Working Paper

HOW AUTONOMOUS DRIVING MAY AFFECT THE VALUE OF TRAVEL TIME SAVINGS FOR COMMUTING

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ABSTRACT

Autonomous driving is being discussed as a promising solution for transportation-related issues and might bring some improvement for users of the system. For instance, especially high mileage commuters might compensate for some of their time spent travelling since they will be able to undertake other activities while going to work. At the same time, there are still many uncertainties and few empirical data on the impact of autonomous driving on mode choices.

This study addresses the impact of autonomous driving on value of travel time savings (VTTS) and mode choices for commuting trips using stated choice experiments. Two use cases were addressed – a privately owned and a shared autonomous vehicle – compared to other modes of transportation. The collected data were analyzed by performing a mixed logit model.

The results show that mode-related factors such as time elements, especially in-vehicle time and cost, play a crucial role for mode choices that include autonomous vehicles. The study provides empirical evidence that autonomous driving may lead to a reduction in the VTTS for commuting trips. We found that driving autonomously in a privately owned vehicle might reduce the VTTS by 31% compared to driving manually and is perceived similarly to in-vehicle time in public transportation. Also, riding in a shared autonomous vehicle is perceived 10% less negatively than driving manually. The study provides important insights on VTTS by autonomous driving for commuting trips and can be a base for future research to build upon.

Keywords: autonomous driving, value of travel time savings, commuting trips, discrete choice experiment, mixed logit

INTRODUCTION

Digitalization trends and rapid technology development have increased automation in all areas of daily life. Road vehicles are also becoming more technologically advanced in terms of automation with a continuing trend toward fully autonomous vehicles (Fagnant & Kockelman, 2015). There are high expectations placed on the technology, such as decreasing the number of road fatalities, reducing congestion, providing individual motorized mobility solutions to people currently not allowed or not able to drive, and to enable users to engage in other activities while driving (Anderson et al., 2014; Fagnant & Kockelman, 2015; Litman, 2014). Certain user groups might benefit more than others mainly depending on regular time spent travelling. This is especially the case for people, such as commuters, who routinely make long trips by car, have a limited time budget and hence mostly a high willingness-to-pay (WTP) for saving travel time.

Commuting trips make up only a third of all trips in Germany but play a crucial role in road traffic as they determine peak travel demand (DLR & Infas, 2008). In the past years, commuting trips in Germany remained unchanged in terms of trip length (57% are shorter than 10km), but increased slightly in terms of trip duration (22% take 30 to 60 min.; 4% increase) suggesting that more commuters are stuck in congestion on the way to and from work (Bundesamt, 2014). Heavy traffic conditions at peak hours suggest that extensive commuting is often felt to be an exhausting and tedious task. A recent study on the relationship between mode choice and commuting stress found that car drivers have the highest stress levels compared to users of other modes. Furthermore, time consumption was among the most important subjective stressors for commuters driving on a daily basis (Legrain, Eluru, & El-Geneidy, 2015). Hence, an important benefit of having the opportunity to ride autonomously for commuters might be that they can compensate time consumption for commuting by using the time in a more efficient or more pleasurable way (Fraedrich, Cyganski, Wolf, & Lenz, 2016; Trommer et al., 2016).

The range of activities that can be performed during a trip depends, however, on the degree of automation of the vehicle. Referring to the definition given by the Society of Automotive Engineers (SAE, 2014), only Level 4 (the system in charge, some driving use-cases) and Level 5 (the system in charge, all driving use-cases) achieve the degree of independence from driving tasks that allow drivers to completely dedicate their attention to alternative activities. Thus, this study deals only with those levels of automation.

