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Would being driven by others affect the value of travel time? Ridehailing as an analogy for automated vehicles

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Abstract
It is widely believed that vehicle automation will change how travelers perceive the value of travel time (VoTT), but the magnitude of this effect is still unknown. This study investigates how highly automated vehicles (AVs) may affect VoTT, using an existing mode—ridehailing services (RHS)—as an analogy for AVs. Both AVs and RHS relieve travelers from the effort of driving and allow them to participate in other activities while traveling. In a stated choice experiment, respondents chose between driving a personal vehicle or taking an RHS, with each mode characterized by a cost and travel time. Analysis results using a mixed logit model indicated that the VoTT was 13% lower when being driven in an RHS than when driving a personal car. We also told half the respondents (randomly selected) that the RHS was driverless; and for half (also randomly selected) we explicitly mentioned the ability to multitask while traveling in an RHS. Mentioning multitasking explicitly led to a much lower VoTT, approximately half that of driving oneself. However, the VoTT in a driverless RHS was 15% higher than when driving a personal car, which may reflect a lack of familiarity and comfort with driverless technology at present. These results suggest sizable reductions in VoTT for travel in future AVs, and point to the need for caution in making forecasts based on consumers' current perceptions of AV technology.

Keywords Value of travel time · Discrete choice model · Ridehailing service · Driverless vehicles · Multitasking

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Introduction

Driving a personally-owned car is the most dominant transportation mode in the US (Santos et al. 2011). However, the emergence of shared mobility services such as car sharing and ridehailing has gradually been disrupting the traditional transportation mode choice (Clewlow and Mishra 2017). Ridehailing services have been developing in the US significantly since 2010 when Uber first launched. Goldman Sachs estimates the ridehailing services to serve 15 million trips a day globally, and expects that number to grow by more than five times by 2030 (Huston 2017). Moreover, vehicle automation is already happening, and is widely expected to accelerate in the coming years. The growth of new mobility services like ridehailing services (RHS) and autonomous vehicles (AVs) will have profound effects on transportation sustainability. Yet, the overall sustainability effects of ridehailing and vehicle automation will depend strongly on travelers' behavioral responses to the technology, particularly how it affects their perceived value of in-vehicle time (Jain and Lyons 2008). Travelers' value of travel time is significant for transportation investment decisions and travel demand estimations, and all else equal, lower values of travel time can be expected to increase vehicle miles traveled.

Value of travel time (VoTT) is a notion referring to the cost of time spent on traveling, and can be understood as a traveler's willingness to pay for time savings. Abrantes and Wardman (2011) investigated the relationship between travel purpose and VoTT, revealing that people are more likely to have higher VoTT on work trips than on non-work trips such as leisure or shopping. It was also shown that choosing different travel modes can be related to VoTT; for example, public transportation travelers showed to have lower VoTT than those who drive their own vehicles (Shires and Jong 2009; Mackie et al. 2003). Ridehailing services and vehicle automation affect the VoTT mainly because they will entirely relieve travelers of the driving task: being driven by a designated driver or by a driverless car, both of which are totally different from driving a conventional car.

Several researchers have tried to discern how being driven by others or an AV may affect the VoTT. In a stated preference (SP) study focused on exploring the potential for AVs as a first/last mile mode for train trips, Yap et al. (2016) showed that VoTT in an AV is not perceived lower than in other modes. This is inconsistent with the belief that the VoTT in an AV would be lower due to the possibility of doing other activities; however, the authors suggested that since AVs are not currently available, there could be uncertainties in the outcomes. In another study in the Netherlands, De Looff et al. (2018) used an SP experiment to estimate potential changes in VoTT due to AVs. Considering different interior environments (office and leisure) for AVs, they compared VoTT in AVs with that in a conventional car. The results revealed that VoTT in the AV office-interior is lower than that in a conventional car; nevertheless, VoTT in the AV leisure-interior is the highest. Steck et al. (2018) conducted a choice experiment for driverless taxis and personal AVs, and estimated a 31% reduction in the VoTT with full automation. Studies previously have also examined the VoTT of different levels of AVs, shared AVs, and others (Krueger et al. 2016; Daziano et al. 2017).

