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A meta-regression of autonomous vehicle value of time estimates

Fuad Yasin Huda[1], Graham Currie[1], Md. Kamruzzaman[2]

[1]Public Transport Research Group, Institute of Transport Studies, Department of Civil Engineering, Monash University

[2] Institute of Transport Studies, Department of Civil Engineering, Monash University

Email for correspondence: fuad.huda@monash.edu

Abstract

Value of Time (VOT) is a key factor in understanding transport benefits for new investment plans and policies. Several studies have estimated the VOT of Autonomous Vehicles (AVs) travel but no consensus has been reached and the heterogeneity of the variables is yet to be explored. Through a systematic review of the literature, this research paper presents a meta-regression analysis of AV VOT estimates from 24 published studies (154 data points). Private AVs have significantly lower VOT than shared or pooled AVs. Travellers perceive more benefits of AV travel in commute trips. However, any secondary impacts on traffic congestion are not included in VOT estimates. AV VOT estimates are significantly lower in rural areas compared to cities. Higher-income riders exhibit higher VOT for AV travel. Methods of estimating AV VOT have a significant influence on the estimated VOT values. Mixed logit models predict VOT estimates a little lower than hybrid choice models. Methods of demonstrating AVs to survey respondents are significant; lower estimates were found for studies adopting animation videos in contrast to written explanations to demonstrate the possible benefits of AV travel. Respondents having a current driving license have lower estimates of AV VOT. Several other variables were tested but found to either have no effect or only a few examples in the published literature making inference of estimates in the analysis weak. Implications of the results for research and practice are discussed.

1. Introduction

Autonomous vehicles (AVs) are now widely accepted as a major transportation technology, which may substantially change transport systems and cities. AVs are presumed to provide better road safety (Victor et al., 2017), increased road capacity (Lazar et al., 2018) and thereby reducing traffic congestion, saving fuel consumption, lower pollution and emissions (Metz, 2018, van den Berg and Verhoef, 2016), and provide greater mobility for the elderly and the disabled (Harper et al., 2016). Since Google's early demonstration in the last decade, AVs have received enormous focus both from the scientific community and car manufacturers (Hartmans, 2016). But most AV research is still focused on technology development rather than the transport benefits or impacts on cities. Although AV research on transport benefits is increasing, the primary focus is on the short-term benefits such as trip generation (Truong et al., 2017), stability of traffic flow (Talebpour and Mahmassani, 2016), and fleet size (Boesch et al., 2016).

The value of time (VOT) is a crucial parameter for transport researchers, planners, modellers and policymakers to understand or predict the travel behaviour and the benefits of a transport scheme. VOT typically refers to a monetary value that travellers are willing to pay for a reduction in their travel time (Jara-Diaz, 2007). Thus, over the past six decades, many studies have estimated VOT for different types of users and transport modes in different contexts and conditions (Abrantes and Wardman, 2011). Recently, researchers have also started quantifying VOT for AV travel under different policy scenarios. AVs with full automation (SAE level 4-5) (SAE, 2021) are assumed to lower the travel disutility of today's conventional vehicle travel, thereby lowering the VOT. However, the validity of such assumption has been questioned in the literature arguing that AV VOT will remain the same as today's conventional vehicles or may even increase (Rashidi et al., 2020b, Singleton, 2019).

A number of studies have recently reported estimates of the VOT effects of AVs. However, the reported results vary widely, for example, Yap et al. (2015) reported that VOT in AV travel will be higher than in today's conventional vehicle (CV) travel, Krueger et al. (2016) reported that AV VOT will be almost same as CV and Cyganski et al. (2019) suggest VOT in AV travel will be significantly lower than CV travel. Our review shows that these studies were conducted in different geographical contexts (urban/rural), applying different data collection techniques (stated preference/revealed preference) and methods (questionnaire/interviews), and employing different analytical methods (discrete choice modelling/activity-based modelling). The sample sizes of these studies also vary widely. Some studies reported findings by including or excluding non-traders (respondents who prefer not to make any trade-off between choice alternatives) and some studies emphasise multitasking in AV travel to their respondents while others don't. Thus, synthesizing the key significant parameters affecting AV VOT estimates is of great importance. In this quest, Huda et al. (2023) identified key factors that are likely to contribute to the variations in estimated VOT. However, this study lacks to provide a meaningful understanding of the importance and significance (more impactful) of the identified factors that drive the heterogeneity in the VOT estimates. This paper aims to fill this void. It aims to understand the leading factors behind the variations in AV VOT estimates. To the best of our knowledge, this is the first study that synthesizes VOT estimates for AVs and identifies influential factors that impact AV VOT estimates through a meta-regression.