High-level automation will also enable new mobility services such as vehicles on demand either as individual ´autonomous carsharing´ service (ACS) similar to today's carsharing and taxi services or as ´autonomous ride sharing´ (ARS), when pooling different trips together similar to uberPOOL[1]. ARS services are expected to exhibit lower costs per mile at somewhat higher waiting times compared to ACS (Kröger & Kickhöfer, 2017). These services could complement traditional public transport (e.g. solving the first/last mile problem) or act as a substitute where it is deficient today (BCG, 2016; Ohnemus & Perl, 2016; Yap, Correia, &

[1] Services like uberPOOL (https://www.uber.com/nyc-riders/products/uberpool) do not exist in today´s mobility market in Germany

Arem, 2015). From a user perspective these services could allow true door-to-door trips for individuals not having access to a car today (Burns, Jordon, & Scarborough, 2013).

In summary, it can be expected that the car – be it privately owned or a shared vehicle – will become more attractive and, at the same time, available to broader user groups. This would lead to rebound effects, resulting in more vehicles on the road, more congestion and/or more vehicle miles traveled (Bahamonde-Birke, Kickhöfer, Heinrichs, & Kuhnimhof, 2017; Gruel & Standford, 2016; OECD/ITF&CPB, 2015). Predicting changes in travel behavior and the traffic situation today is hard to do, but is more and more relevant in light of uncertainties about the future of mobility against the background of urbanization, demographic trends, and environmental challenges.

The aim of this paper is to analyze how autonomous driving may change mode choices for commuting trips. For this purpose, two different concepts of autonomous driving are considered. The first use case is privately owned autonomous vehicles (AVs) able to drive autonomously but with the option of switching off the autopilot. The second use case is shared autonomous vehicle (SAVs), which combines (Uber-like) the concepts of taxi and carsharing, where people can use a vehicle on demand. The results of the study should provide empirical insights on future modal choice preferences for commuting trips.

LITERATURE REVIEW

The concept of value of travel time savings (VTTS) plays a crucial role in theoretical and empirical literature in transportation research. In accordance with the microeconomic theory, individuals are supposed to take transportation decisions under the assumption that the daily time budget is constrained. Hence, people choose whether they spend their time in one activity compared to another or how much are they willing to pay to save the time spent in one particular activity (Hensher, 2011). The subjective VTTS can be defined, therefore, as the willingness-to-pay to reduce the travel time (Jara-Diaz, 2000). VTTS usually depends on trip purpose and trip length and differs between modes of transportation. Studies on VTTS estimated higher values for commuting trips than for leisure or shopping trips (Abrantes & Wardman, 2011; Shires & Jong, 2009). Also, the VTTS for commuting by car are in some studies lower but in other higher than for public transportation and car passengers tend to have a lower VTTS compared to car drivers (Abrantes & Wardman, 2011; Mackie et al., 2003; Shires & Jong, 2009). Furthermore, various empirical studies found that the VTTS of business travelers and commuters is higher in congestion than in free-flowing traffic (Abrantes & Wardman, 2011; Hensher, 2011; Rizzi, Limonado, & Steimetz, 2012). This suggests that even lower levels of automation might provide benefits for car users, for instance by enabling automated stop-and-go functions in dense traffic. Furthermore, it can be assumed that autonomous driving may potentially reduce VTTS for commuting trips in terms of perceiving the travel time less negatively.

Lately, a significant body of literature has addressed the possible impact of AVs on travel behavior (Childress, Nichols, Charlton, & Coe, 2015; Gucwa, 2014; Trommer et al., 2016). However, given the lack of empirical studies, potential reductions in VTTS are usually considered on the basis of plausible assumptions.

Filling this research gap is, however, a difficult task, as AVs are not currently available, so there is no existing behavioral data. Alternatively, it is possible to rely on stated preferences, but, in this case, respondents' lack of experience can affect the reliability of the results. Thus, it is advisable to center the analysis on high-level features, while acknowledging the limitations of the technique. Hence, while attempting a detailed analysis of ground-breaking mobility options may prove difficult, focusing the analysis on potential reductions in the VTTS appears as a more plausible task for respondents. As far as we know, only a few stated-choice studies addressing this topic have been conducted to date.