However, none of these studies is directly applicable to the specific effect of being "driven by others." Also, few published studies have explored the VoTT of RHS (Daziano et al. 2017), although RHS is an analogous mode to AVs, in the sense that both AVs and RHS relieve travelers from the effort of driving and allow them to participate in other activities while traveling.

A review of the state of knowledge on the VoTT noted that better in-vehicle amenities, mobile communications, and entertainment devices would lower the VoTT by making travel time less onerous or more productive (Small 2012). Another study using an SP experiment found that listening to music decreased the VoTT, while reading for work increased it (Ettema et al. 2012). Moreover, studies have acknowledged the effect of multitasking opportunities on traveling. Kenyon and Lyons (2007) argued that multitasking is an influence that cannot be ignored when examining activity participation. They concluded that consideration of multitasking would have significant implications on travel behavior studies, and suggested that it could affect the attraction of optional trips. Rasouli and Timmermans (2014) also found significant impacts of multitasking on traveling, stating that taking multitasking into consideration is the key to the next generation of activity-based models.

When being driven by a human driver in an RHS, or by an AV, travelers are expected to experience a reduced mental burden and will ultimately be free to multitask and to engage in other activities, such as working, reading, listening to music, and other leisure activities, decreasing the disutility of time spent traveling, which would consequently change the VoTT (Jamson et al. 2013; König and Neumayr 2017; Lyons and Urry 2005). This is corroborated by another study (Ian Wallis Associates Ltd. 2014) which found that the car passengers' VoTT was 0–40% lower than that of drivers, as they can do other things on the trip instead of driving. Malokin et al. (2015a) conducted a survey in Northern California to investigate how multitasking would affect the utility of traveling, especially for commute trips, and found that the perceived ability to perform other activities while traveling significantly adds to the utility of all travel modes. In another study, Malokin et al. (2015b) attempted to measure the effects of multitasking attitudes and behaviors on different travel modes, and found that without the option of multitasking, commuter rail and carpool/vanpool shares would respectively be 0.38% and 3.22% lower, while the drive-alone share would be 3% higher. It was also found that in the hypothetical AV scenario with the multitasking possibility, drive-alone and carpool/vanpool shares would increase by 0.95% and 1.08% respectively.

The present study employs a stated choice experiment in which respondents choose between being driven in an RHS and driving themselves in a personal car, to zero in on how the VoTT differs between these two modes. Furthermore, respondents are presented with one of two forms of RHS—regular human-driven RHS or driverless RHS—to test whether this difference elicits different values of time. The survey also examines the effect on VoTT from priming respondents to think about the possibility of multitasking when riding the RHS.

This paper is structured as follows. The next section describes the methodology including survey design and sample analysis. Next is the analysis method. Model results will be presented afterwards, along with the discussion of findings and VoTT estimates. The final section presents the conclusions drawn by the study and suggestions for future research.

Survey method

Survey design

The survey used in this study was structured as follows: First, the description of the survey and the corresponding alternatives were presented. The choice sets (in the form of a stated preference (SP) experiment) were presented next, and finally the respondents were asked some basic socio-demographic questions such as age, average household income, education level, home location ZIP code, job status, and their frequency of using ridehailing services.

In each SP experiment, two alternatives were given to the participants: personal car and ridehailing service (RHS). RHS was presented in one of two forms: regular human-driven (like the current services offered by Uber and Lyft) and driverless. The type of RHS presented to each respondent was selected randomly. Also, to test the effect of multitasking opportunities on the perception of VoTT, the possibility of engaging in other activities was explicitly mentioned to half of the respondents, again selected randomly. As a result, there were four groups of choice sets in the survey: (a) personal car versus regular human-driven RHS; (b) personal car versus driverless RHS; (c) personal car versus regular human-driven RHS with explicit mention of multitasking possibility; and (d) personal car versus driverless RHS with explicit mention of multitasking possibility. In the two choice set groups with the explicit mention of multitasking ability [groups (c) and (d)], a sentence was included prior to presenting the SP experiment to explain multitasking as "*You will have the option of doing other tasks* (*e.g. working, reading, watching videos, texting,* etc.) *or just relaxing during the trip, because you don't need to pay attention to driving*". Such text was not shown in the other two groups. The choice set presented to respondents in the multitasking scenarios also included "Activity" as an attribute of the mode (Fig. 1). A similar process was done for the scenarios including driverless RHS [groups (b) and (d)], by including a sentence describing what is meant by a driverless RHS: *"A driverless ridehailing service is similar to services offered by Uber and Lyft, where you can request a ride using an application on your smartphone, but the car will be driven by the computer rather than a human driver"*. Respondents were randomly assigned to one of the four choice set groups at the beginning of the survey, such that any given respondent would be making all of their choices between a personal car and one of the four specific forms of RHS.