The rest of the paper is organized as follows. Section 2 discusses the background literature on AV VOT estimates. Section 3 elaborates the methodological approach. Section 4 discusses the various factors that influence AV VOT estimates through regression analysis and section 5 concludes with a discussion on the wider implications of the study findings.

2. Literature review

To understand the impact of AV over CV, several studies have estimated the values of travel time (VOT) of both CV and AV. From a meta-analysis of several studies concerning the VOT estimates of both AV and CV, Huda et al. (2023) reported the mean VOT of different types of AVs and CVs. The reported mean VOT of private AV is significantly less than conventional car (12.7% less), transit (22.5% less) and train (53.6% less). Huda reported that several factors such as geographical context (urban vs rural), trip type (work vs non-work), time of the day to perform the trip, would have significant impact on these variations.

In terms of the type of AVs, (such as private AV, shared AV, and pooled AV) one group of researchers estimated that private AVs will have a lower VOT compared to other AV types (Steck et al., 2018, Kolarova et al., 2019b, Zhong et al., 2020) while another group contradict this view and reported that AVs with car sharing or ride sharing concepts will have a lower VOT (Kröger and Kickhöfer, 2017, Yap et al., 2016). A higher VOT estimate was reported by the travellers residing in urban city centres than those in peri-urban and rural areas (Zhong et al., 2019, Sun et al., 2020). In-vehicle activities such as work activities and non-work activities are reported to affect VOT estimates significantly (Sun et al., 2020, Correia et al., 2019). Some studies reported that travelers perceive the benefits of AV travel differently based on trip direction such as inbound and outbound (Wadud and Huda, 2019) and trip type e.g. commute, business and leisure (Wadud and Huda, 2018). Thus, studies have reported AV VOT estimates in several contexts such as trip type (Kolarova et al., 2019a), trip duration (Kolarova and Steck, 2019), income level (Kolarova et al., 2018), trust in technology (Kolarova and Cherchi, 2021) and residential location choice (Krueger et al., 2019). But the VOT estimates show much heterogeneity between these studies. As such, a review of VOT studies focusing on these factors is important to better understand their impact on AV VOT.

In a review paper, Singleton (2019) discussed the positive utilities of travel time in AVs and mentioned that activities performed while travelling in an AV could be more of coping with the time rather than utilizing the in-vehicle time in a productive way. Rashidi et al. (2020a) performed some alternative theoretical framework analysis on the impact of VOT change on AV travel and suggested that VOT in AV travel may remain the same as the conventional vehicles (CVs) or may even increase in the long run. Milakis et al. (2017) reviewed the policy and societal impact of AV travel and reported that travel time reliability, travel safety, personal comfort and performing non-driving activities in an AV will have significant positive impact on VOT reduction. In a different study, Milakis along with other researchers reported that AVs will have great impact on accessibility (Milakis et al., 2018) and increased travel demand might erode the benefits of AV travel in the long run. Milakis also stated that AV ownership might increase social inequity together with two opposite scenarios for urban formation: densification of city centres and low-density urban suburbs.

Nordström and Engholm (2021) performed a morphological analysis on the impact of AV VOT based on several variables which they summarised under four broad categories: vehicle characteristics, operating principles, journey characteristics, and traveler characteristics and proposed different AV mobility concepts (e.g. private AV, AV with ride-sharing concept, shuttle AV) for each of these variables.

In summary, several studies have reported VOT estimates for future AV travel in various contexts and a few of them reviewed the probable impacts of AV travel based on a wide variety of factors. Although Huda et al. (2023) attempted to synthesize some key factors which are believed to have significant impact on AV VOT estimates, this study attempts to quantify their effect size using regression analysis methods.

