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The Potential Impact of Informational Cues on Willingness-to-Pay for Driverless Cars

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1.Introduction

This study investigates the impact from informational cues on willingness-to-pay (WTP) for autonomous vehicles (AVs). The studied informational cues comprise social media and mass media sentiments, market penetration, and word-of-mouth from social contacts. The effect of word-of-mouth from social contacts is adjusted according to the trust associated with the social contacts. It is argued that informational cues affect AV consideration which in turn exerts influence on preferences towards AVs. A behavioural framework is proposed to link informational cues to AV consideration, and to model AV selection and AV purchase as a function of AV consideration. The parameters of the model are estimated using a representative sample comprising 862 residents from Sydney, Australia. A latent class approach is used to capture heterogeneity in the sample. WTP for automation has been studied in the past. Daziano et al. (2017) calculated WTP for full automation as $4,900, Bansal et al. (2016) reported this value as $7,253, and Ellis et al. (2016) reported $6903. Studying a sample of Japanese citizens, Morita and Managi (2020) found a lower WTP for full automation at $2,473. Kyriakidis et al. (2015) reported 22 per cent of their respondents not to be willing to pay for automation and nearly 5 per cent to be willing to pay more than $30,000. However, the reported WTP in all these studies are constant. We argue WTP can vary depending on consumers' attitudes, which is formed based on received informational cues. Thanks to the novel structure of the proposed behavioural framework, WTP for automation is estimated based on the status of informational cues. According to the results, one per cent increment in market penetration will increase WTP by $650; and one per cent increment in the mass media and social media sentiments will increase marginalised WTP by $398 and $219, respectively. The impact from word-of-mouth depends on the trust associated with social contacts. For an average-trusted social contact, a negative recommendation from the contact will reduce WTP by $13,399 or $5,290 depending on whether the social contact is an AV-owner or a non-AV-owner respectively. a positive recommendation will increase WTP by $8,099 or $14,080 if received from non-AV-owner or AV-owners respectively. Finally, our framework offers new insights on the timing of policy interventions seeking to incentivise innovation uptake. In general, when informational cues are positive, policy interventions are only needed in the very early stages of diffusion. Once market penetration has crossed a critical threshold, it generates sufficient confirmatory signal to persuade more customers to adopt the innovation, the policy interventions can be withdrawn, and the diffusion process becomes self-sustaining. However, if signals from informational cues are not positive enough, strong policy support is needed to sustain the diffusion process.

2. Data

The survey instrument used by this study comprises five sections: (1) media engagement, (2) social network name generator, (3) preference for AVs, (4) social network interactions, and (5) sociodemographic attributes. The survey was conducted in December 2019, from a sample of 862 participants from Sydney, Australia. The survey was administered online, and the assistance of a market research company was used for participant recruitment. We would like to refer readers to Ghasri and Vij (2021) for more details about the survey instrument.

3. Econometric Framework

We use a latent class choice model (LCCM) (Vij and Walker, 2014) to study preferences towards different vehicle attributes, including automation, and the impacts of informational cues on the same. The LCCM in this study has four components: (i) a class membership model, (ii) a class-specific AV consideration model, (iii) a class-specific vehicle-choice model, and (iv) a class-specific vehicle-purchase model. The class membership model is formulated as a multinomial logit function (equation 1).

$$P(q_{ns} = 1) = \exp(\boldsymbol{z}_n \boldsymbol{\gamma}_s) \Big/ \sum_{s=1}^{S} \exp\,(\boldsymbol{z}_n \boldsymbol{\gamma}_s) \qquad (1)$$

The class-specific AV consideration model pertains to the first part of the DCE where respondents specify their persuasion towards AVs given a hypothetical scenario of informational cues. AV consideration is assumed to represent respondents' attitudes towards AVs under each scenario. The attitude towards AV is assumed to be derived based on the utility received from informational cues and this utility is assumed to be a linear function of received information plus a disturbance (equation 2). The disturbance is assumed to be i.i.d logistic with location zero and scale one across decision-makers and tasks. Under this assumption, the class-specific AV consideration model will collapse to an ordered logit model.