Yap et al. (Yap et al., 2015) address the use case of SAVs as egress transport for first/last mile trips in multimodal train trips considering time and costs for the trip as well as sharing levels (carsharing and ridesharing). The results of the study suggest that first/last mile AVs can be attractive, especially for first class train travelers. Furthermore, the sensitivity of users for in-vehicle time is higher in autonomous compared to manually driven vehicles, resulting in higher VTTS, which the authors attribute to attitudinal and perceptual concerns toward the technology. Along these lines, the results by Winter et al. (Winter, Cats, Martens, & Arem, 2016) show strong differences between early and late adopters (with a clear preference for SAVs in the early adopters group) in the context of modal-choice, while including an SAV alternative. The results of Krueger et al. (Krueger, Rashidi, & Rose, 2016) on the adoption of SAVs show a similar trend. The authors found a strong impact of service attributed including travel time, waiting time and fares as well as significant effects of individual-specific charactersistics, such as age and individual's modality style on mode choices.

All three studies, while providing initial empirical insights on user preferences regarding AVs, focus on the introduction of SAVs as an alternative to current modes of transportation. In doing so, they ignore non-motorized alternatives, such as walking or cycling, but also the option of privately owned AVs. Hence, we cannot gain from these studies insights on the willingness to use privately owned AVs compared to SAVs.

Some recent studies also address user preferences toward privately owned AVs. However, these studies focus on the impact of autonomous driving on car ownership or possession of a public transportation pass. Becker & Axhausen (Becker & Axhausen, 2017) used a stated choices approach to assess the impact of SAVs and privately owned AVs on mode choices. Their pilot study with 62 participants suggests a decrease in car ownership rate by introducing autonomous driving, especially as a sharing service. Another stated-choice study on impact of AVs for commuting trips found that, besides cost, various attitudinal variables, such as technology interest and enjoyment of driving, influence the user preferences toward the technology (Haboucha, Ishaq, & Shiftan, 2017). However, the study focuses more on long-term choice decisions than on influencing factors on trip mode choices.

In summary, we did not find any study focusing on the evolution of the VTTS related to the introduction of AVs, nor studies addressing both privately owned AVs and SAVs simultaneously, and compared to all other relevant modes of transportation.

METHODS

Study Design

In order to address the research questions, an online survey was conducted using a questionnaire with the following structure: questions on existing mobility behavior, questions on the commuting trip the person usually takes (i.e. reference trip), short introduction to the concept of autonomous driving, a discrete choice experiment (DCE), questions on willingness to purchase and pay for AVs as well as socio-demographics.

The study design was based on an earlier methodological approach which combines revealed and stated preference data (Axhausen, 2014; Rose, Bliemer, Hensher, & Collins, 2005). In the revealed preference part of the questionnaire, the respondents were asked to describe a recent trip. In the stated choice experiments, hypothetical mode choice situations for the same trip were constructed using the individual trip length of the respondents. In each choice situation, the time and the cost for the trip were reduced or increased around reference values using estimated average speeds and cost for each mode of transportation. The choice experiment consisted of eight choice situations in which the respondents had to choose between one of the following five transportation options: walk, bike, public transportation, privately owned AV and an SAV. The SAV was called "driverless taxi" in order to provide a better understanding of the concept to the participants. The attributes and their levels used in the experiments are summarized in Table 1. It was assumed that an AV drives up to users, drops them off and finds a parking spot by itself. Hence, access and egress time for the autonomous vehicles were excluded as attributes and waiting time was considered.

