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Public preferences for testing and trialling of CAV technologies

Ali Ardeshiri [1], Akshay Vij [2]

[1] UniSA Business, University of South Australia, Adelaide 5000, Australia,

[2] Institute for Choice, University of South Australia, Adelaide, SA 5000, Australia

Email for correspondence: Ali.Ardeshiri@unisa.edu.au

Abstract

Government regulations on testing and trialling of CAV technologies have had to balance short-term risks to public safety with long-term benefits from technological innovation. For example, Australian and European regulations have tended to prioritise the former, while US regulations have tended towards the latter. However, there is little evidence on how citizens value these trade-offs, and whether or not their preferences are reflected in government regulations. This study examines public preferences towards testing and trialling of CAVs in Australia. Data for our analysis comes from a nationwide online stated preference survey of 2,993 demographically and geographically representative Australians administered in 2022. We find that from the public's perspective, safety is paramount, even if it slows technology development and deployment. We estimate that roughly 20 per cent of Australians do not want any testing on Australian roads. An additional 50 per cent have a zero tolerance for risks to public safety, and do not want to see any injuries or deaths caused by testing. Most Australians would prefer to see the inclusion of standby drivers in any tests or trials, and for testing and trialling to be limited to low traffic suburban and regional areas. In summary, our findings indicate that the current Australian government approach is consistent with public sentiment.

Keywords: Connected and autonomous vehicles, testing and trailing, public preference, CAV pilots, latent class model

1. Introduction

Connected vehicles are vehicles that use information and communication technologies to communicate with the driver, other road users, roadside infrastructure and other wireless services. Autonomous vehicles are vehicles where one or more primary driving controls, such as steering, acceleration and braking, do not require human input for sustained periods of time. Together, connected and autonomous vehicles (CAVs) have the capacity to offer a number of social benefits that include greater safety, better fuel economy, reduced fuel consumption and emissions, more productive use of travel time, and increased mobility and accessibility, especially for those who do not have access to a private car (Vij, 2020, Lee and Hess, 2020, Bansal and Kockelman, 2017).

Most vehicles currently available on the market offer low levels of automation, through driver assistance features such as lane keeping, adaptive cruise control and self-parking. More advanced levels of automation, where the vehicle is able to perform all driving functions completely, are currently being trialled all across the world, including Australia, both on public roads and more controlled, 'closed-loop' conditions, such as university campuses and retirement villages. However, fully autonomous vehicles that offer Level 3 automation or higher remain commercially unavailable at this stage. As US Department of Transportation

(DOT) (2021) notes, "the timeline for development of Level 4 or 5 capabilities is highly uncertain, but widespread adoption is not generally predicted to be imminent."

A revolutionary or disruptive scenario in which CAVs will be deployed in one giant leap is unlikely, at least in the near future (Soteropoulos et al., 2020). It is more likely that the deployment of CAVs will be a lengthy process of evolutionary vehicle connectivity and automation, progressing from specialized, controlled and restricted conditions, i.e. operational design domains (ODDs), to ever more complex ones (Shladover and Nowakowski, 2019). Consequently, in the near future, high levels of vehicle automation are likely to be feasible only in specific ODDs. Such staggered deployment, combined with lengthy processes for the planning and implementation of transport infrastructure, has important implications for government approaches to preparing and managing these disruptions.

As Shladover and Nowakowski (2019) point out, government regulations on testing and trialling of CAV technologies and service models 'need to balance two competing goals: (1) protecting public safety from undue risks posed by immature and inadequately engineered automated driving systems that could cause crashes; [and] (2) encouraging innovations in vehicle technology that could produce better performing and safer vehicles in the long run'. Different local, state and national governments have adopted different approaches in their attempt to balance these competing goals. The Australian and European approach has tended to prioritise short-term public safety over long-term technological innovation, while the US approach has been the opposite. For example, current Australian regulations require a human safety driver to be present inside the vehicle at all times during testing. This is in contrast to regulations in many US cities, such as San Francisco, where for example General Motors has been testing its self-driving cars without driver monitors since 2020 (Wayland, 2020). Similarly, in the case of an accident involving a partially autonomous vehicle, legal liability is more likely to rest with the vehicle manufacturer and/or technology developer in Australia, whereas legal liability is more likely to rest with the vehicle owner and/or driver in the US.

While numerous studies have examined consumer preferences for different CAV technologies and service models, to the best of our knowledge, no study has examined public preferences for how these technologies and service models ought to be tested and trialled. There is little evidence on how citizens value the trade-off between short-term public safety and long-term technological innovation in the context of CAV technologies and service models, and whether or not current government approaches are reflective of the preferences of the populations that these governments purport to represent. This study seeks to address this research gap through a stated preference nationwide survey of Australian residents designed to measure their preferences on when, where and who should participate in testing and trialling of CAV technologies and service models on Australian roads.

