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Estimation of the value of time for automated driving using revealed and stated preference methods

Viktoriya Kolarova[a,b*], Felix Steck[a], Rita Cyganski[a], Stefan Trommer[a]

[a]Institute of Transport Research, German Aerospace Center (DLR), Germany

[b]Humboldt-Universität zu Berlin, Geography Department, Germany

Abstract

In recent years the transportation system, and in particular road vehicles, are becoming increasingly automated and connected. Thus there is the expectation that in the near future there will be fully automated vehicles on roads. Support for road vehicles automation include increased safety, more efficient transport system, as well as increase of the comfort level and enabling users to do other activities while travelling. Especially the last two aspects might potentially change the way people perceive the time spent travelling by car and hence lead to a reduction of the value of time in terms of willingness to pay for saving travel time. Additionally, automation enables new mobility options and access to car use for people who are currently not able or not willing to drive. As a result, mode choice preferences and travel behaviour might change in favour of the individual motorized transport. Understanding these changes is crucial when predicting the impact of automation in the context of developing a sustainable and efficient future transportation system.

This study addresses the potential mode choice preference changes once automated driving becomes available. For this purpose, a stated choice experiment for currently available modes of transport and a second experiment on potentially future available alternatives were conducted. Two concepts of automated vehicles are considered – a privately owned vehicle and a vehicle on demand (i.e., a driverless taxi). This paper describes the survey design as well as the methodology used in the study and presents the first results of model estimations using simple multinomial logit for the analysis of the study data. The results suggest a potential reduction in the value of time for automated driving. Solutions for the integration of the results into a microscopic travel demand models as well as further analysis are discussed.

Keywords: value of time, automated driving, stated preference, stated choice, mode choice

* Corresponding author:
E-mail address: Viktoriya.Kolarova@dlr.de

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1. Introduction

In the recent years, due to increased digitalization and further technology development, road vehicles are becoming more technologically advanced with a continuing trend toward fully automated vehicles (Fagnant and Kockelman 2013). Experts expect that the technology might bring many benefits, amongst them increased safety on roads and less congestion, and might provide individual mobility to people currently not able or not willing to drive (Anderson et al. 2014; Trommer et al. 2016; Milakis, Arem and Wee 2017). One of the most discussed benefits for the users is that high-level automation will enable them to take their hands off the steering wheel and undertake other activities while traveling in a more comfortable way (Anderson et al. 2014; Fraedrich et al. 2016). Hence, the perception of the time spend travelling by car might become more positive and the value of time (VoT) in terms of willingness to pay for saving travel time might get lower. At the same time, high-level automation can provide new mobility options, such as automated vehicles on demand, which are similar to today´s car sharing or taxi services.

Having a reduction of VoT on the one hand and new mobility services on the other might potentially change mode choice preferences and travel behaviour. To understand how and to which extend automated driving will impact mobility is more and more relevant in light of urbanization, demographic trends, and environmental challenges. Results of recent studies suggest, for instance, an increase in vehicle miles travelled after introducing automated driving caused among other factors by VoT reduction and new mobility options (Childress et al. 2015; Gucwa 2014; Kröger, Kuhnimhof and Trommer 2016; Gruel and Standford 2016; OECD/ITF 2015). Hence, besides the discussed potentially positive effects of automated driving, there is also a risk that the technology might cause traffic-related issues instead of solving them. At the same time, the results of the studies mentioned above are based rather on plausible assumption and simulations than on empirical data. The question of how to address the topic in empirical works arises in order to be able to predict possible travel behaviour related changes caused by automated driving more accurately. Also, it is important to discuss how to integrate insight from empirical studies into travel demand models in order to scale up the results.

The remainder of this conference paper is structured as follows: In section 2, we introduce the concept of VoT providing a brief review of literature on empirical works on VoT in transportation. In section 3 we describe the design and analysis methods used in a study on the impact of automated driving on the VoT presented in this paper. In section 4 we present first study results and discuss how to integrate them in an existing travel demand model. Conclusions and next steps are summarized in the last section of this paper.