3. Methodology

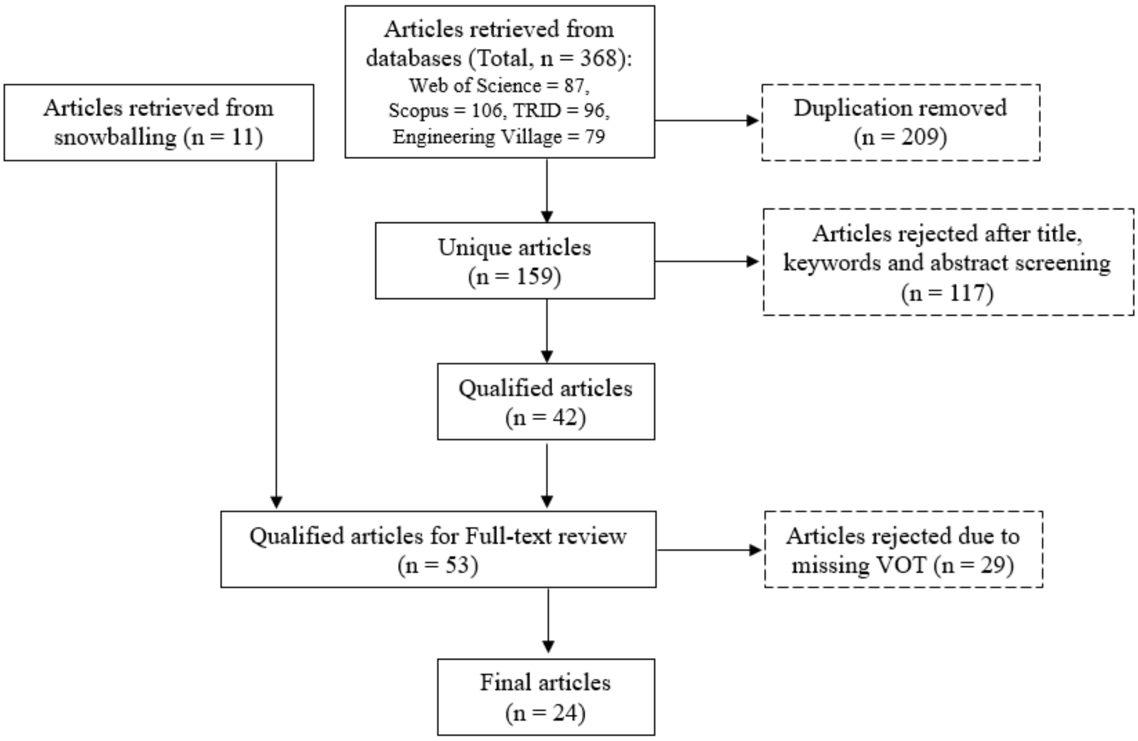
This study conducted a meta-regression analysis to estimate the effects of various factors on the variations in AV VOTs reported in primary studies. Meta-regression is a statistical process of analyzing the effect of multiple explanatory variables to be investigated simultaneously on a response variable (Stanley and Jarrell, 2005). This is often considered as an extension to sub-group analysis of categorical as well as continuous variables through regression models by combining, comparing and synthesizing the research findings of empirical studies while adjusting the effects of the available covariates (e.g. independent variables) on response variable (e.g. dependent variable) (Van Houwelingen et al., 2002). In this study, we selected primary studies by following the systematic literature review approach similar to Huda et al. (2023).

3.1. Literature selection

In any literature review, selection of empirical studies, particularly the inclusion and exclusion criteria are of significant importance. Fink (1998) defines the systematic literature review as "*a systematic, explicit, and reproducible design for identifying, evaluating and interpreting the existing body of recorded documents*". We collected empirical studies using the Web of Science, SCOPUS, Engineering Village (Compendex, Inspec and GEOBASE), and Transport Research International Documentation (TRID) databases. Two keywords and their alternative phrases were entered into these databases on 18 April 2022. The keywords were "autonomous vehicle" and "value of time". Using the Boolean operators along with these keywords resulted in 368 primary articles.

To be inclusive of this study, primary articles were screened through the following four criterias: (a) articles need to be peer-reviewed and published in English, (b) VOT estimates of at least one type of AV (private, shared, pooled, transit) need to be reported, (c) VOT estimation and analysis method need to be reported, and (d) at least one socio-demographic variable need to be reported with AV VOT estimates. Figure 1 presents the detailed literature selection process.

Figure 1: Literature selection process (adopted from Huda et al. (2023)).



After screening the duplicates and reviewing the title and abstract, 42 articles were selected for full text review. Backward snowballing technique (Wee and Banister, 2016) resulted in an additional 11 articles to go through the screening process as well. Finally, 24 unique articles have been considered for this study. The number of data points for each study with other characteristics are reported in Table 1.