Our study contributes to the existing debate on whether governments should speed up CAV technology development at the expense of road safety or they should continue to prioritise road safety even if it slows technology development. Findings from this study will also help governments to encourage, facilitate and/or fund trials that are acceptable by the public to build community support and acceptance through increased visibility and exposure of these new technologies.

2. Literature review

Most urban jurisdictions across the developed world have trialled some form of autonomous vehicle service in recent years. In 2020, the NTC published the report '*Lessons learned from automated vehicle trials in Australia*' (NTC, 2020) that reviews four years of automated vehicle trials in Australia. The report notes that at the time of conducting the research, thirtytwo automated vehicle trials had taken place in Australia, and at least one in every state and territory. Twenty-two trials had involved automated shuttle buses, two trials involved automated pods, six trials involved an automated car, one trial involved a research vehicle, and one trial involved an automated Ute. Automated vehicles have been tested as first- and last-mile solutions, operated around pedestrianised precincts such as waterfronts and campuses, and to understand their capability in different environments such as CBDs, regional roads and urban motorways.

The NTC report notes that "the United States is the leading automated vehicle developer and has the largest trials in terms of scale and numbers. While there are national policies, trial regulation is undertaken by states and many encourage and compete for trials. Technology developers have undertaken broad-scale trials over the past few years, with California (large IT industry), Arizona (conducive regulatory environment) and Michigan (automotive manufacturing, state facilitation and test facilities) among the leading states. The European Union supports cross-border trialling of national endeavours, with strong collaboration with manufacturers in Germany (a number of test beds) and Sweden (strength in heavy vehicles). Japan and South Korea also undertake testing, including on-road automated vehicles, 'last mile' mobility and heavy-vehicle platooning. In 2020, China released its *Strategy for innovation and development of intelligent vehicles*, a policy document setting out how the Chinese government will boost the development of automated vehicles over the next 30 years. China also invests and participates in partnerships with international developers, including in relation to trials on public roads in cities throughout China" (NTC, 2020: 31-32).

As noted in the introduction, government regulations on testing and trialling of CAV technologies and service models need to trade-off short-term risks to public safety against long-term benefits. In the short-term, CAV technologies are still under development, and a number of technological challenges still need to be resolved. For example, CAV sensors need to be able to faultlessly detect humans with different physical characteristics in different weather conditions (e.g., rain, snow, fog), identify if they are stationary or in motion, or if the detected object is inanimate. Even with inanimate objects in their path, it is critical for CAVs to recognise their material composition to be able to act accordingly (e.g. cardboard box v. concrete block). These are substantial impediments to their commercial deployment. By May 2022, the Departments of Motor Vehicles in California reported 465 Automation vehicle collisions (Departments of Motor Vehicles, 2022). Other studies have reported CAV collision rates ranging from 3.2 (Blanco et al., 2016) to 23.4 (Leilabadi and Schmidt, 2019) crashes per million miles. Although Goodall (2021) claims that in 73% of the incidents, CAVs were struck from behind, with a crash rate of 17.2 crashes per million miles it is still significantly higher than 3.6 crashes per million miles for human-driven vehicles. These statistics show that more trialling and testing of CAVs is required before they can be deployed on public roads.

However, in the long-term, CAV technologies could offer significant benefits. Human error is a key factor for roughly 90 per cent of road crashes (National Highway Traffic Safety Administration (NHTSA), 2008, Green and Senders, 2004). In Australia, there were 1,094 road crash deaths in 2020 (BITRE, 2022a), and 39,755 hospitalised injuries due to road crashes in 2018-19 over a 12-month period ending in June 2019 (BITRE, 2022b). The Bureau of Infrastructure and Transport Research Economics (BITRE) estimates the social cost of road crashes in Australia to be in the range of A$18-27 billion annually (BITRE, 2014) for a country with a population of 27 million. If CAV technologies can successfully eliminate road crashes caused by human error, the safety benefits could be profound. By reducing the cost of travel, CAV technologies could offer additional benefits in terms of mobility, accessibility and productivity. For example, DAE (2018) estimate that CAV technologies could increase economic output in the state of Victoria in Australia by 2 per cent by 2046.