2. The concept of the value of time

In microscopic theory, the concept of VoT reflects in general the fact that individuals take transportation decisions under the assumption of a constrained daily time budget. Accordingly, people choose whether they spend their time rather on one activity than on another or how much would they be willing to pay for saving time spend in a particular activity (Hensher 2011). The subjective value of travel time savings is, along these lines, the willingness to pay for saving travel time (Jara-Diaz 2000).

There is a large body of theoretical and empirical works on the VoT for current available transportation modes. It shows that the valuation of travel time varies with respect to a variety of aspects, foremost on modes of transportation and trip purpose. For instance, empirical work on VoT found a higher value for commuting trips than for leisure or shopping trips (Abrantes and Wardman 2011; Shires and Jong 2009). Heterogeneous results were reported on mode specific differences in the value of time. Some studies found a higher VoT for using public transportation compared to VoT for riding in a car which might, among other factors, be attributed to lower comfort in public transportation. Other studies, however, found higher VoT for car users than for bus or train users (Abrantes and Wardman 2011). But even with the same means of transport, differences of time valuation can be identified: Following the results from a previous study, car passengers are found to have lower VoT than car drivers (Mackie et al. 2003).

The insights on VoT suggest that riding in an automated vehicle without driving task might change time perception by enabling people to travel as passenger similar to using a taxi or public transportation. However, empirical evidences are needed to estimate the perceived difference between travelling automatically in a private car compared to riding in a conventional private car or in a shared vehicle as well as to using other modes of transportation.

There are some empirical studies on VoT for automated driving which provide first insights on the influence of time and cost on mode choices in the context of automated driving and also estimate VoT for automated driving (Krueger, Rashidi and Rose 2016; Winter et al. 2017; Yap, Correira and Arem 2015). However, these studies focus only on shared automated vehicles and also do not consider any non-motorized modes of transportation. Furthermore, they address only future preferences, i.e. users´ preferences in a case where automated vehicles are already available on the market.

In summary, there is large body of empirical literature on VoT for current available modes of transportation and some first empirical studies on VoT for automated driving. However, we did not find any study which addresses current and future users´ preferences at once. At the same time, we suggest that only a comparison of both can provide conclusive insights on possible impacts of the technology on future mode choices.

For this reason, the aim of the study presented in this paper was to estimate the VoT changes for automated driving addressing users´ preferences under current and future conditions. In this paper, we introduce first study results but also discuss potential and challenges related to VoT estimation for new mobility concepts. Furthermore, we present a brief outlook on how to integrate the results into an existing microscopic transport demand model.

3. Materials and methods

3.1. Study design

To assess the factors influencing mode choices and estimate the VoT for automated driving we applied a similar approach as used in earlier studies combining revealed and stated preferences (Rose et al. 2005; Axhausen et al. 2014). The survey included additionally questions on general mobility behavior and socio-demographics as well as willingness to use and pay for an automated vehicle. The implementation of the survey as a web-based questionnaire was done by a professional external service provider. The study was carried out in March 2017 with an initial sample consisted of 511 participants.

The revealed preference part of the survey was dedicated to current mobility patterns of the participants. Each of the participants reported details on a commuting, leisure or shopping trip which he/she usually does. The trip was used as a personalized reference for creating an individual decision situation in the stated preference part of the survey by reducing or increasing the trip time and cost around the reported values.

The stated preferences part included two discrete choice experiments. Incorporating both experiments in one survey enabled us to estimate potential VoT changes in more detail by comparing the importance of different user and mode attributes for current and future choices. The first choice experiment addressed users´ mode choice preferences under current conditions for the reference trip. The respondents had to choose between the following (currently available) modes of transportation: walk, bicycle, car and public transportation. The second choice experiment examined users´ preferences in a situation where additionally automated vehicles were available for the same trip. In this experiment, the participant could choose between the same modes of transportation as in the first one, but instead of a conventional car a privately owned fully automated vehicle or the use of an (shared) automated taxi, which we called “driverless taxi”, were presented as options. The driverless taxi presented in the experiment could be used either as individual automated car sharing service similar to today´s taxi or car sharing services or as an automated ride sharing service. For the ride sharing service, people could share a trip (i.e. a ride) with other passengers with the same trip destination which had the advantage of lower cost per kilometer. In order to address the ride-sharing affinity of respondents, we added an additional attribute (“other passengers”) to the alternative driverless taxi which indicated whether the person would travel alone when choosing this alternative or he/she had to share the ride with other passengers.