3.2. Data extraction

All the selected empirical studies were reviewed carefully and coded according to their study characteristics which resulted in 22 different factors to investigate if the variations in these factors may explain the reported heterogeneity in VOT values. We categorized all these variables under five broad categories: (a) study context, (b) experimental characteristics, (c) model characteristics, (d) trip characteristics, and (e) socioeconomic variables. The variables by broad categories and descriptions are provided in Table 2.

For variables like Advanced Driver-Assistance System (ADAS) and multi-tasking, if an empirical study failed to report them, we considered that under sub-category 'No'. Similarly, for the variable 'NonTrader' (refers to those respondents who prefer not to make any trade-off between choice alternatives (Correia et al., 2019, Hamadneh and Esztergár-Kiss, 2022), if studies fail to report excluding them, we considered as to be included. For 'TripType' variable, we considered leisure, shopping and mixed trips together as 'others'. In terms of the 'DayTime' variable, studies that reported the sub-category 'AM peak' was considered as it is and for rest of the studies, we considered their sub-category as 'others'.

Table 1: Sample characteristics of the studies.

Study no.	Country	Survey year	Survey type	Sample size	Data points
1	Australia	2015	Online	435	2
2	Netherlands	2014	Online	761	1
3	Switzerland	2018	Paper	N/A	3
4	Germany	2017	Online	485	6
5	Germany	2017	Online	172	6
6	Australia	2017	Online	108	4
7	Netherlands	2017	Online	324	24
8	USA	2018	Online	502	3
9	USA	2019	Online	614	2
10	Germany	2017	Online	485	12
11	Germany	2017	Online	441	3
12	Australia	2017	Online	512	1
13	USA	2017	Online	1607	2
14	USA	2018	Online	1717	3
15	Cross-country	2020	Online	Different per country	6
16	Singapore	2019	Interview	204	2
17	USA	2017	Online	1881	6
18	Germany	2019	Simulation	-	1
19	Israel	2019	Online	713	6
20	USA	2019	Online	953	3
21	Germany	2017	Online	484	52
22	South Korea	2019	Online	500	4
23	Hungary	2020	Online	525	1
24	USA	2019-20	Interview	71	1

Finally, VOT estimates were reported in different years and for different countries. As the aim of this study is to compare the AV VOTs from different published studies, monetary units have been converted to Australian Dollar (AU$) of 2021 rate using Purchasing Power Parities (PPPs) published by the OECD (OECD, 2022) to control the misrepresentation of ordinary currency exchange rates and the effect of inflation over time (Eftec, 2009).

Table 2: Description of the explanatory variables.

Category	Variable	Definition	Sub-categories
Study context	Country	Country where the empirical study was perofrmed	Australia, USA, Germany, Iceland, Netherlands, Switzerland, Cyprus, UK, Slovenia, Montenegro, Hungary, Singapore, Israel and South Korea
	Geo-location	Geographical location of the empirical study performed	Rural, urban
Experiment characteristics	Vehicle type	Type of AV mode	Private, shared, pooled, public transit
	AVDemo	AV demonstration approaches to respondents	Written as AV, written as chauffeur-driven, animated video
	Survey instrument	Types of instruments used to collect data to estimate VOT	Online, paper, travel diary
	Survey method	Type of method applied to collect the survey data	Stated preference (SP), revealed preference (RP)
	Sample size	Number of samples used to collect data	Continuous variable
	Choices	Number of alternatives given to choose from	Continuous variable
	Observation	Total number of observations used to analyze and estimate the VOT	Continuous variable
	ADAS	Respondents experience on Advanced Driver Assistance System (ADAS)	Categorical variable (Yes, No)
	MultiTask	Survey respondents were explicitly mentioned about multitasking in AV	Categorical variable (Yes, No)
Model characteristics	Analysis	Types of analysis model used	MNL, ML, HCM
	NonTrader	Non-traders are included in the analysis	Categorical variable (Yes, No)
Trip characteristics	TripType	Type of trips considered	Commute, others (leisure, shopping)
	DayTime	Time of the day	AM peak, others
	TripLength	Length of a one-leg trip	Continuous variable
	TripTime	Time duration of a one-leg trip	Continuous variable
Socio-economics	Age	All respondents are above 18 years	Categorical variable (Yes, No)
	Gender	Gender distribution of the respondent	Male, Female
	Education	Respondents are university degree holder	Categorical variable (Yes, No)
	Income	Income level of respondent	Low, medium, high
	License	Respondents are current driving license holder	Categorical variable (Yes, No)