Different local, state and national governments have prioritised these short and long-term objectives differently, resulting in different frameworks for testing and trialling CAV technologies. For example, most Australian trials have involved low-speed autonomous bus shuttles with standby drivers operating on fixed routes in closed-loop conditions, such as university campuses and retirement villages (NTC, 2020). In contrast, many cities and states in the US have authorised testing of driverless vehicles on public roads in mixed traffic conditions, in some cases without standby drivers (Lee and Hess, 2020). Singapore and China have adopted similar approaches to the US, placing greater importance on long-term technological innovation, while Europe and Japan have adopted a more cautious approach akin to Australia that prioritises short-term safety. For a comprehensive discussion on the governance arrangements adopted by different countries with regards to the testing and trialling of CAV technologies, the reader is referred to Taeihagh and Lim (2019).

Numerous studies have examined consumer preferences for different CAV technologies and service models (e.g. Wang et al., 2021, Bansal and Kockelman, 2017, Tsouros and Polydoropoulou, 2020, Shabanpour et al., 2017). However, we are not aware of any study that has examined public preferences for how these technologies and service models ought to be tested and trialled. Given that government regulations on testing and trialling of CAV technologies could have profound implications for local populations, research is needed to understand how different individuals value these trade-offs between short-term risk and long-term benefit, and if their preferences are reflected in the actions and decisions of their local government representatives.

We address this gap through the use of stated preference (SP) experiments that allow us to measure the relative appeal of different hypothetical regulatory frameworks for testing and trialling CAV technologies. SP data is especially useful as it allows us to assess the popularity of regulatory frameworks that may not have been trialled anywhere in the world. With revealed preference (RP) data, we would only be able to test the appeal of regulatory frameworks that have been enforced in practice, and we would need additionally to control for differences in the local context across different frameworks.

While SP experiments are typically used to measure consumer preferences for private consumption of goods and services (e.g. Louviere et al., 2000), they have been used more limitedly to measure public preferences for government policy as well. For example, Abate et al. (2020) used SP experiments to measure public preferences for reducing marine plastic pollution in the European Arctic. Similarly, Howard et al. (2016) used SP experiments to examine community preferences for organ donation policy in Australia. In a transport context, SP experiments have been used to measure public preferences most commonly for investment in road safety (e.g. Mouter et al., 2017). We build on this body of work to use SP experiments to measure public preferences for testing and trialling of CAV technologies.

In summary, different countries have adopted different approaches to the development of rules and regulations for on-road testing of CAVs with different priorities. A gap in the literature exists with regards to public preferences towards testing and trialling of CAVs, and the trade-offs that individual citizens make between short-term risk to public safety and long-term benefits from greater technological innovation. To the best of the research team’s knowledge, this study is the first application of SP experiments to the study of public preferences for testing and trialling of CAVs.

3. Data and descriptive analysis

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. Respondents were recruited to represent the Australian population demographically by age and gender as well as geographically by the proportion of the population by state. The average completion time of the survey was 23:40 minutes. We have removed the speeders who completed the survey in under a third of the average time. After cleaning the data, 2993 respondents were retained for further analysis. The survey was tested and piloted in December 2021. The final instrument was administered online to the full sample in January 2022 using a web-based interface.

The final survey instrument comprised five broad sections:

1. **Familiarity and comfort with different CAV automation levels:** Respondents are introduced to different levels of vehicle automation, from driver assistance (Level 1) to full automation (Level 5). For each level, they are asked about their familiarity with the technology, relevant past experiences, and degree of comfort.
2. **Perceived benefits and concerns of CAVs:** Respondents are presented Likert-scale and other similar questions to measure their perceptions of the relative importance of different potential benefits and concerns regarding CAV technology.
3. **Consumer preferences for CAV use:** Respondents are presented multiple stated preference (SP) experiments designed to elicit their preferences for potential future CAV technologies and service models.
4. **Public preferences for CAV testing:** Respondents are asked about their preferences for where, when and how CAV technologies should be tested on Australian roads, using a combination of SP experiments and other questions.
5. **Demographics:** Respondents are asked about their age, gender, education, place of residence, household size and structure, and income.

The survey concluded with an open text question to elicit any feedback from respondents about the survey itself. Respondent feedback was largely positive, and specific comments indicated a high level of engagement.

This paper focuses specifically on findings from our analysis of data collected from Section 4 of the survey on public preferences for CAV testing. As part of this section, respondents were asked whether they would support trials of automated vehicles in Australia. As shown in Figure 1, roughly four-in-five Australians expressed support. Table 1 shows how support varies by gender and age. On average, women tend to be less supportive than men, and older adults tend to be less supportive than young and middle- aged individuals. These patterns are consistent with familiarity with CAV technology, as well as willingness to use these technologies, which also tend to lag among women and older adults. Consequently, any measures seeking to build public acceptance need especially to target these sub-populations.