$$u_{nt|s} = v_{nt|s} + \epsilon_{nt|s} = \boldsymbol{x}_{nt} \boldsymbol{\beta}_s + \boldsymbol{X}^*_{nt} \boldsymbol{\tau}_n \boldsymbol{\beta}^*_s + \epsilon_{nt|s} \qquad (2)$$

A multinomial logit formula is used to mode the vehicle-choice component. The vehicle-choice component is a labelled SP task where respondents select the most preferred vehicle out of the four presented alternatives. We assume the systematic utility of alternatives is a linear function of vehicle attributes plus the utility of AV consideration, if the alternative is an AV. In other words, the attitude formed towards AVs according to the received information is assumed to have an additive effect on the utility for AVs (equation 3).

$$U_{ntv|s} = V_{ntv|S} + \varepsilon_{ntv|s} = AC_s d_{tv} + \boldsymbol{f}_{tv} \boldsymbol{\varphi}_s + \sigma_s v_{nt|s} d_{tv} + \varepsilon_{ntv|s} \qquad (3)$$

The vehicle-purchase model predicts the probability that respondent n chose option j when indicating the tendency to purchase the most preferred vehicle in the last part of the DCE. We assume the purchase tendency is derived from the same systematic utility construct defined for the vehicle choice model plus a logistic error term with location zero and scale one (eq 4).

$$u_{ntv^*|s} = \delta_s V_{ntv^*|S} + \varepsilon_{nt|s} = \delta_s \left(AC_s d_{tv^*} + \boldsymbol{f}_{tv^*} \boldsymbol{\varphi}_s + \sigma_s u_{nt|s} d_{tv^*} \right) + \varepsilon_{nt|s} \qquad (4)$$

When the error term is assumed i.i.d logistic with location zero and scale one across decision-makers and tasks, the vehicle-purchase component takes the form of an ordered-logit model. In order to construct the likelihood function for the proposed framework, the probabilities for the AV consideration, vehicle-choice and vehicle-purchase components need to be wrapped up over tasks and respondents and marginalised over classes.

4. Results

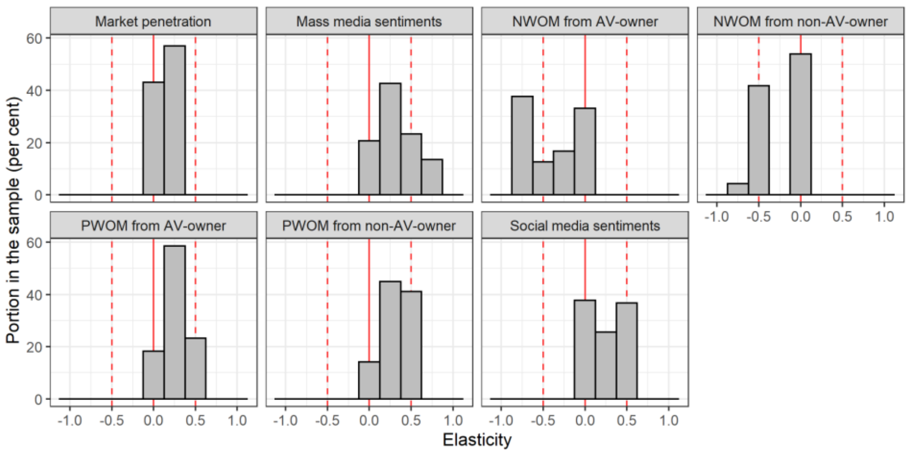
The proposed model is implemented in Python Biogeme (Bierlaire, 2003) and the parameters of the model are estimated. The number of latent segments in the proposed framework is exogenously determined through a stepwise exploratory process. The statistical information criteria and behavioural interpretability of the model suggest an eleven-class specification.