Table 1: Attributes and attributes´ levels

Transport mode	Attribute	Levels
Walk	Time	-30%|-10%|+20% reference Time [Speed: 4.9 km/h]
Bike	Time	-30%|-10%|+20% reference Time [Speed: 15 km/h]
	Access Time	2 Min. | 5 Min.
Autonomous vehicle (AV)	Time	-30%|-10%|+20% reference Time [Speed: between 26-68 km/h, distance dependant]
	Waiting Time	2 Min. | 5 Min. | 10 Min.
	Cost	-30%|-10%|+20% current costs [0.20 euro ct./km]
Shared autonomous vehicle (SAV)	Time	-30%|-10%|+20% reference time [Speed: between 26-68 km/h, distance dependant]
	Waiting Time	2 Min. | 5 Min. | 10 Min.
	Other passengers	alone / other passengers
	Cost	-30%|-10%|+20% reference costs "alone" [0.20 euro/km] -30%|-10%|+20% reference costs "other passangers" [0.20 euro/km]
Public Transportation	Time	-30%|-10%|+20% reference time [Speed: between 18-51 km/h, distance dependant]
	Access 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 dependant]

In order to present realistic alternatives to the study participants, we used ´average speeds´ and ´cost per transportation mode´ for the German case. Average speeds were estimated using the German National Household Travel Survey from 2008, called MiD 2008 (DLR & Infas, 2008). The costs per kilometer for the private car were drawn from ADAC (ADAC, 2017). Only fuel and maintenance cost were taken into account. Cost related to the purchase of the vehicle or parking cost were not considered. The kilometer price for the shared autonomous vehicles followed existing analysis (Kröger & Kickhöfer, 2017). The cost for public transportation was drawn from existing rates for public transportation systems in Germany. We used fixed cost for different distance classes with a minimal price of 1.50 euro. Season, annual or student tickets for public transportation were not considered.

In order to enhance the data quality of the experiments by maximizing the information obtained from each choice situation, we created a Bayesian efficient design using the software Ngene (ChoiceMetrics, 2012). Efficient design is recommendable when some initial information about the value of the parameters is available prior to the field test, as it can improve the design significantly and reduce the standard error (Bliemer & Rose, 2006). In our study, the prior values for the estimation of the efficient design were drawn from a pilot study with 30 respondents. The design was optimized for short and medium/long trips in order to consider the effect of trip distance on trip and mode related attributes.

Introduction of the concept of autonomous driving

The two concepts of autonomous driving privately owned and shared AVs were presented to the study participants in two short animated videos before the choice experiment. In the first video the main character, Ms. Schmidt, calls her vehicle using an app on her phone, rides to her pre-programmed destination, gets out of the car as she arrives and the vehicle drives further autonomously and parks itself. In the second video, the concept of an SAV is introduced. It is shown that one can order the vehicle, ride autonomously to one's destination, get out of the car and the vehicle drives on to collect its next passenger(s). The main difference between the two introduced concepts was that, in the privately owned vehicle, there is an option to switch off the autopilot. In the SAV there were no steering wheel and brakes, it could not be driven manually. The two concepts were presented as neutrally as possible (without using evaluative adjectives) in order to influence the preferences toward autonomous driving as little as possible.

To find out if respondents prefer to drive their hypothetical privately owned vehicles autonomously or manually, we added an additional question with a Likert scale related to this preference after the choice experiment. Based on the responses, two dichotomous variables were created which indicate whether they prefer to use their privately owned vehicles autonomously or use them manually.

Implementation and Sample

For the online implementation of the questionnaire including the choice experiment the software Sawtooth was used. Survey participants were recruited using a professional panel service. A sample of 485 respondents representative for Germany by age and gender was recruited. The sample included car users as well as non-car users and was limited to participants older than 18. The duration of filling in the online survey was 13 minutes on average. The respondents were randomly selected to provide information about one of three different trip types - commuting trips, shopping trips and leisure trips. However, in this paper a reduced sample size of 172 respondents was used since the rest of the sample reported other trips than commuting.

A comparison between the reported commuting trips of our sample and commuting trips from the German national travel survey MiD 2008 (DLR & Infas, 2008) shows that the key parameters are largely similar (see Table 2). A critical point is the overrepresented public transport use and by contrast, the underrepresented car use in our sample. The mode-specific distances and times of commuting trips fit quite well. However, using trip length and trip duration as reference parameters of the presented choice experiments the existing data seem to be suitable.