Next, respondents were asked multiple questions about their preferences for where, how and when CAV technologies should be tested, trialled and deployed. Most respondents would prefer a cautious approach. For example, in terms of where CAV technologies should be tested, as shown in Figure 2, the majority would prefer testing in restricted and private environments away from the public (62 per cent) and only 19 per cent believe that CAVs should be tested in public urban environments with no restrictions. Similarly, most do not want to see children participating in trials (see

Figure 3), reiterating likely public concerns around the safety of these new technologies.

Figure 1: Would you support trials of automated vehicles in Australia

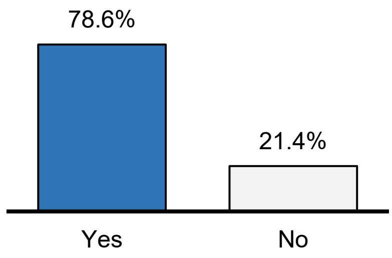


Table 1: The split of supporting the trials of CAV's in Australia by age and gender

		Would you support the trials of automated vehicles in Australia?		Sample size
		Yes	***No***	
Gender	*Male*	78.3%	21.7%	1,486
	Female	73.3%	26.7%	1,490
	Other	82.4%	17.6%	17
	Total	***75.8%***	***24.2%***	***2,993***
Age category	*18-24*	87.4%	12.6%	167
	25-29	87.4%	12.6%	286
	30-34	82.6%	17.4%	293
	35-39	79.7%	20.3%	295
	40-44	80.2%	19.8%	273
	45-49	78.8%	21.2%	274
	50-54	69.7%	30.3%	264
	55-59	69.6%	30.4%	257
	60-64	72.7%	27.3%	231
	65+	65.8%	34.2%	653
	Total	***75.8%***	***24.2%***	***2,993***

Respondents were also asked when they would prefer to see CAVs on Australian roads, and their responses are shown in Figure 4. 31 per cent wanted to see deployment as soon as possible, and an additional 28 per cent wanted to see deployment by 2030, indicating significant enthusiasm within the Australian public for the technology, despite the cautionary approach suggested by previous responses. However, 22 per cent indicated they would prefer that CAVs did not operate on public roads at all, reiterating that roughly one-in-five Australians is potentially strongly opposed to the development and deployment of CAV technology.

Respondents were subsequently presented multiple SP policy scenarios, such as the example shown in Figure 5, where they were offered a choice between two different government policies towards testing and trialling automated vehicles on Australian roads. The policy options varied broadly in terms of how restrictive or permissive they are, the risks that they pose to public safety, and their impacts on technology deployment readiness. The attributes of the two policy options were varied systematically across different scenarios, across the range of potential values listed in

Table 2 based on a statistically robust experiment design. Data from the hypothetical scenarios were used in conjunction with other demographic information collected as part of the survey to estimate models of public preferences for testing and trialling automated vehicles on Australian roads. We introduce the econometric framework used for the analysis of the SP data in Section 4, and describe the key findings from our analysis in Section 5.