If you had to make a **15-mile commute trip**, which of the following options would you choose?

Personal Car	Ride-hailing Service
Travel Time: 20 min	Travel Time: 15 min
Travel Cost: $5 (fuel, tolls, parking, etc.)	Travel Cost: $15 (fare)
Waiting Time: 0 min	Waiting Time: 2 min
Activity: Driving	Activity: Non-Driving(e.g. work, read, rest, using cellphone...)

○ **Personal Car**

○ **Ride-hailing Service**

Fig. 1 Example of a choice set presented to a respondent in the survey

Table 1 shows the attributes and their corresponding levels used in the experimental design. In order to depict a unique trip scenario, a 15-mile commute trip was considered, and the corresponding attribute levels are defined based on such a trip in the US. For travel cost, the cost associated with the personal car is assumed to include fuel, tolls, parking fee and so forth, while the cost of RHS is only the out-of-pocket fee that customers pay (via the app) for the service. Since we are not concerned here with the effects of waiting time, we kept wait times the same in all choice scenarios: 2 min for RHS and zero for personal car. The 2-min wait time for the RHS is low enough to avoid a situation where the disutility of waiting is so large that nobody ever chooses RHS, and allows us to identify the effects of varying travel time more readily. This is also a reasonable value for a future world with heavily-used ridehailing services. For the personal car alternative, waiting time is set to zero because it is assumed that people can access their cars any time they desire.

To generate the attribute values in the survey, a full factorial experimental design was used. This led to a total of 81 SP scenarios. Respondents were randomly assigned to one of the four choice set groups, and each respondent was given six choice scenarios (all from the same choice set group), which were randomly selected from among the 81 scenarios. Figure 1 shows an example of a choice set on personal car versus regular RHS.

In the real world, travel cost, travel time, and trip distance are often positively correlated (though this is not always the case, as when a toll road offers a shorter travel time at a higher cost). The confounding between these variables, and other unobserved variables, makes it difficult (or in some cases, impossible) to use revealed preference data to establish credible causal estimates of how time, cost, and distance affect choices. Setting the travel times and costs independently, via a designed experiment, ensures that these variables are uncorrelated. This is the essential feature that allows us to identify the causal effect of travel times and costs on choices, and in turn to obtain valid estimates of the value of travel time in different modes.

Survey administration and sampling

To collect data for this study, respondents were recruited through Amazon's Mechanical Turk (MTurk). MTurk is a national online crowdsourcing platform that connects individuals and businesses (employers) to workers who are willing to complete a certain task in return for payment. Employers (researchers) can post tasks (surveys) on MTurk, and workers (respondents) can browse among existing tasks and complete them in exchange for a monetary payment set by the employer. MTurk has seen widely used among researchers in social and behavioral studies, and is more representative than

Table 1 Attributes and their corresponding levels used in the SP experiment

Attribute	Attribute level(s)		
Travel time personal car	15 min	20 min	25 min
Travel time RHS	15 min	20 min	25 min
Travel cost personal car[a]	$5	$10	$15
Travel cost RHS	$10	$15	$20
Wait time personal car	0 min		
Wait time RHS	2 min		

[a]Includes fuel, tolls, parking, etc

typical convenience samples, though less so than internet panels or probability samples (Berinsky et al. 2012; Chandler et al. 2014; Paolacci and Chandler 2014). MTurk has a large participant pool, an integrated participant compensation system, and a streamlined respondent filtering process based on demographic and geographic distributions (Buhrmester et al. 2011).

The survey was implemented in Survey Monkey, and respondents were directed from MTurk to the Survey Monkey website to complete the survey. Upon successful completion they were provided with a code to enter in MTurk to verify completion and receive their payment. The survey was conducted in July 2018. Overall, 535 respondents participated in the survey, from which 502 (93.83%) valid responses were obtained, which resulted in a total of $502 \times 6 = 3012$ choice observations.