4.1. Market Elasticities for AVs

To compare the effect of attributes, we calculate class-specific market elasticities of AV selection with regards to informational cues and vehicle attributes. The market elasticity of AV selection is calculated using the probability of selecting AVs through sample enumeration.

Figure 1 plots the elasticities for informational cues as histograms. On average, mass media sentiment has a higher impact compared to social media sentiment, indicating the higher effect of the former on the broader diffusion process (Talebian and Mishra, 2018). Digital communication and social media platforms enable individuals to receive information from their inter-personal network as well as the broader community (e.g. Erdoğmuş and Cicek, 2012, Lipsman et al., 2012). Despite the recent popularity of these platforms in shaping public opinion on a wide array of issues including AV consideration (Ghasri and Vij, 2021), it appears that mass media reportage is still more important to our sample when it comes to the subject of AVs. The average impact of word-of-mouth is significant as well, but there is some heterogeneity across the sample. In particular, the histograms for negative word of mouth (NWOM) from AV-owners and non-AV-owners both resemble bi-modal distributions. For nearly 55 per cent of the sample, the elasticity for NWOM from non-AV-owners is close to zero, while for more than 40 per cent of the sample, this value is close to -0.5. Positive word of mouth (PWOM) from both AV-owners and non-AV-owners have a significant impact, comparable to the effect of mass media. Interestingly, the average impact of PWOM from non-owners is estimated to be greater than PWOM from owners. While this may seem counterintuitive at first, it could be that non-AV-owners are perceived to be more impartial than AV-owners when it comes to positive recommendations. For NWOM, the sample average elasticity is higher for AV-owners than non-AV-owners, indicating the discouraging effect of NWOM is higher when it is received from AV-owners. This observation underpins the role of inter-personal communication channels in the process of diffusion (Talebian and Mishra, 2018, Granovetter, 1973).

In the process of innovation diffusion, high market penetration serves as a signal confirming the usefulness of the innovation (Rasouli and Timmermans, 2016, Ghasri et al., 2019, Rogers, 2010). However, we find that the average effect of market penetration is lower when compared to the corresponding impact of mass and social media sentiment, as well as word-of-mouth. Interestingly, elasticity with respect to market penetration also shows the least heterogeneity, with demand being nearly perfectly inelastic (i.e. close to zero) for roughly 40 per cent of the sample.



Variable	Average
Market penetration	0.14
Mass media	0.33
Social media	0.23
NWOM from AV-owner	-0.39
PWOM from AV-owner	0.27
NWOM from non-AV-owner	-0.26
PWOM from non-AV-owner	0.32

Figure 1 – Non-parametric distribution of market elasticity of demand for informational cues

4.2. Willingness-to-Pay for Automation

Class-specific willingness-to-pay (WTP) for automation is defined as the ratio of class-specific marginal utility of automation over the class-specific marginal utility of price. Since the utility of AV consideration is a function of informational cues, the WTP for automation will be a function of informational cues as well.

Table 1 shows the sample average marginal WTP in response to signals from informational cues. The second column in this table presents the incremental change in the informational cues. According to Table 1, one per cent increase in market penetration will increase the WTP for automation by $650, one percent increment in social media sentiments will increase WTP by $219, and one percent increment in mass media sentiments will increase WTP by $398.