Table 2: Comparison of the commuting trips between the German National Travel Survey MiD 2008 (DLR & Infas, 2008) and the study sample

	Walk	Bicycle	Car	Public Transport	Mean
			German National Travel Survey		
Modal split (in %)	7	10	70	12	-
Commuting time (in min.)	11	15	26	53	27
Commuting distance (in km)	0.9	3.5	20.0	25.8	17.7
			Study sample		
Modal split (in %)	9	8	60	23	-
Commuting time (in min.)	17	14	24	46	27
Commuting distance (in km)	2.0	3.8	19.7	25.2	18.1

Analysis method

The most common alternatives in mode choice with multiple alternatives are the multinomial logit (MNL) and the more advanced mixed logit (ML) models (Hensher & Greene, 2002). The MNL model developed and described by McFadden (McFadden, 1974) estimates the probability of each individual *n* selecting alternative *i*. Here it is assumed that *n* assigns a given utility to every alternative *i* in the sampling, opting for the alternative that maximizes the expected utility. Asuming additive linearity, the expected utility is given by the following expression:

$$U_{n,i} = \beta_n X_{n,i} + \varepsilon_{n,i} \quad (1)$$

$X_{n,i}$ is a vector of explanatory variables including attributes of the alternatives as well as socio-economic characteristics of the respondent, and β_i are parameters to be estimated. The error term $\varepsilon_{n,i}$ repreesents a stochastic component, accounting for all relevant attributes that are ignored by the modeler. An MNL imposes the condition that $\varepsilon_{n,i}$ follows an independent and identically (iid) extreme value type 1 distribution (McFadden, 1974). However (and because of the restriction imposed upon the distribution of the stochastic elements), the MNL does not allow considering heteregoneity among respondents nor capturing the panel nature of our data. Thus, we rely on an ML to relax the assumptions that the coefficients are the same for all individuals (Algers, Bergström, Dahlberg, & Dillen, 1998; Train, 2002) and to allow correlation across choice situations (Hensher & Greene, 2002; Revelt & Train, 1997). The utility function of an ML with panel data extends equation (2) as followed:

$$U_{n,i,t} = bX_{n,i,t} + \eta_n X_{n,i,t} + \varepsilon_{n,i} \quad (2)$$

Here, the coefficient vector β_i from equation (1) is expressed as $b_i + \eta_n$. In this framework, b_i accounts for the population mean and η_n is a random term following a distribution to be established by the analysis with a given mean (normally zero) and denstity to be estimated. This allows accounting for different valuations of $X_{n,i}$ across individuals. *t* represents the different choice situations a given individual *n* is confronted with, and therefore $b_i + \eta_n$ is not assumed to vary across different choice sitatuions *t*, taking the panel effect into account (i.e. the valuation of the attibutes remain constant for all observations associated with the same individual). The ML probabilities of choosing given alternative *i* is, consequently, a weighted mean of the MNL probabilities at a specific η, weighted over thedistribution of η.

$$P_{n,i} = \int L_{n,i}(b, \eta) f(\eta)\, d\eta \qquad (3)$$

In (3) the choice probability $L_{n,i}$ respresents the MNL probabilities for a given value of η. Due to the fact that an individual is faced with *t* choice situations, the probability of observing a given sequence of choices is given by the following expression:

$$L_{n,i}(\Omega) = \prod_{t=1}^{T} \left(\frac{e^{\beta x_i}}{\sum_{j=1}^{J} e^{\beta x_j}} \right) \qquad (4)$$

Model specification

To obtain the final model specification, an iterative procedure was used. In the first step of the analysis, an MNL was estimated only considering time and cost parameters. Afterwards, socio-economic variables were introduced (solely siginificant socioeconomic variables were finally part of the models). The final specification of the model considers the following explanatory variables:

TT_i: travel time of mode i (in minutes)

TC_i: travel cost of mode i (in €)