Each of the two choice experiments consisted of 8 choice situations. The attributes for each alternative and the attributes´ levels used in the experiments are summarized in Table 1. In order to provide more realistic choice situations to the participants, we computed for each trip individual time and cost values using average speeds and rates for the German case.

The study was performed as an online survey using the software Sawtooth (Orme 2017). Figure 1 shows an example of a choice situation as implemented in the online questionnaire.

To enhance the design efficiency of both discrete choice experiments, we created a Bayesian efficient design using the software Ngene (ChoiceMetrics 2012). The optimization of the study design toward an efficient design is advisable in presence of prior information on the parameters´ values as it can reduce the standard error of the estimates (Bliemer and Rose 2006). The prior parameter values used for creating an efficient design for our survey were drawn from a pilot study with 30 participants.

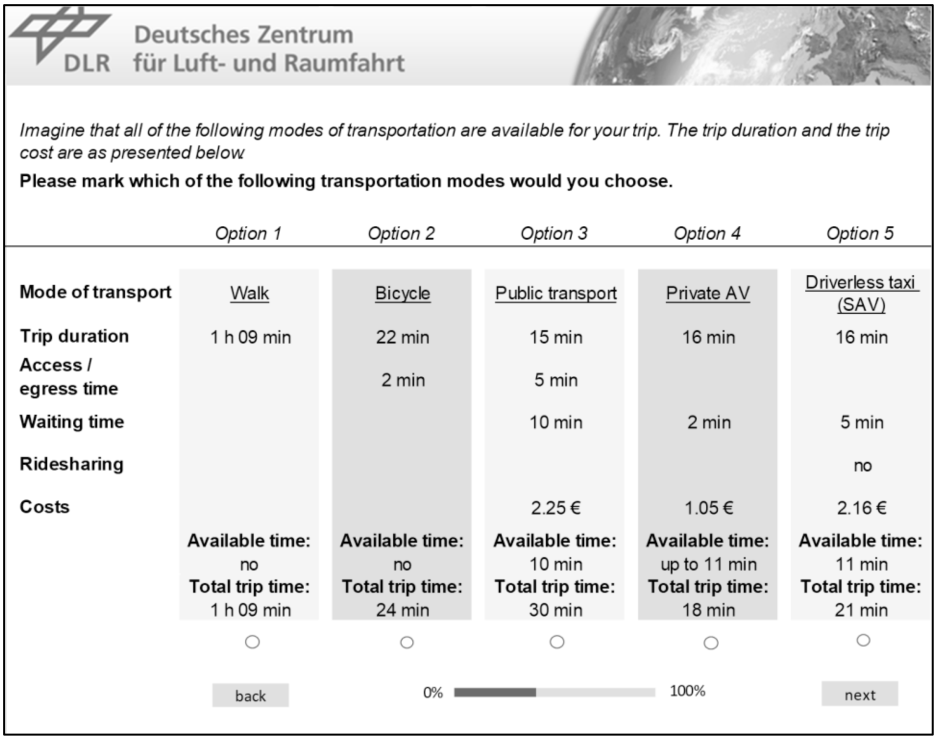
Table 1. Attributes and attributes´ levels.