The 502 respondents came from 446 different areas in the US (shown in Fig. 2), 97% of them owned a car, and most of them reported having used RHS, with 22% being frequent users (once a week or more) (See Fig. 3).

Since our survey was concerned with driving a personal car, and due to human subjects protocols, we only allowed respondents over 18 to participate. A comparison of socio-demographic characteristics between our sample and the US adult population ($\geq$ 18 years old) is presented in Table 2. As can be seen, males, people in the range of 18–25 years old, and those with mid-level household income ($ 30,000–74,999) were overrepresented in our sample, while seniors ($\geq$65 years old) and people with high-level household income ($100,000 and above) were underrepresented. Employment is also slightly overrepresented in our sample, and it was shown that the sample contained more people with higher education levels compared to the national population.

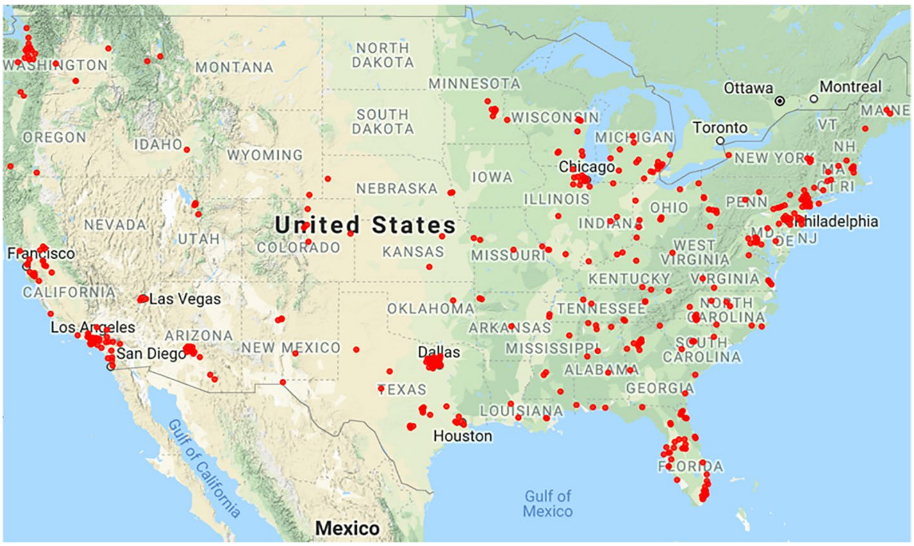

Fig. 2 Residential distribution of the respondents

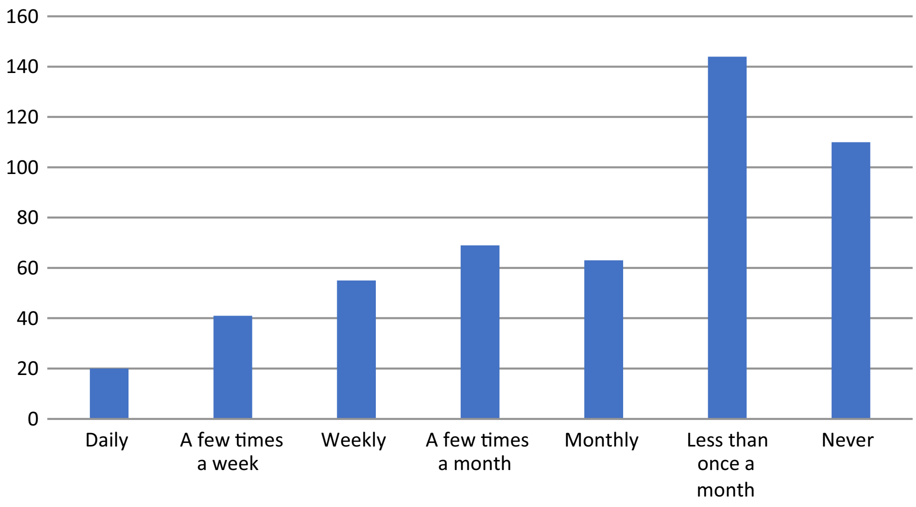

Fig. 3 Frequency of ridehailing service use in the sample

Table 2 Distribution of socio-demographic characteristics among the respondents in our sample versus the US population

