	-	-	-	-
Yes	0	-	-	-	-	-	-	-	0.582	0.08	0.548	0.06	0.698	0.02
Total household income	0	-	0.566	0	-	-	-	-	0.317	0.01	-	-	-	-

Table 4: Class-specific choice models of preferences for use of different level of automation for transportation

Variables	Class I CAV sceptics		Class II		Class III		Class IV		Class V		Class VI		Class VII CAV enthusiasts	
	Est	*p-value*	*Est*	*p-value*	*Est*	*p-value*	*Est*	*p-value*	*Est*	*p-value*	*Est*	*p-value*	*Est*	*p-value*
Vehicle automation level														
No automation (reference)	0	-	0	-	0	-	0	-	0	-	0	-	0	-
Driver assistance	-1.709	0	0.379	0.03	-	-	-	-	-	-	-	-	0.169	0.02
Partial Automation	-2.844	0	-	-	-	-	-	-	-	-	-	-	0.208	0
Conditional Automation	-2.817	0	-	-	-0.412	0	0.579	0	-	-	-	-	0.233	0
High Automation	-5.048	0	-	-	-1.031	0	-	-	-	-	-	-	0.375	0
Full Automation	-6.002	0	-	-	-2.675	0	-0.717	0.01	-	-	-	-	0.385	0
Driver or chaperone														
Drive (standby) yourself (reference)	0	-	0	-	0	-	0	-	0	-	0	-	0	-
Comes with a (standby) driver	-	-	-	-	-	-	-	-	-	-	-0.176	0.12	0	0
Comes with a chaperone only	-0.473	0.11	-	-	-0.482	-	-	-	-	-	-0.227	0.01	-0.106	0.06
No chaperone nor standby driver	-	-	-	-	0	-	-	-	-	-	-	-	-	-
Interior design & functionality														
Car with regular seats (reference)	0	-	0	-	0	-	0	-	0	-	0	-	0	-
Car with airplane style seats	-	-	-	-	-0.473	0	-	-	-0.308	0	-0.692	0	-	-
Shuttle bus	-	-	-	-	-0.486	0	-0.434	0	-0.45	0	-	-	-	-
Shared use														
Not sharing the vehicle (reference)	0	-	0	-	0	-	0	-	0	-	0	-	0	-
Sharing with 2 passengers	-	-	-0.648	0	-	-	-0.682	0	-2.277	0	-	-	0	0
Sharing with 5 passengers	-0.409	0	-0.708	0	-0.434	0	-1.62	0	-3.924	0	-0.35	0	-0.144	0.01
Sharing with 10 passengers	-	-	-1.169	0	-0.391	0	-2.12	0	-4.146	0	0	0	-0.183	0.01
Maximum vehicle speed	0.005	0	0.052	0	0.005	0	0.014	0.01	0.013	0	0.011	0	-	-
Cost of use	-0.346	0	-1.826	0	-0.585	0	-2.475	0	-0.856	0	-4.086	0	-0.159	0.03

Table 5: High-level summary of different market segments, or classes

	Class I CAV sceptics	Class II	Class III	Class IV	Class V	Class VI	Class VII CAV enthusiasts
Sample share	12 per cent	6 per cent	15 per cent	12 per cent	21 per cent	11 per cent	23 per cent
Preferences for CAV technology levels	Less automation the better	Like driver assistance, but don't want more automation	Like driver assistance and partial automation, but don't want more automation	Strong preference for conditional automation	Indifferent between different levels of automation		Prefer greater automation (willing to pay $2 more per km in usage cost)
Other features	Do not want standby drivers or chaperones, do not want to share vehicle with other passengers, prefer regular seating, prefer higher speeds and lower costs (willing to pay roughly $0.6 - $1.2 more per km to not to have to share vehicle and $0.10 more per km to travel faster by 10 km/h)						
Demographic characteristics	More likely to be older, have low incomes and high car ownership rates	More likely to be young and employed, have high incomes and car ownership rates	More likely to be female, older, have low incomes and high car ownership rates	More likely to be female	More likely to be middle-aged, highly educated and employed, have low car ownership rates, and live in metropolitan areas	More likely to be female, have lower car ownership rates, and report difficulties in getting around	More likely to be young, highly educated and employed, have low car ownership and license rates, and live in metropolitan areas