Figure 2: Where should automated vehicles be tested and trialled

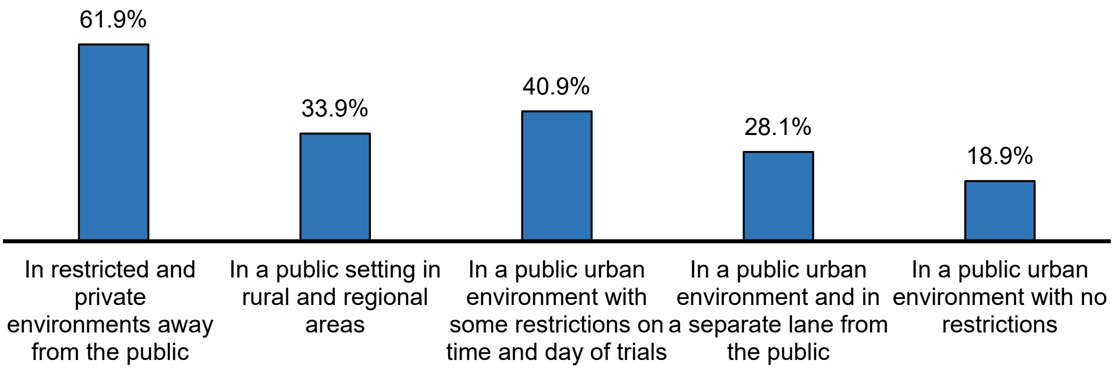


Figure 3: Who should be able to participate in automated vehicle trials

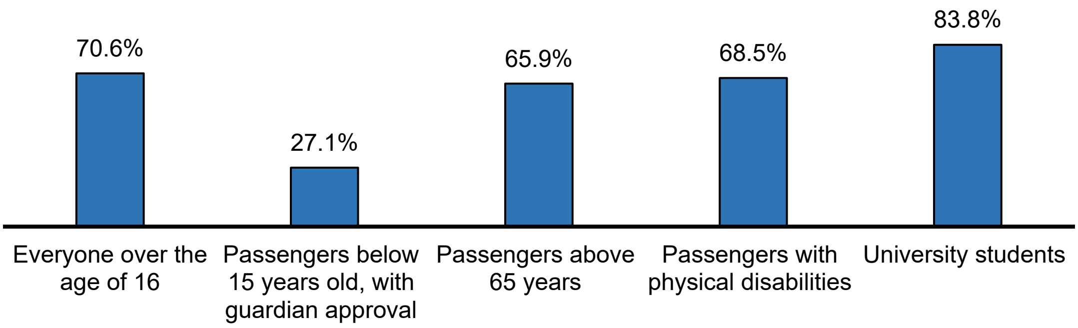


Figure 4: When would you like to see automated vehicles operate on Australian roads

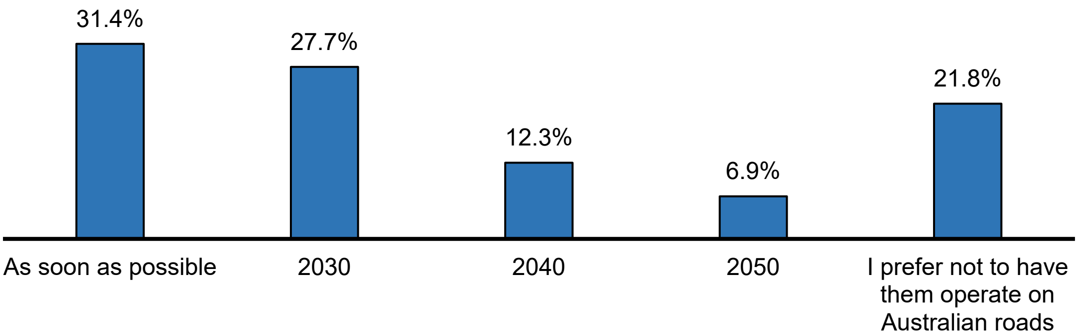
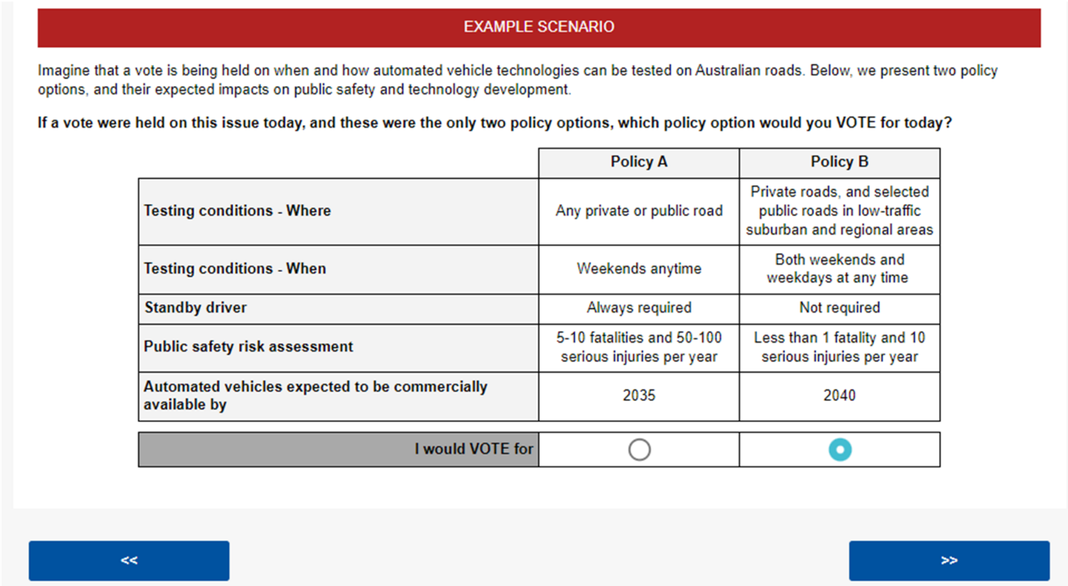


Figure 5: Example SP task to elicit public preferences for testing and trialling of CAV technologies


EXAMPLE SCENARIO

Imagine that a vote is being held on when and how automated vehicle technologies can be tested on Australian roads. Below, we present two policy options, and their expected impacts on public safety and technology development.