Socio-demographic characteristic	Category	Our sample (%)	National population (%)[a]
Gender	Male	56.6	50.1
	Female	43.0	49.9
Age	18–24	25.7	11.9
	25–64	68.7	68.1
	>=65	5.6	20.0
Income level	Under $15,000	8.6	12.6
	$15,000 to $29,999	16.1	16.1
	$30,000 to $49,999	24.7	18.1
	$50,000 to $74,999	23.5	17.0
	$75,000 to $99,999	13.9	11.6
	$100,000 to $150,000	9.0	13.7
	Over $150,000	4.2	10.9
Education level	High school and lower	27.3	38.2
	College degree	57.9	51.2
	Master's degree and higher	14.8	10.6
Employment	Employed	65.7	60.6
	Unemployed	34.3	39.4

[a]Only respondents over 18 were allowed to participate in the survey, so the US adult population (≥ 18 years old) is considered for comparison

Analysis methods

Discrete choice model

In this paper, a discrete choice model is applied to analyze the survey data. The response variable is the mode choice between conventional car and ridehailing service, which is a binomial variable, and the predictors include numeric and categorical variables. Therefore, a binary choice model is suitable. Since the basic binary logit model assumes that the error terms are independent and identically distributed, it cannot reflect the heterogeneity among respondents, nor can it account for the repeated choices made by each respondent (Hensher and Greene 2003). Therefore, we employed the mixed logit (ML) model in this study. The mixed logit model (aka, random parameter logit model) is a logit model for which some parameters are assumed to vary across respondents, and so the ML model can represent the heterogeneity of the respondents. The utility function in an ML model is shown in Eq. (1), where β represents the estimated coefficients, and $\alpha_{i,j}$ is a vector of intercepts (alternative-specific constants) which vary across respondents.

$$U_{i,j} = \alpha_{i,j} + \beta x_{i,j} + \varepsilon_{i,j} \tag{1}$$

Moreover, in our dataset, we had repeated observations for each individual, which is referred to as panel data, and the ML model can also handle panel data (27). In an ML model structure, the probability that alternative j is chosen for the observation n of the individual i is:

$$P_{i,n,j} = \frac{e^{\alpha_{i,j}+\beta x_{i,n,j}}}{\sum e^{\alpha_{i,j}+\beta x_{i,n,j}}} \tag{2}$$

The likelihood for the individual i choosing the observation n is:

$$P_{i,n} = \prod_{l} P_{i,n,l}^{y^{i,n,l}} \tag{3}$$

And therefore, the likelihood for the N observations of I individuals is:

$$P_i = \prod_{n} \prod_{l} P_{i,n,l}^{y^{i,n,l}} \tag{4}$$

Results and discussion

Model estimation results

Two mixed logit models with different variables were built to model the choices and to estimate the value of travel time when driving versus being driven. In both models, time, cost and intercept are defined as alternative-specific variables, with the intercept assumed to be normally distributed across respondents to control for the repeated choices by each respondent.

Being driverless/regular RHS, and mention/no-mention of multitasking are also defined as two dummy variables in both models: DriverlessRHS and MultitaskingMention. These capture the *average* difference in the utility of a ridehailing trip when it is specified as driverless, and when multitasking is explicitly mentioned, respectively. Model 2 also includes two additional variables as interaction terms: TimeDriverlessRHS (RHS travel time interacted with the dummy variable for driverless RHS) and TimeMultitaskingRHS (RHS travel time interacted with the dummy variable for the mention of multitasking). These capture how the *time-dependent* component of utility depends on the service being driverless and multitasking being mentioned. This allows us to investigate whether VoTT would change between driverless and regular RHS and whether reminding travelers of the multitasking possibility will make a difference in VoTT. These variables are built as the interaction of the travel time variable and the respective dummy variables for driverless and multitasking.

The model results are summarized in Table 3. For the intercept and the coefficients on cost and time, the estimated parameters from the two models are very similar. The mean intercept for RHS is negative in both models, which means that without anything else considered, driving a personal car is preferred over RHS. This is unsurprising, as driving is the most popular mode in the US. The standard deviation of the intercept shows that there is heterogeneity among respondents in the sample.

The cost parameter was employed as an alternative-specific parameter with a generic coefficient. The estimated coefficient for cost remains almost the same in the two models with negative signs. Travel time was also employed as an alternative-specific parameter but with different coefficients across alternatives. The coefficients for time are intuitively negative in both models, yet the absolute value of time coefficient for driving is larger, implying that travel time of driving affects travelers' choices more than that of RHS.