Transportation mode	Attribute	Levels
Walk	Time	-30%|-10%|+20% reference time [speed: 4.9 km/h]
Bicycle	Time	-30%|-10%|+20% reference time [speed: 15 km/h]
	Access/ egress time	2 min. | 5 min.
Public transportation (PT)	Time	-30%|-10%|+20% reference time [speed: between 18-51 km/h, distance dependent estimation]
	Access/ egress time	2 min. | 5 min. | 10 min.
	Waiting Time	2 min. | 5 min. | 10 min.
	Cost	-30% | -10% | +20% current costs [between 1.5 and 6 euros, distance dependent estimation]
Private car	Time	-30%|-10%|+20% reference time [speed: between 26-68 km/h, distance dependent estimation]
	Access/ egress time	2 min. | 5 min.
	Cost	-30% | -10% | +20% current costs [0.20 euro Ct./km]
Private automated vehicle (AV)	Time	-30% | -10% | +20% reference time [speed: between 26-68 km/h, distance dependent estimation]
	Waiting time	2 min. | 5 min. | 10 min.
	Cost	-30%|-10%|+20% current costs [0.20 euro Ct./km]
Driverless taxi (SAV)	Time	-30% | -10% | +20% reference time [speed: between 26-68 km/h, distance dependent estimation]
	Waiting time	2 min. | 5 min. | 10 min.
	Other passengers	no, travelling alone | yes, the ride is shared with other passengers
	Cost	-30% | -10% | +20% current costs “riding alone” [0.30 euro Ct./km] -30% | -10% | +20% current costs “shared ride” [0.20 euro Ct./km]

Note: mode-specific speeds were estimated using the German National Travel Household Survey (DLR and Infas 2008); cost per km for the privately owned vehicles were drawn from ADAC (ADAC 2017); price per km for the shared automated vehicle followed existing analysis (Kröger and Kickhöfer 2017); cost for public transportation were drawn from existing rates for the public transportation system in Germany

3.2. Introduction of automated driving in the survey

Since automated driving is not yet available, it was important to provide a common understanding of the concept to the survey´s participants. In order to do this, two types of automated vehicles were introduced to the participants prior to the second choice experiment using animated videos. In the first video, a privately owned automated vehicle was introduced. In this video the main character, Ms. Schmidt, calls her private vehicle using an app on her phone, the vehicle picks her up, drives her to a pre-programmed destination, Ms. Schmidt gets out of the car, and the vehicle moves away to park itself.



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Imagine that all of the following modes of transportation are available for your trip. The trip duration and the trip cost are as presented below

Please mark which of the following transportation modes would you choose.

	Option 1	*Option 2*	*Option 3*	*Option 4*	*Option 5*
Mode of transport	Walk	Bicycle	Public transport	Private AV	Driverless taxi (SAV)
Trip duration	1 h 09 min	22 min	15 min	16 min	16 min
Access / egress time		2 min	5 min		
Waiting time			10 min	2 min	5 min
Ridesharing					no
Costs			2.25 €	1.05 €	2.16 €
	Available time: no **Total trip time:** 1 h 09 min	**Available time:** no **Total trip time:** 24 min	**Available time:** 10 min **Total trip time:** 30 min	**Available time:** up to 11 min **Total trip time:** 18 min	**Available time:** 11 min **Total trip time:** 21 min

back 0% 100% next

Figure 1: An example of future choice situation (English translation of the originally German questionnaire)

In the second video, the concept of an automated vehicle on demand, which combines taxi and car sharing concepts, was introduced. We called this concept “driverless taxi” in order to provide better understanding of the concept to the respondents. In this video, Ms. Schmidt orders a vehicle which drives her to her destination, drops her off and drives on to collect its next passenger(s). Main difference between the two presented concepts of automated driving was that users of the vehicle on demand could not drive the vehicle manually. The vehicle therefore had no steering wheel or brakes. In contrast to this, users of the privately owned vehicle could choose whether he/she wanted to drive manually or to switch on an automated driving mode. Selected scenes from the first video are depicted in Figure 2.

In both videos, the concept of automated driving was introduced as neutral as possible (without using evaluative adjectives) in order to avoid influencing the respondents´ perception of the technology.

Fig. 2 Scenes from video 1 (privately owned automated vehicle).

3.3. Study sample

The recruitment of the participants was done by extern service providers. By stratifying the sample by selected socio-economic characteristics, such as age, gender and resident location, the composition of the German population was represented in the best possible way for the sample size (see Table 2). Participants which gave implausible or incomplete answers were removed from the final data set, resulting in a final sample size of 485 respondents. The average duration of filling in the online questionnaire was 13 Minutes.

Table 2. Overview of sample´s characteristics compared to data for the German population.