3.3. Analysis process

This study followed a five-step process to conduct the meta-regression. *First*, given the high number of explanatory factors considered in this study, a correlation analysis was conducted among the continuous explanatory factors to identify if there is a strong correlation among them. The factors that had a correlation coefficient greater than 0.7 were excluded from further analysis. Between two correlated variables, one was retained based on their power to explain the VOT. *Second*, a single variable ordinary least square (OLS) regression model was estimated using each of the remaining explanatory factors and regressed on VOT. The variables that were found to have a statistically significant effect on the estimated VOT were considered for the next step. *Third*, the previous step resulted in 12 explanatory factors with significant effect on

VOT in a single variable model. All these factors were then entered into an OLS model (maximally adjusted model). *Fourth*, the effects of the different factors in the maximally adjusted model were examined and any insignificant factors were gradually removed until a parsimonious model was achieved. *Fifth*, multicollinearity among the explanatory factors were checked based on variance inflation factor (VIF) and any factor with a VIF > 5 was gradually removed from the parsimonious model. Finally, we considered the model that have higher goodness-of-fit according to R^2 value and discussed their effects in results section.

4. Results

We have found 8 variables that fits our regression model with higher R^2 value (0.615). Except sample size, rest of the seven variables are categorical in nature. All these variables with their reference (dummy variable) and performance measure is presented in Table 3. The results for each explanatory variable are discussed below:

Table 3: Estimation results of the meta-regression analysis. (outcome variable: Value of Travel Time, AU$/hr)

Variable	**Marginal effect**	**Std. Error**
Constant	6.344	4.320
Sample size	0.003	0.008
Vehicle type (*ref: private AV*)		
Shared AV	2.085	2.806
Pooled AV	2.318	3.109
Transit AV	2.572	5.985
TripType (*ref: commute*)		
Others	0.035	2.214
Income (*ref: low*)		
Middle	1.263	2.430
High	8.049	2.379
Geo-location (*ref: urban*)		
Rural	-6.468	2.647
Analysis (*ref: HCM*)		
ML	-1.154	2.426
AV Demo (*ref: written as AV*)		
Animated video	-3.870	5.842
License (*ref: No*)		
Yes	-3.668	5.409
R^2 value	**0.615**	
F-statistic	**3.630**	
Significance (*p*)	**0.004**	

4.1. Effect of sample size

Huda et al. (2023) in their meta-analysis of AV VOT estimates, reported that higher sample size exhibits higher AV VOT estimates. We've cautiously checked this over and over again through our regressional analysis and found to be true. The marginal effect indicates that an additional unit increment of sample size will increase the VOT estimates by 0.003 AU$/hr. This have a significant impact on AV VOT estimates. Since AV VOT experiments are primarily carried out using stated-preference choice experiments due to their absence in the current world, we hypothesize, based on our overall understanding, that employing larger sample sizes will enhance our comprehension of AV VOT estimates. Thus, we also suggest future studies to consider a higher sample size for AV VOT estimate.

4.2. Effect of vehicle type

Type of AV modes e.g. private, shared, pooled, transit, is found to have significant impact on VOT estimates (Huda et al., 2023). Our regression analysis also show that AV types have significant marginal effect on VOT estimates. Compared with private AVs, VOT estimates will be 2.1 AU$/hr higher for shared AVs, 2.3 AU$/hr higher for pooled AVs and 2.6 AU$/hr higher for transit AVs. Thus, indicating that benefits of AV travel will be maximized if used as a privately-owned AV. Although this could have several other rebound effects on congestion and capacity, this interpretation is also consistent with the results reported by Wadud and Mattioli (2021).

4.3. Effect of trip type

In terms of trip type, we found that commuters will have lower VOT estimates than other types of trips such as leisure and shopping. This may have a significant impact on future AV planning. While some researchers argue that travel time in AV will not be productive (Rashidi et al., 2020b), our regression model shows that commuters will benefit from lower VOT estimates. We assume that modern-day commuters have come to recognize the drawbacks of daily driving and perceive the enhanced benefits of making use of their in-vehicle travel time within an AV by engaging in different other activities. Consequently, the time-constraint function (such as leaving home early or reaching the destination quickly) in order to save travel time no longer applies to these commuters. However widespread AV commuting may result in higher vehicle miles traveled (VMT) and thus can impact other factors like emission and traffic congestion. These factors are not included in the VOT estimates provided by respondents.