6. Conclusion

The wider *societal* benefits to CAVs, in terms of their impacts on safety, mobility and accessibility has been acknowledged by both governments and academic researchers. This study contributes to the large and rapidly growing body of work on consumer preferences for CAV technologies and service models by examining consumer preferences for different levels of automation using vehicle and service attributes that have not received as much attention from previous studies. Furthermore, this study offers novel insights on the demographic determinants of CAV uptake through an examination of citizens/consumers preferences towards using different CAV technologies and service models in Australia. Data for our analysis comes from a nationwide online stated preference survey of 2993 demographically and geographically representative Australians administered in January 2022.

Based on our survey, we estimate that 45 per cent would prefer to use cars with low levels of automation (Level 3 or lower) or no automation at all, 33 per cent are indifferent to different automation levels, and only 23 per cent would prefer high levels of automation (Level 4 or 5). Individuals most likely and willing to adopt CAV technologies are, unsurprisingly, those most likely to personally benefit from the technology – individuals with low car ownership levels, no driving license, and those that report difficulties getting around. Conversely, those with high car ownership rates are usually reluctant to adopt high levels of automation themselves. However, these individuals do see value in lower levels of automation that do not entirely replace the driver, such as driver assistance and partial automation (Levels 1 and 2). With these individuals, the journey to adoption might need to be more incremental.

Other demographic factors also seem to be correlated with willingness to use CAVs – younger employed university-educated men living in metropolitan areas are most likely to have a positive view of the benefits of CAV technology, to support its testing and trialling on Australian roads, and to use it themselves when it is commercially available. Conversely, older

retired high school-educated women living in regional areas are least likely. These findings are consistent with those from previous studies. For example, studies have repeatedly found that men are more likely to accept CAV technology, and younger individuals are more willing to adopt CAV technology (Cunningham et al., 2019; Becker and Axhausen, 2017).
Conditional automation (Level 3), where the driver must be ready to take control at all times with notice, seems to be an unpopular option. The majority of those surveyed would prefer an “all or nothing” approach to vehicle automation. We estimate that only 12 per cent of the population has a positive preference for conditional automation, and 33 per cent are neutral, but the remaining 55 per cent would either prefer less or more automation.
While high levels of vehicle automation might enable more attractive public transport services in the future, we find that private car ownership will likely still remain a dominant form of transport access. Shared CAV services could offer both private access to vehicles for individual trips, as well as ‘pooled’ services, where multiple passengers unknown to each other have to share a vehicle for a single trip. Our findings, similar to those from previous studies, indicate that most consumers perceive these two types of shared mobility services as distinct options, and the two service models appeal to different consumer groups (Krueger et al., 2016). Across the population, we find a strong aversion to sharing the vehicle with other passengers. On average, we estimate that most Australians are willing to pay roughly \$0.6 - \$1.2 more per trip km to not have to share a vehicle. Based on a survey of 435 Australians in Apr 2015, Krueger et al. (2016) found that private shared CAV services were 1.2 times more likely to be preferred than pooled shared CAV services (but in 70 per cent of the cases, respondents indicated they would prefer not to use either service). This willingness to pay value is 2-4 times greater than what reported in Vij et al.(2020) for the Australian population. It is anticipated that during COVID-19 period, public health has become a major concern and while CAVs might reduce private car ownership, private car use is not likely to decline nearly as much, and pooled use is likely only to appeal to existing public transport users. Therefore, if governments want to reduce vehicle kilometre travel, they will need to be proactive and cannot leave it to the market. This study is a step forward in understanding the different behaviour toward different levels of automation using vehicle and service attributes. This research could further be developed by including latent variables to capture and explain attitudes and perceptions of the respondents such as the influence of COVID-19 on travel choices.

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