SR: dummy for shared ride for driverless taxi

MAN: dummy for individual who prefers driving PAV manually

AUT: dummy for individual who prefers driving PAV autonomously

LH: dummy for license holder

AGE^{middle}: dummy for middle aged individual (between 30 and 50 years old)

AT_i: access and egress time for mode i (in minutes)

WT^i: waiting time for mode i (in minutes)

INC: dummy for income class (low: up to 1.500 euros, middle: 1.500-3.000 euros, high: more than 3.000 euros)

MALE: dummy for male gender

All explanatory variables are assumed to have a linear additive impact on the utility functions, although not all of them affect the utility of all alternatives. Furthermore, it is assumed that the alternative-specific constants (ASC) and the valuation of the generalized travel time (see below) exhibit stochastic variations across individuals. The distribution of the β_i associated with the ASC and the generalized travel time is assumed to be normally distributed. The $\boldsymbol{\beta}$ parameter associated with the cost of the alternatives is assumed to exhibit variation among income classes.

In order to consider a decreasing marginal utility of time and costs on mode choices, we use a Box-Cox transformation (Box & Cox, 1964). From a behavioral standpoint, this might - especially in the case of commuting trips – provide important insights on time perception and VTTS depending on travel distance. The considered transformations are depicted in equation (5).

$$\beta_{Time,i} \cdot \frac{(TT_i + \beta_{Acc} \cdot AT_i + \beta_{Wait} \cdot WT_i)^{\lambda_{Time}} - 1}{\lambda_{Time}} \quad \text{and} \quad \beta_{\mathrm{Cos}t} \cdot \frac{(TC_i)^{\lambda_{\mathrm{Cos}t}} - 1}{\lambda_{\mathrm{Cos}t}} \qquad (5)$$

Here, the expression considered in association with the time parameter represents the generalized travel time, which takes into account that access and waiting time are perceived differently from in-vehicle travel time. Here, β_{Acc} and β_{Wait} are also parameters to be estimated, which also exhibit variability across individuals. However, in contrast to β_{Time}, the distribution of β_{Acc} and β_{Wait} is considered to be uniform, in order to avoid problems with negative values inside the Box-Cox transformation.

Finally, two ML models were estimated; one of those did not consider non-linearity, whereas the other one considered the Box-Cox transformation. As previously mentioned, parameter variability across individuals were only considered for time-related variables (i.e., travel time, access and egress time and waiting time) and the ASCs. The estimation of the models was preformed using PythonBiogeme (Bielaire, 2003). The distributions of the random parameters were simulated by using 5,000 MLHS draws (Hess, Train, & Polak, 2006).

RESULTS

Estimated model coefficients

The results of the two final estimated ML models are summarized in Table 3. In general, the coefficients exhibit the expected signs and plausible values. We obtain a significantly better model fit by modeling possible non-linearity for the time and cost parameters (χ^2 (2, N=172)=9.65, p<.01). Hence, our results confirm the existence of decreasing marginal utilities.