If a vote were held on this issue today, and these were the only two policy options, which policy option would you VOTE for today?

	Policy A	Policy B
Testing conditions - Where	Any private or public road	Private roads, and selected public roads in low-traffic suburban and regional areas
Testing conditions - When	Weekends anytime	Both weekends and weekdays at any time
Standby driver	Always required	Not required
Public safety risk assessment	5-10 fatalities and 50-100 serious injuries per year	Less than 1 fatality and 10 serious injuries per year
Automated vehicles expected to be commercially available by	2035	2040
I would VOTE for		

Table 2: Attributes and the values they can take across different SP scenarios

Attribute		Potential value
1	Testing conditions - where	Private roads only
		Private roads, and selected public roads in low-traffic suburban and regional areas
		Any private or public road
2	Testing conditions - when	Weekends only between 10 pm and 6 am
		Weekends anytime
		Both weekends and weekdays, but only between 10 pm and 6 am
		Both weekends and weekdays at any time
3	Standby driver	Always required
		Not required under certain conditions
		Not required
4	Public safety risk assessment	Less than 1 fatality and 10 serious injuries per year
		1-2 fatalities and 10-20 serious injuries per year
		2-5 fatalities and 20-50 serious injuries per year
		5-10 fatalities and 50-100 serious injuries per year
5	Automated vehicles expected to be commercially available by	2025
		2030
		2035
		2040

4. Econometric framework

In order to capture test heterogeneity in the choice process we use a latent class choice model (LCCM) (Vij and Walker, 2014) to model public preferences towards testing and trialling of CAVs on Australian roads. Readers are referred to Vij et al. (2013) and Ardeshiri & Rashidi (2020) for reasons why LCCM is more suitable over other forms of the random utility choice 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 testing and trialling of CAV technology.

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.

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:

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

, 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 two policy 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 ***j*** for scenario ***t*** and decision-maker ***n***, conditional on the decision-maker belonging to class ***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 ***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 ***j*** is preferred, and zero otherwise; and ***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}.: (4)

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

, where $\mathbf{y_n} = \langle \boldsymbol{y_{n11}}, \ldots, \boldsymbol{y_{nTJ}} \rangle$; 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 $\mathbf{y_n}$, which in turn may be combined iteratively over decision-makers to yield the following likelihood function for the data:

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

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 3 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 four-class LCCM as the preferred model specification. In terms of fit, the four-class LCCM has the lowest BIC and the five-class had the lowest 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 four-class LCCM proved to be the most satisfying.

Table 3: Summary statistics for LCCMs with varying numbers of classes

Classes	Parameters	Log-likelihood	ρ^2	AIC	BIC
2	47	-10977.13	0.167	22048.26	22330.45
3	83	-10465.07	0.203	21096.13	21594.47
4	49	-10340.38	0.215	20778.76	**21072.96**
5	68	-10290.52	0.217	**20717.05**	21125.32

Table 4 presents the estimation results for the class-specific choice models of public preferences for testing and trialing of CAV technologies and Table 5 presents the estimation results for the class membership model. The coefficients that were not statistically significant with 80 per cent confidence level have been omitted from the final model. To ease comprehension, the classes have been ordered in terms of increasing enthusiasm for testing and trailing. The descriptions of the different classes are summarized in Table 6. Over following paragraphs, we discuss some of the key findings.

First, roughly one-in-five Australians (Class 1) would prefer to see the technology available later rather than sooner, regardless of other considerations. We find further that individuals that are more opposed to the technology are also more likely to be female, older and not in the workforce, have lower incomes and education levels, and live in regional areas. The size of this segment is similar to the proportion that indicated that they would not support CAV trials, and that also indicated that they would prefer that CAVs did not operate on public roads at all.

Together, these findings reveal that there is significant resistance to testing of CAV technologies, and policies aiming to build greater public acceptance will need to tailor their messages differently for these sub-populations.

Second, roughly one-in-two Australians (Class 2) is willing to have automated vehicles tested on Australian roads, but they have a zero tolerance for any negative impacts on road safety. Safety is paramount for these individuals, even if it slows technology development and deployment. They do not want any fatalities or serious injuries due to CAV testing. They have a similar demographic profile to Class 1. As discussed previously, governments in Australia have tended to prioritise safety when it comes to the testing and trialling of CAV technology. Our findings show that public sentiment is in favour of this approach.