4.4. Effect of income

People with higher-income group will have significantly higher VOT estimates compared to middle- and low-income groups of the society. In a general concept, higher-income groups of people value their time more than any other groups. Thus, their time valuation will be higher in general. Although AVs are advertised to provide the benefits of having in-vehicle working facilities, for which higher-income group of people might not have to reduce their travel time and their VOT estimates are expected to be lower than today's conventional vehicle.

4.5. Effect of geographical location

Geographical location is another important factor to have significant importance on the VOT estimates. Based on the regression analysis, we found that VOT estimates of urban dwellers will be higher than those living in the rural areas. This interpretation is also consistent with the findings reported by Zhong et al (Zhong et al., 2020) where researchers estimated a higher VOT for urbanites than rural dwellers.

4.6. Effect of analysis model

In exploring type of data analysis model adopted as a variable, we found that mixed logit (ML) models predict VOT estimates a little lower than hybrid choice models (HCM). This seems to be true as multinomial logit (MNL) models are the basic SP data analysis models which cannot consider the heterogeneity of the latent variables as current HCM models can (Ben-Akiva et al., 2002). In addition, MNL models consider that taste parameters are a fixed constant (indicating that respondent preferences do not vary, which is unrealistic) while ML models assume that the taste parameters are randomly distributed (McFadden and Train, 2000). Thus, to understand the heterogeneity of latent variables associated with several exogenous (e.g. socio-economic) variables on VOT estimates, HCM models would be the best choice.

4.7. Effect of SP demonstration type

There is no widespread adoption of AV's at present hence all studies estimating AV VOT need to demonstrate AV systems and experiences to users using a variety of methods. Researchers primarily used two approaches to demonstrate AV travel to their respondents: either by a descriptive writing about AVs or by showing an animation video of AVs to depict the futuristic AV travel. Our results found that travelers perceive greater benefits of AV travel by showing an animation video compared to written explanation of AV travel. These findings emphasise the difficult problem in reliabily estimating VOT when respondents have never actually experienced widespread AV travel.

4.8. Effect of driving license

In our regressional analysis, we considered having a current driving license as an independent variable. Although AVs will be able to complete all the driving tasks by itself and AV users may not need a driving license in future when AVs will be available, we found that respondents who possess a current driving license have lower AV VOT estimates. Perhaps an understanding of driving enables a greater valuation of the benefits of not having to drive?

5. Discussion and Conclusions

This paper reports the influential factors that are presumed to have significant impact on AV VOT estimates. In this quest, a meta-regressional analysis has been performed following the PRISMA guideline for systematic literature review, to identify the potential factors based on the VOT estimates from 24 empirical studies. We've initially identified 22 variables, out of which, we found 8 to have significant influence on AV VOT estimates. We found that studies focused with private AVs reported a significantly lower VOT compared to those studied other AV types. Travellers perceieve more benefits of AV travel in commute trips than shopping and leisure trips. An increased demand at commute time may result in increasing traffic congestion and emissions which are not included in estimated direct VOT estimates.

Our results also indicate that AV VOT estimates will be significantly different between people living in the rural areas and urban dwellers and also between high-income and low-income group of people. Considering the hybrid choice model (HCM) for analyzing the data will provide better understanding of the latent variables and their influences on AV VOT estimates although mixed logit (ML) model is found having generally lower VOT estimates. Sample size provide significant change in AV VOT estimates with higher sample sizes depicting higher AV VOT estimates. But as a general rule larger sample size will enable more accurate prediction of AV VOT estimates. We also found that methods of demonstrating AVs to survey respondents has a significant impact on AV VOT estimates. Lower VOT estimates were found for studies that adopt animated video to demonstrate the benefits of AV travel.

There are several other variables such as trip time, trip duration, gender and education, which we identified as potential factors having an impact on the VOT estimates but due to lower sample size we could not analyze them through the regression analysis. Future studies can focus on these variables and their probable impact on AV VOT estimates. The findings of this study will form critical inputs for future research, transport policy and AV design. For example, research community will be aware of how their research design (sample characteristics, sample size, experimental set-up) might affect their research findings. Similarly, a policy maker would be able to estimate the true benefits/costs of a policy decision such as the effects of a new AV service (transit) in rural vs. urban settings, effects of a new toll road. AV manufacturers would be able to design a more passenger friendly vehicles to make the journey more pleasant (i.e. reduced VOT).

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