Table 3: Results of the two mixed logit model estimation

	Model 1: Mixed logit		Model 2: Mixed logit with a Box-Cox transformation for time and cost	
Coefficient	**Estimated Value**	**t-value**	**Estimated Value**	**t-value**
ASC_{PED}	11.9	(4.02)	14.6	(4.75)
ASC_{BIKE}	4.42	(4.62)	8.25	(4.32)
ASC_{PT}	-3.39	(-3.27)	-2.68	(-2.07)
ASC_{SAV}	-1.74	(-2.89)	-1.62	(-2.29)
$\eta_{\_PED}$	0.857	(0.71)	-0.372	(-0.35)
$\eta_{\_BIKE}$	3.64	(5.86)	3.53	(5.73)
$\eta_{\_PT}$	2.81	(3.35)	2.25	(2.92)
$\eta_{\_AV}$	1.38	(2.88)	-0.559	(-0.82)
$\eta_{\_SAV}$	-1.65	(-4.01)	-1.83	(-5.08)
β_{TIME_PED}	-0.423	(-4.56)	-1.31	(-1.87)
$\eta_{\_TIME\_PED}$	-0.168	(-4.34)	-0.292	(-2.34)
β_{TIME_BIKE}	-0.314	(-7.51)	-1.35	(-1.90)
$\eta_{\_TIME\_BIKE}$	-0.116	(-5.51)	-0.394	(-2.45)
β_{TIME_PT}	-0.0825	(-3.60)	-0.402	(-1.62)
$\eta_{\_TIME\_PT}$	0.0703	(4.19)	0.254	(2.12)
$\beta_{TIME\_AV\_AUTONOM}$	-0.0784	(-3.69)	-0.307	(-1.65)
$\eta_{\_TIME\_AV\_AUTONOM}$	0.062	(2.48)	0.213	(2.17)
$\beta_{TIME\_AV\_MANUAL}$	-0.114	(-5.84)	-0.442	(-1.93)
$\eta_{\_TIME\_AV\_MANUAL}$	-0.0355	(-1.66)	-0.109	(-1.76)
β_{TIME_SAV}	-0.102	(-4.68)	-0.403	(-1.84)
$\eta_{\_TIME\_SAV}$	0.0183	(0.80)	0.0324	(0.51)
$\beta_{WAIT\ (uniform\text{-}bottom)}$	1.08	(3.83)	1.01	(4.05)
$\eta_{\_WAIT\ (uniform\text{-}top)}$	3.28	(3.82)*	2.12	(4.45)*
β_{ACC}	1.08	(3.22)	1.07	(3.97)
$\beta_{COST\_LOW\_INC}$	-1.14	(-5.72)	-1.52	(-4.49)
$\beta_{COST\_MID\_INC}$	-0.947	(-6.1)	-1.24	(-3.54)
$\beta_{COST\_HIGH\_INC}$	-0.543	(-5.61)	-0.79	(-3.24)
β_{SHARED}	0.0191	(0.07)	-0.033	(-0.13)
λ_{COST}	-	-	0.787	(5.89)
λ_{TIME}	-	-	0.566	(3.50)
β_{PT_CARD}	1.43	(1.71)	1.98	(2.54)
$\beta_{LICENCE\_PED}$	-4.74	(-2.22)	-4.6	(-2.91)
$\beta_{MID\_AGE\_PED}$	-4.14	(-2.70)	-4.11	(-3.62)
$\beta_{MID\_AGE\_BIKE}$	-3.27	(-3.09)	-3.62	(-3.40)
Model Fit				
Log-likelihood (final)	-948.011		-943.187	
Estimated Parameters	32		34	
Observations	1376		1376	

*The t-values are referred to the bottom level of the uniform distribution.

Overall, the results show that cost and travel time elements influence mode choices significantly, both having an expected negative impact. The coefficients in Model 2 are higher than in Model 1 but have similar relations to eachother, suggesting stable tendencies.

The generalized time coefficients show differences between the modes. Travel time in privately owned AVs is perceived less negatively by people using the automation function on commuting trips compared to people driving manually. The accros-population variability of the estimated coefficients suggests a wider heterogeneity among driving AVs automatically than manually. Also, riding autonomously to work is perceived less negatively than the travel time of any of the other available motorized alternatives. However, the differences are not statistically significant.

When considering the ASCs, the general preference for SAVs is significantly lower compared to privately owned vehicles; however the mode is more attractive than public transportation. At the same time, looking at the travel time coefficients suggests that riding autonomously in an SAV is perceived less negatively than driving, but is less attractive than riding autonomously with a privately owned vehicle.

However, a comparison between the modes is only possible when considering all time elements, including waiting and access/egress time. The coefficients for these two time elements were estimated in relation to in-vehicle time. While there are no major differences between acces and in-vehicle travel time (access tiem is perceived as slightly more negative), waiting time is perceived 2.12 to 3.28 times more negatively (depending on the model) than the in-vehicle time.