It is the estimated effects of driverless RHS and multitasking that differ between the two models. Model 1 indicates that if an RHS is driverless, the probability of people choosing it over driving will decrease (negative sign for the DriverlessRHS parameter), which may be due to the fact that driverless cars do not yet exist in the market and people are reluctant to give full control of the wheel to a computer. In Model 2, however, this parameter (DriverlessRHS) is not significantly different from zero.

The parameter of multitasking (associated with the RHS alternative) is found significant in both models with a positive sign, although the effect is smaller in Model 2. This signifies that pointing out the opportunity for multitasking and the ability to engage in other activities while riding affects people's stated mode choices.

In Model 2, the two additional variables of TimeDriverlessRHS and TimeMultitaskingRHS are considered. The coefficient of TimeDriverlessRHS is negative, meaning that if the RHS is driverless, the disutility of travel time riding an RHS ($-0.0536-0.0171=-0.0707$) becomes larger than the disutility of time spent driving oneself (-0.0620). The TimeMultitaskingRHS parameter, on the other hand, is found to be positive, indicating a decrease in the coefficient of travel time for RHS ($-0.0536+0.0200=-0.0336$) and consequently an increase in the RHS overall utility. This again implies that explicit mention of multitasking to respondents increases the probability of choosing RHS over driving and is in line with the results associated with MultitaskingMention parameter.

It is noteworthy that although Model 2 includes two additional, statistically significant predictors, the log-likelihoods of the two models are very close. According to the likelihood ratio test, Model 2 would not be preferred to Model 1 ($\chi^2=1.2$, n $=2$, $p>0.5$); this is also confirmed by the adjusted rho-squared values. What appears to be happening here is that a portion of the variance captured in the fixed effects in Model 1 (DriverlessRHS and MultitaskingMention) is being explained by the interaction terms (TimeDriverlessRHS and TimeMultitaskingRHS) in Model 2, as the fixed effects are reduced in magnitude. Although Model 2 does not significantly improve on the goodness of fit, it has an important

Table 3 Estimation results of mixed logit models

Variable name	Variable description	Model 1		Model 2	
		Coefficient	Significance level	Coefficient	Significance level
InterceptRHS	Alternative-specific constant (for RHS)	−0.8973	*	−0.8604	*
SdIntercept	Std. deviation of alternative-specific constant	−0.1169		−0.1124	
Cost	Travel cost ($)	−0.1517	***	−0.1516	***
Time drive	Personal car travel time (min)	−0.0619	***	−0.0620	***
Time RHS	RHS travel time (min)	−0.0516	***	−0.0536	**
Driverless RHS	(0: Regular; 1: Driverless)	−0.2282	*	0.1060	
Multitasking mention	(0: No mention; 1: Explicit mention of multitasking)	0.263	**	0.1289	**
Time driverless RHS	Driverless RHS * Time RHS	–		−0.0171	*
TimeMultitaskingRHS	MultitaskingMention * TimeRHS	–		0.0200	*
Log-likelihood		−1427.6		−1427.0	
Null model log-likelihood		−1623.4		−1623.4	
Rho-squared		0.1206		0.1210	
Adjusted rho-squared		0.1191		0.1190	
No. of observations		3012		3012	

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’

behavioral interpretation, namely that the VoTT is significantly affected by the RHS being driverless and by the explicit mention of multitasking opportunities.

It is also worth mentioning that we investigated (but do not report) several model specifications that included socio-demographic predictors. Including these predictors did not affect the estimated coefficients on time and cost, which is unsurprising since the choice scenarios were randomly assigned to respondents, ensuring that socio-demographic variables were uncorrelated with the variables of interest (cost and travel time). Moreover, including socio-demographic variables did not improve goodness of fit, and the estimated coefficients tended to be nonsensical. In light of this, and because the main focus of this study was to investigate the VoTT when driving versus being driven, we have reported here the simpler models omitting socio-demographic predictors.