Variable (values)	Study sample (N=485)	German population (DESTATIS 2017)
Gender		
female	53%	52%
male	47%	48%
Age (years)		
18-30	18%	18%
31-50	31%	31%
50+	51%	51%
Net income (Household)		
up to 1.500 € (low)	28%	31%
1.500€ – 3.000€ (mid)	42%	29%
more than 3.000€ (high)	30%	40%

The socio-economic characteristics of the study sample corresponded to the official population data of Germany from 2016 (DESTATIS 2017), especially with respect to gender and age. Solely persons of households with a high income level were underrepresented in our study sample probably due to the online panel recruitment.

Regarding the trip purpose and distance, the descriptive statistics show well balanced sample size across the trip purposes – commuting trips to work/education n=172, leisure trips n=142, shopping n=171. The reported commuting trips are with an average of 18.1 km (SD=17.5; median=14.5) longer than leisure (mean=10.7; SD=15.5; median=5.5) and shopping (mean=4.7; SD=6.7; median=3) trips. For all trip purposes, more than the half of the trips are made by car (commuting = 61%; leisure = 55%; shopping = 61%). The second most preferred mode of transport for commuting is the public transport (23%) and for leisure and shopping is walking (leisure = 20%; shopping = 31%) probably due to the short distances by the last two trip purposes.

3.4. Analysis method

For the analysis of the data we applied a multinomial logistic regression (MNL) (McFadden 1974) which is beside mixed logit approaches the most commonly used method for analysing discrete choice experiments in transportation (Bhat and Guo 2004). Choice experiments are based on the Random Utility Theory (Domencich and McFadden 1975; Ortuzar and Willumsen 2001) which assumes that an individual associates an utility with each alternative and chooses the alternative with the maximum utility. In the MNL an additive linearity is assumed and hence, the expected utility of an alternative is given by the following expression:

$$U_{n,i} = \beta_n X_{n,i} + \varepsilon_{n,i} \tag{1}$$

In equation 1 $X_{i,n}$ is a vector of explanatory variables relating to alternative i and person n that are observed by the analyst and β_n are the parameters which are to be estimated. These parameters can be seen as constant for all variables (in the MNL) or as varying over the population (in the mixed logit). The stochastic part of the utility function $\varepsilon_{i,n}$ is independent and identically distributed (i.i.d.) extreme value type 1. Under this condition the choice probability is a logit:

$$P_{n,i} = \frac{e^{\beta_i X_i}}{\sum_{j=1}^{J} e^{\beta_i X_i}} \quad (2)$$

In the first step of the analysis, we estimated two MNL models for current and future mode choice including only the attributes used in the experiment (time, cost, sharing level). In the second step, we included also individual mobility characteristics, such as possession of public transportation pass and driving´ license. Also, the effect of the trip purpose (commuting, shopping or leisure) on mode choices was examined. In the final estimated MNL models, only the statistically significant or only the relevant individual characteristics were included. All model estimations presented in this paper were performed using the software PhytonBiogeme (Bielaire 2003). Note that in this paper only first model estimation results using a simple MNL are presented.

4. Results and discussion

4.1. Model estimations

The results from the first model estimations including socio-economic as well as individual mobility characteristics showed, surprisingly, no significant effect of gender or age on preferences toward automated vehicles. Although some interrelation between age and use of non-motorized modes of transportation were found, we did not include the variable in the final model estimations since it did not play an important role by the explanation of the effect of automated driving.

Another part of the first model estimations was to examine the effect of the interaction between time elements and trip purpose on mode choices. The aim of the test was to found out whether the perception of in-vehicle time differs depending on the trip purpose. The MNL provided no plausible results. Thus, trip purpose was considered in the final estimated models as an independent variable without including any interaction of it with other variables.