Third, roughly 28 per cent of Australians (Classes 3 and 4) are willing to tolerate negative impacts on road safety, if that would expedite technology development and deployment. Class 3 (19 per cent) is willing to wait, on average, 4 years longer, to keep fatalities due to testing under 5 per year and serious injuries under 50 per year. Class 4 (9 per cent) is willing to accept greater risks of up to 10 fatalities and 100 serious injuries per year if that expedites commercial deployment. Both classes are more likely to be male, younger and employed, have higher incomes and education levels, and live in metropolitan areas. Note that the literature finds that these same sub-populations also perceive greater benefits from the technology, and are usually more likely to use the technology for their own mobility needs (e.g. Cunningham et al., 2020).

Fourth, in general, Australians seem to prefer a cautious approach to testing. Most Australians would prefer that standby drivers are required during all testing. 21 per cent (Class 1) do not want any testing on public roads, and 51 per cent (Class 2) would like testing limited to public roads in low traffic suburban and regional areas. However, the majority are open to automated vehicles being tested on both weekends and weekdays.

Table 4: Class-specific choice models of public preferences for testing and trialing of CAV technologies

Variables	Class I CAV sceptics		Class II		Class III		Class IV CAV enthusiasts	
	Est	*p-value*	*Est*	*p-value*	*Est*	*p-value*	*Est*	*p-value*
Testing conditions - where								
Private roads only (reference)	0	-	0	-	0	-	0	-
Low traffic suburban and regional areas	-	-	0.46	0	-	-	1.961	0
Any private or public road	-0.403	0	-	-	-	-	1.437	0.01
Testing conditions - when								
Weekends only between 10 pm and 6 am (reference)	0	-	0	-	0	-	0	-
Weekends anytime	-0.194	0	-	-	-	-	1.803	0.01
Both weekends and weekdays, but only between 10 pm and 6 am	-	-	0.138	0.15	-	-	1.174	0
Both weekends and weekdays at any time	-	-	0.243	0.01	-	-	1.462	0
Standby driver								
Standby driver always required (reference)	0	-	0	-	0	-	0	-
Standby driver not required under certain condition	-0.813	0	-0.285	0.01	-	-	-0.492	0.04
Standby driver not required	-1.182	0	-0.525	0	-	-	-0.29	0.03
Public safety risk assessment								
Less than 1 fatality and 10 serious injuries per year (reference)	0	-	0	-	0	-	0	-
1-2 fatalities and 10-20 serious injuries per year	-	-	-2.548	0	-	-	-	-
2-5 fatalities and 20-50 serious injuries per year	-	-	-2.894	0	-	-	-	-
5-10 fatalities and 50-100 serious injuries per year	-	-	-4.269	0	-0.251	0	-	-
Year commercially available CAV	0.083	0	-0.023	0.1	-0.062	0	-0.811	0

Table 5: Class membership model

Variables	Class I CAV sceptics		Class II		Class III		Class IV CAV enthusiasts *(reference)*	
	Est	*p-value*	*Est*	*p-value*	*Est*	*p-value*	*Est*	*p-value*
Class-specific constant	1.893	0	2.425	0	0.908	0.01	0	-
Gender								
Male	-0.677	0	-0.751	0	-0.05	0.08	0	-
Female *(reference)*	-	-	-	-	-	-	0	-
Age								
18-24 years *(reference)*	-	-	-	-	-	-	-	-
25-34 years	-	-	-	-	0.673	0	0	-
35-44 years	-	-	-	-	-	-	0	-
45-54 years	-	-	-	-	-	-	0	-
55-64 years	-	-	-	-	-	-	0	-
65 years and plus	-	-	0.339	0.01	-	-	0	-
Number of vehicles								
No vehicle	-	-	-	-	-0.437	0.16	0	-
One vehicle	-	-	-	-	-	-	0	-
Two Vehicles	-	-	0.111	0.20	-	-	0	-
More than two *(reference)*	-	-	-	-	-	-	0	-
City location								
Regional *(reference)*	-	-	-	-	-	-	0	-
Metro	-0.458	0.01	-0.172	0.2	-	-	0	-
Household type								
Couple family with no children	-	-	0.221	0.02	-	-	0	-
Couple family with children	-	-	-	-	0.121	0.08	0	-
One parent family	-	-	-	-	-	-	0	-
Single person household	0.049	0.05	-	-	-	-	0	-
Group household	-	-	-	-	-	-	0	-
Multi-generational families *(reference)*	-	-	-	-	-	-	0	-
Driving licence								
Yes	-	-	-	-	0.299	0.02	0	-
No *(reference)*	-	-	-	-	-	-	0	-
Household income								
Low-income category	-	-	-	-	-	-	0	-
Mid-income category *(reference)*	-	-	-	-	-	-	0	-
High-income category	-0.324	0.04	-	-	-	-	0	-
Total household income	-	-	-	-	0.009	0.04	0	-
Employment								
Employed full time	-0.149	0.01	-0.435	0	0.21	0.07	0	-
Employed part time	-	-	0.038	0.05	-	-	0	-
Unemployed	-	-	-	-	-	-	0	-
Not in the labour force *(reference)*	-	-	-	-	-	-	0	-
Education								
College degree	-	-	-	-	-	-	0	-
Diploma/certificate degree	0.51	0	0.248	0.02	-	-	0	-
Year 12 or below *(reference)*	-	-	-	-	-	-	0	-