Value of travel time (VoTT) results

Based on the estimated coefficients for travel time and cost parameters, the VoTT ($/h) can be calculated as stated in Eq. (5).

$$\text{VoTT} = \frac{\beta_{time}}{\beta_{cost}} * 60 \tag{5}$$

Table 4 presents the values found for VoTT, and since the coefficients of travel time vary across different travel modes, the VoTT are different for different travel modes. Note that the coefficient of travel time for driverless RHS in Model 2 will be the sum of coefficients for the TimeRHS and TimeDriverlessRHS parameters, or the sum of coefficients for the TimeRHS and TimeMultitaskingRHS parameters if multitasking was explicitly mentioned.

The lower VoTT of RHS compared with driving indicates that respondents will pay less for time savings with RHS than with driving, which makes sense because for most people the disutility of travel time is larger when driving than when being driven by others. This result is consistent between the two models.

The VoTT for driverless RHS (in Model 2) was found to be higher than that of regular RHS and driving. This result is counterintuitive, as in theory it is believed that being driven by others would decrease the VoTT. One possibility is that since AVs are not yet commercially available, people are not familiar enough with driverless cars and their stated choices today may not reflect choices they make in the future. Relatedly, since AVs are an unproven technology, respondents may be nervous about the idea of riding in them; letting the AV drive might create a state of anxiety that negates the multitasking benefit. This highlights

Table 4 The results of VoTT

Travel mode	VoTT ($/h)	
	Model 1	Model 2
Driving	24.47	24.47
RHS	20.53	21.32
Driverless RHS	–	28.03
RHS with explicit mention of multitasking	–	13.42

VoTT are presented in 2018 US Dollars

the importance of focusing on analogous modes such as regular RHS, which are less likely to generate biases through lack of familiarity.

Finally, it was shown that multitasking would increase VoTT, which is intuitive, because when people are able to engage in other activities during their commute trips, the disutility of travel time decreases for them and they are willing to pay less for time-savings.

Conclusion

A stated preference survey was implemented in this survey, with respondents choosing between a ridehailing service and a personal car. This allows identification of how being driven by others will affect the value of travel time compared to driving a personal car. Furthermore, we also considered the driverless RHS and additional influence in value of travel time by mentioning multitasking explicitly.

The lowest VoTT was found when multitasking was explicitly mentioned, suggesting that people's disutility of travel is lowest when they are aware of the opportunity to multitask. This is in line with theory and with findings from previous studies that found being able to multitask when traveling positively affects the utility of travel (Ian Wallis Associates Ltd. 2014; Malokin et al. 2015a, b). Overall, the results suggest that ridehailing services provide a 13% reduction in VoTT, but this grows to 45% when travelers are explicitly reminded of the ability to multitask. We caution that priming survey respondents to think about multitasking may bias them toward selecting the RHS option, leading to an overestimate of the effect of multitasking on VoTT. On the other hand, we suspect that given the low mode share of RHS today, survey respondents may neglect the benefits of multitasking when making choices in a stated preference setting, if they are not reminded of it. As such, it seems reasonable to conclude that the true VoTT effect would fall somewhere between the two extremes of 13% and 45%. This emphasizes that the perception of travel time would play an important role in the adoption and use of AVs that enable multitasking.

It was also found that respondents were significantly less likely to choose an RHS when it was identified as being driverless, and that their VoTT in a driverless RHS was actually higher than in a personal car. Although this is counterintuitive, similar results have been found in other studies (Yap et al. 2016; De Looff et al. 2018). This may reflect a current lack of familiarity and comfort with emerging driverless technologies. In the long run, if driverless technology proves to be reliable and safe, it is likely that people will come to perceive it more like a conventional ridehailing service, and the observed "driverless penalty" could be reduced or eliminated. Thus, the long term VoTT impact of AVs will likely be closer to the 13–45% reduction estimated for RHS, rather than the increase estimated when people are asked directly about AVs today. As such, researchers and practitioners should be careful about forecasting long-term demand impacts based on surveys that ask specifically about AVs, as estimates of demand growth in such surveys may be attenuated by the novelty of the technology.

This study was limited to the two modes of personal car and RHS, and only considered commute trips. A possible direction to extend this research is to also include other travel modes and other trip purposes in studying VoTT. Moreover, as shown by the results, since the automated driving technology is not currently available, people are not familiar enough with AVs and their perception of travel time in an AV may not be accurate. This could be improved by surveying a larger population and by providing respondents with a better explanation of automated driving technology (e.g. through sample videos) prior to the start of the survey.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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