The results of the two final MNL models for the current and future mode choice preferences are summarized in Table 3. The reference mode of transportation for mode-specific coefficients was under current conditions (in model 1) the private car, and when automated vehicles were available (in model 2) the private automated car. The following coefficients were part of the final estimated models:

ASC_i: Alternative-specific constant of alternative i

$\beta_{TIME,i}$: Travel time coefficient for alternative i

β_{WAIT}: Coefficient for waiting time; only relevant for public transportation, private automated vehicle and driverless taxi

β_{ACC}: Coefficient for access and egress time; only relevant for bicycle, public transportation and private car

$\beta_{COST,j}$: Travel cost coefficient for each income group j

β_{SHARED_RIDE}: Coefficient for the attribute "other passengers"; only relevant for the driverless taxi (reference: "travelling alone")

$\beta_{PURPOSE,i}$: Coefficient for trip purpose by mode of transportation i (reference: "commuting")

$\beta_{LICENSE,i}$: Coefficient for possession of driving license interacted with the alternative i

$\beta_{PT\_PASS,i}$: Coefficient for possession of public transportation pass interacted with the alternative i

Overall, the models´ results in table 3 were plausible in terms of expected signs and values of the parameters. Also, all for the estimation of VoT relevant parameters, such as time and cost, were statistically significant.

Regarding the perception of the time spent travelling by car, the models estimations showed that in-vehicle time in public transportation was perceived less negative than in a car in both decision situations - under current conditions (model 1) as well as when automated vehicles were available (model 2). However, the difference between the perception of the in-vehicle time in public transportation and in a car was in model 2 smaller than in model 1. This suggests that the time spent travelling in an automated vehicle was perceived more similar to public transportation than in a conventional one. Waiting and access/ egress time were perceived overall more negatively than in-vehicle time in motorized modes of transportation. In first model estimations within the presented study, differences in the perception of waiting time for public transportation compared to automated vehicles were found. For instance, the waiting time for automated vehicles was perceived as less negative than waiting time for public transportation. However, due to implausible values for the access/ egress time and in order to focus on in-vehicle VoT, the final estimations included coefficients for waiting and for access/egress time which were both not mode-specific.

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The cost parameters were estimated in both models depending on household income. As expected, there was a strong negative relationship between cost sensitivity and income. People having a higher household income perceived cost less negative than people with lower income.

When analysing the coefficients for the alternative driverless taxi, a preferences toward sharing a ride could be seen. Although the effect was not statistically significant, the observed tendency could be attributed to the lower cost for driverless taxi when sharing the ride compared to using the taxi alone.

As indicated in the literature review and the descriptive evaluation above, the trip purpose plays an important role for mode choices. Our analysis confirmed this influence in many respects. In the model estimations, we compared commuting trips to leisure and shopping trips. The results suggest that public transportation and/or bicycle were less preferred for shopping trips compared to car or – in case of model 2 – to privately owned automated vehicle. For leisure trips, however, motorized individual transport was perceived as a less attractive option than walking.

Analysing the effect of driving license possession on mode choice showed that having a driving license influenced the preference for walking or using public transportation negatively compared to using a privately owned (automated) vehicle in both models. While in model 1, possession of driving license influenced also the preference for bicycle negatively, the effect was not significant in model 2. Furthermore, in model 2, there was no significant effect of possessing a driving license on preferences for SAV. Possession of public transportation pass influenced mode choices as well. People holding a public transportation pass were more likely to walk, use a bicycle or use a public transportation than using a car. However, also for possession of public transportation pass no effect on the preference for SAV was found.

Estimating the determinants of current and future available transportation alternatives allows analysing the effect of automated driving on mode choices. In further analysis steps, the value of time in euro per hour for each mode of transportation can be computed using the estimated time and cost parameters. We used the following equation for computing the VoT:

$$\boldsymbol{VoT = \frac{\beta_{TIME,i}}{\beta_{COST,j}} * 60} \qquad (3)$$

Table 3 - Results of the two MNLs

	Model 1: MNL for users´ preferences toward current available modes of transportation		Model 2: MNL for users´ preferences when automated vehicles are available	
Variable	Est. value	t-value	Est. value	t-value
ASC_{WALK}	3.02	10.6	2.39	8.64
$ASC_{BICYCLE}$	0.742	3.09	*0.289*	*1.21*
ASC_{PT}	*0.224*	*0.79*	*-0.0104*	*-0.04*
$ASC_{DRIVERLESS\_TAXI}$	-	-	*-0.823*	*-0.273*
$\beta_{TIME,WALK}$	-0.0959	-22.51	-0.0918	-21.67
$\beta_{TIME,BICYCLE}$	-0.0705	-19.37	-0.0719	-20.91
$\beta_{TIME,PT}$	-0.0137	-3.3	-0.00981	-2.68
$\beta_{TIME,CAR}$	-0.0226	-3.61	-	-
$\beta_{TIME,PRIVATE\_AV}$	-	-	-0.0126	-2.57
$\beta_{TIME,DRIVERLESS\_TAXI}$	-	-	-0.0191	-3.37
β_{WAIT}	-0.0469	-2.49	-0.0536	-7.72
β_{ACC}	-0.0575	-6.83	-0.0339	-2.32
$\beta_{COST,LOW}$	-0.478	-8.15	-0.584	-10.78
$\beta_{COST,MIDDLE}$	-0.302	-6.26	-0.379	-9.50
$\beta_{COST,HIGH}$	-0.287	-6.52	-0.277	-7.87
β_{SHARED_RIDE}	-	-	*0.0944*	*0.91*
$\beta_{SHOPPING,WALK}$	*-0.259*	*-1.5*	*0.186*	*1.02*
$\beta_{SHOPPING, BICYCLE}$	-0.873	-7.06	-0.665	-5.51
$\beta_{SHOPPING,PT}$	-0.826	-4.23	-0.671	-3.68
$\beta_{SHOPPING,DRIVERLESS\_TAXI}$	-	-	-0.272	-1.94
$\beta_{LEISURE,WALK}$	0.635	3.44	0.776	3.94
$\beta_{LEISURE, BICYCLE}$	*-0.13*	*-1.06*	*-0.131*	*-1.06*
$\beta_{LEISURE,PT}$	*-0.118*	*-0.75*	*0.118*	*0.82*
$\beta_{LEISURE,DRIVERLESS\_TAXI}$	-	-	*0.248*	*1.89*
$\beta_{LICENSE,WALK}$	-2.11	-9.36	-1.40	-6.61
$\beta_{LICENSE, BICYCLE}$	-0.696	-3.27	*0.2623*	*1.27*
$\beta_{LICENSE,PT}$	-2.45	-11.25	-1.51	-7.58
$\beta_{LICENSE, DRIVERLESS\_TAXI}$	-	-	*-0.0901*	*-0.38*
$\beta_{PT\_PASS,WALK}$	1.48	10.26	0.757	5.25
$\beta_{PT\_PASS, BICYCLE}$	1.42	12.6	0.650	5.86
$\beta_{PT\_PASS,PT}$	2.31	16.93	1.27	9.88
$\beta_{PT\_PASS,DRIVERLESS\_TAXI}$	-	-	*0.00947*	*0.07*
Model Fit				
LL (null model)	-5378.82		-6244.62	
LL (final)	-3065.114		-4424.71	
Est. Parameters	24		31	
Observations	3380		3380	
Likelihood ratio test	32157.858		56295.825	

Note: Gray, italic values are not significant at a 95% - level (|t|>1.96)

4.2. Estimation of VoT and integration of the results in travel demand models

Table 4 summarized the values computed using the coefficients from the estimated models presented in table 3. As indicated above, the willingness to pay for travel time savings depends on the income class which respondents belongs to. VoT for automated vehicles – privately owned vehicle or vehicle on demand - were found to be lower than for conventional car.

However, more advanced data analysis is recommendable before estimating the final VoT for automated driving since it can improve the model fit and provides more accurate values. In particular, a mixed logit model is essential to consider heterogeneity within the population and the panel effect within the data (8 choice situations per person). Also, the estimated values, especially the VoT for public transportation, were overall lower than values from the literature. One reason for the lower values could be a possible non-linearity of time utilities. Analysis considering heterogeneity and non-linearity will be topic of future work and therefore there were not part of the results presented in this paper.