Table 6: High-level summary of different market segments, or classes

	Class I CAV sceptics	Class II	Class III	Class IV CAV enthusiasts
Sample share	21 per cent	51 per cent	19 per cent	9 per cent
Preferences for CAV testing and trialling	Would prefer the technology to be available later rather than sooner	Would like the technology to be available soon, but zero tolerance for any risk to safety	Willing to wait, on average, 4 years longer, to keep fatalities due to testing under 5 per year and serious injuries under 50 per year	Don't care as much about impacts on road safety, want to see technology available as soon as possible
Testing conditions - where	No testing on public roads	Prefer testing on public roads in low traffic suburban and regional areas	No preferences	Strong preference for testing on public roads
Testing conditions - when	Outside of weekends	Both weekdays and weekends	No preferences	Both weekdays and weekends
Standby driver during testing	Standby driver should be required during testing		No preferences	Standby driver should be required during testing
Demographic characteristics	More likely to be female, older and not in the workforce, have lower incomes and education levels, and live in regional areas.		More likely to be male, younger and employed, have higher incomes and education levels, and live in metropolitan areas.	

6. Conclusions

CAVs could offer significant societal benefits through increased road safety, greater mobility, higher traffic flows, greater travel time productivity, and improved energy efficiency (Vij, 2020, Lee and Hess, 2020, Bansal and Kockelman, 2017). However, CAV technologies are still under development, and a number of technological challenges still need to be resolved. For example, studies have reported CAV collision rates ranging from 3.2 (Blanco et al., 2016) to 23.4 (Leilabadi and Schmidt, 2019) crashes per million miles, with an average crash rate of 17.2 crashes per million miles, still significantly higher than 3.6 crashes per million miles for human-driven vehicles (Goodall, 2021).

Government regulations on testing and trialling of CAV technologies have had to balance these short-term risks to public safety with long-term benefits from technological innovation (Shladover and Nowakowski, 2019). Different local, state and national governments have adopted different regulations in their attempt to reconcile these competing goals. The Australian and European approach has tended to prioritise short-term public safety over long-term technological innovation, while the US approach has been the opposite. However, there is little evidence on how citizens value the trade-off between short-term public safety and long-term technological innovation in the context of CAV technologies and service models, and whether or not current their preferences are reflected in government regulations.

This study aimed to address this gap through an online survey of 2,993 Australian residents in January 2022 about their attitudes, perceptions and preferences towards CAV technologies. The survey included questions on testing and trialling. In particular, participants were showed SP experiments where they were offered a choice between different government regulations that vary broadly in terms of risks to public health and time to commercial deployment. Based on this survey data, we find that from the public's perspective, safety is paramount, even if it slows technology development and deployment. We estimate that roughly 20 per cent of Australians do not want any testing on Australian roads. An additional 50 per cent have a zero tolerance for risks to public safety, and do not want to see any injuries or deaths caused by testing. Most Australians would prefer to see the inclusion of standby drivers in any tests or trials, and for testing and trialling to be limited to low traffic suburban and regional areas.

Interestingly, these public views are in contrast to the views of industry stakeholders that we also interviewed as part of this study, who criticised the government's present approach of prioritising short-term public safety over long-term technological innovation. Our survey findings indicate that the current government approach is consistent with public sentiment. However, that does not imply that the current government approach is necessarily "correct" - such normative judgments are beyond the scope of the present study.

Future research can build on these findings in two notable ways. First, it would be interesting to observe how preferences for testing evolve over time, as the technology matures over time. Second, it would be equally interesting to examine how these preferences vary across geographies, cultures and societies, and if the preferences of local citizens are reflected in the regulations of their governments, as appears to be the case in the Australian context.

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