Table 1 – Marginal willingness-to-pay for automation in response to changes in informational cues

Informational cues	description	WTP ($)
Market penetration	Calculated by Δx =0.01. Market penetration is measured on a scale from 0 to 1 and Δx =0.01 represents a one per cent increment.	650.32
Mass media	Calculated by $\Delta x = 0.03$. Sentiments are measured on a scale from 1 to 4 and $\Delta x = 0.03$ represents a one per cent increment.	398.40
Social media	Calculated by $\Delta x = 0.03$. Sentiments are measured on a scale from 1 to 4 and $\Delta x = 0.03$ represents a one per cent increment.	219.37
NWOM from AV-owner	Calculated by $\Delta x^* = 1$ for average-trusted social contact.[6]	-13,399.21
PWOM from AV-owner	Calculated by $\Delta x^* = 1$ for average-trusted social contact.[6]	8,098.65
NWOM from non-AV-owner	Calculated by $\Delta x^* = 1$ for an average-trusted social contact.[6]	-5,289.93
PWOM from non-AV-owner	Calculated by $\Delta x^* = 1$ for an average-trusted social contact.[6]	14,079.89

Regarding WOM from social contacts, the marginal WTP is dependent on the trust associated with social contacts. The marginal WTP with respect to PWOM and NWOM in Table 1 are calculated for an average-trusted[1] social contact. According to this table, NWOM can reduce WTP by $13,399 or $5,920, depending on whether it is received from an AV-owner or non-AV-owner. NWOM is more discouraging when received from AV-owners, which means decision-makers value owners' extra knowledge and experience, and they take negative feedback more seriously when it is received from a social contact who has tried this innovation before. PWOM shows an increasing effect on WTP suggesting positive recommendations from social contacts will increase persuasion towards AVs. However, PWOM from AV-owners has a lower impact on WTP compared to PWOM from non-AV-owners. This may seem counterintuitive at first, but it could be that non-AV-owners are perceived to be more impartial than AV-owners when it comes to positive recommendations, and the consequent impact on WTP (and elasticities) is greater.

5. Conclusion

This paper put forward a behavioural framework to study the influence exerted by informational cues on the persuasion to consider autonomous vehicles (AVs). The proposed framework can also measure the impact from informational cues on willingness-to-pay (WTP) for autonomous vehicles. Data was collected from a representative sample of 862 residents in Sydney, Australia. A latent class choice model was utilised to address the taste heterogeneity in the sample. The result confirmed a significant impact from informational cues on persuasion towards AVs. It also showed AV selection is affected by the propensity of AV consideration. Class-specific market elasticity of demand was calculated, and histogram of market elasticity was investigated. For market penetration, social media sentiments, and positive word-of-mouth from AV-owners or non-AV-owners the elasticity does not exceed 0.5. For negative word-of-mouth a bimodal distribution was observed which suggests high variability in reaction to negative recommendations. The marginalised values across classes showed mass media sentiments have the highest impact on the market elasticity, followed by the inter-personal communications. Negative word-of-mouth from AV-owners has a higher effect compared to non-AV-owners.

We argued that the received information can create a favourable or unfavourable attitude towards AVs, and the attitude towards AVs can exert influence on preferences towards AVs

[1] The inferred trust values from Ghasri and Vij (2021) varies from 0.04 to 1.4. We use 0.7 to represent an average-trusted social contact.

and consequently on the WTP for automation. Our analyses showed receiving positive word-of-mouth from an averagely trusted social contact can increase then WTP up to $14,080, and receiving negative word-of-mouth from an averagely trusted social contact can reduce the WTP by $13,399. We studied positive and negative WOM as binary variables, so this work can be continued by studying the quality and strength of recommendations from social contacts. Furthermore, the reported impacts from informational cues on WTP is more reliable for the examined range in the choice experiment. Further research is needed to understand the behaviour outside these ranges.

Several hypothetical scenarios for informational cues were examined and the findings suggest during the early phases of AV market uptake, positive recommendation from social contacts is essential to create a positive WTP, even if the sentiments from social median and mass media are above average. Under this condition nearly 10 per cent of the sample have a positive WTP for automation. A 10 per cent increment in market penetration plus a positive recommendation from an averagely trusted AV-owner will increase this portion to 40 per cent. At this point, negative word-of-mouth from AV-owners can reduce the WTP across all the classes to below zero.

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