Table 4 - Value of time [in €/h]

	Low income [n=135]		Middle income [n=205]		High income [n=145]	
	model 1	model 2	model 1	model 2	model 1	model 2
Walk	12.04	9.43	19.05	14.53	20.05	19.88
Bicycle	8.85	7.39	14.01	11.38	14.74	15.57
Public transportation	1.72	1.01	2.72	1.55	2.86	2.12
Private car	2.84	-	4.49	-	4.72	-
Private AV	-	1.29	-	1.99	-	2.73
Driverless taxi	-	1.96	-	3.02	-	4.14
Waiting time	5.89	5.51	9.32	8.49	9.80	11.61
Access/ egress time	7.22	3.48	11.42	5.37	12.02	7.34

As discussed in the first part of this paper, integrating the results in transport demand models enables scaling-up the possible impact of automation on travel behaviour and allows for a detailed analysis of the implications for the transport system within the region of interest. While using parameter estimates from a mode choice model developed directly on a database collected for the analysis region is usually the most desirable way of integration new transport mode options into the model world, often simplified approaches have to be applied. This can, for instance, be the case when survey data for the analysis region is missing or – on the other extreme – the transport model has been set up with highly specialised data that cannot be provided by the stated choice experiments. Using the VoT-values derived directly can be a good approach in these cases, even though this might bear problems with respect to limitations in transferability of the parameter estimates. Also, as the potential of using in-vehicle time for alternative activities heavily depends on the duration of the trip, accounting for trip length when calculation VoT for the usage of automated vehicles seems therefor strongly advised. But changes in (perceived) travel time and travel time valuation are only some of the many aspects, which make integrating automated vehicles and especially the driverless taxi in transport models a challenging task. Reservations towards letting loose of the steering wheel or towards sharing a vehicle are only two examples of hindrances where the impact on mode adoption is currently hardly quantifiable and calling for enhancements in survey and experiment design.

5. Conclusions and outlook

The study presented in this paper aimed to estimate VoT for automated driving using revealed and stated preference methods. We proposed an approach that integrates two choice experiments in one survey addressing current and future users´ mode choice preferences. Also, a reported current trip was used as a reference for creating individual choice sets. Data was analyzed using simple multinomial logit model in order to proof the sign and effect of relevant parameters, and their integration into an existing travel demand model was discussed.

This paper presents first model estimation results. The results of the presented model estimations were plausible and in the expected range confirming the important role of time and cost elements by mode choices. Interestingly, gender and age were not found to influence preferences toward automated driving. At the same time, possible changes in the perception of time when driving automatically could be observed. Time spent riding in an automated vehicle was found to be perceived less negative than driving in a conventional car. Also, riding automated resembled riding in public transportation. Regarding differences between the two addressed concepts of automated driving – privately owned vehicle and vehicle available on demand – we found that privately owned vehicle was perceived as more attractive alternative than a shared vehicle. Future work need to be done to address users´ concerns related to the usage of vehicles on demand.

Overall, we believe that the analysis of possible effects of new mobility concepts, such as automated driving, on mode choices benefits from the integration of two choice experiments in the same survey. Important arguments for this is that using the same sample for the estimations of current and future users´ preferences allows direct comparison and quantification of possible changes. Also, using a reported trip as a base for creating individual choice sets allows introducing more realistic decision situations to the participant than using completely hypothetical one.

All study results have to be, however, interpreted acknowledging the limitations of stated choice approaches, especially in the context of an unknown and vague alternative. Bearing in mind potentially existing hypothetical bias is especially important when addressing alternatives such as the automated driving.

Moving a step further, we also briefly sketched ways to integrate the study results in existing travel demand models. Main challenges are seen particularly for the introduction of the new mode of transport of the driverless taxi. With many factors hindering or promoting usage lacking empirical foundation, there is surely challenging work for survey and experiment designers ahead. Experiences from currently ongoing work of different integration strategies in the agent based demand model TAPAS applied at DLR are discussed in upcoming contributions (e.g., Cyganski et al., 2018).

In the next steps of the analysis, applying more advanced data analysis methods can improve these first estimations. For instance, when using mixed logit model in a further estimation allows considering heterogeneity between the participants and solving some methodological limitation of the MNL. Also, the effect of decreasing time and/or cost utility depending on trip length should be analysed. Detailed analysis using mixed logit and final estimation of VoT for the automated driving use cases presented are reported in following works (e.g., Steck et al., 2018). Also, the estimation of a joint model including the current and future preferences has to be considered.

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