Furthermore, as expected, there is a relationship between cost sensitivity and household income. People with low income are more cost-sensitive, perceiving travel cost more negativily than people with middle or high income. This is reflected in the WTP differences described in the following section.

The analysis of the perception of autonomous carsharing compared to autonomous ridesharing (represented throught β_{SHARED}) did not provide any statiscally significant evidence on whether people would prefer to share a ride with others or to ride alone in an SAV. This suggests a smaller role of the sharing aspect compared to other factors.

Regarding the impact of socio-demographic factors, we included in the final model only the variables found to exhibit a stattiscally significant effect. We found no significant effect of gender on mode preferences in the final estimations. Regarding age, the analysis shows that middle-aged people (between 30 and 50 years old) are less inclined to walk or cycle to work than younger or older people. Possession of a public transportation pass influences preferences for that mode positively. Furthermore, people who possess a driver's license are less inclined to walk to work. We did not find any socio-economic varaibles which were directly related to preferences toward autonomous vehicles.

Estimation of VTTS

As previously mentioned the main objective of the analysis is to establish the differences among the valuation of the travel time savings depending on transportation mode, when AVs are available. This allows us to establish to which extent relieving the users from the driving task may impact the time perception.

Establishing the VTTS is straightforward for Model 1, as we consider constant marginal utilities of both travel time and costs, so that the VTTS can be established in accordance with the following expression:

$$VTTS = \frac{\partial U_i / \partial TT_i}{\partial U_i / \partial TC_i} = \frac{\beta_{Time,i}}{\beta_{Cost,n}} \tag{6}$$

For Model 2, considering decreasing marginal utilities for both travel time and cost, the VTTS depends on the actual travel time and cost experienced by the user, as in the following expression:

$$VTTS = \frac{\partial U_i / \partial TT_i}{\partial U_i / \partial TC_i} = \frac{\beta_{Time,i} \cdot (TT_i + \beta_{Acc} \cdot AT_i + \beta_{Wait} \cdot WT_i)^{\lambda_{Time}-1}}{\beta_{Cost,n} \cdot (TC_i)^{\lambda_{Cost}-1}} \tag{7}$$

Therefore, it is only possible to calculate an average for the considered population. Furthermore, as the marginal utility of the price depends on the actual cost, the VTTS would exhibit slight variation (<5% in our case) depending on alternative used as reference. In this work, we have considered the marginal utility of the cost of SAVs as the reference to establish the VTTS. The estimated values are summarized in Table 3.

Table 4: Estimated VTTS for different modes of transportation and income classes (in euro/hour)

	Walk	Bike	Public transport	AV autonomously	AV manually	SAV
Model 1: Mixed logit						
Low income	22.26	16.53	4.34	4.13	6.00	5.37
Middle income	26.80	19.89	5.23	4.97	7.22	6.46
High income	46.74	34.70	9.12	8.66	12.60	11.27
Model 2: Mixed logit with a Box-Cox transformation for time and cost						
Low income	8.88	13.41	3.93	3.74	5.39	4.85
Middle Income	10.88	16.44	4.81	4.59	6.60	5.94
High Income	17.08	25.88	7.56	7.20	10.36	9.32

The results for the VTTS reflect the results from the estimations presented above. People with a high income have a higher willingness-to-pay for saving commuting travel time. Here, again, the VTTS for people who prefer autonomously driving privately owned AVs is lower than the VTTS of people driving manually by 31% in both models. It reflects the perceived benefits of relieving the user from driving tasks and allowing them to dedicate their attention to activities deemed as more meaningful. The VTTS for driving autonomously is in the range of VTTS for in-vehicle time in public transportation, suggesting a similar perception for both modes of transportation. However, it does not include waiting and access/egress time, which can be, as estimated above, up to 2 or 3 times more negative than in-vehicle time (this phenomenon negatively affects the perception of public transportation). At the same time, the VTTS for SAVs is slightly higher than autonomously driven vehicles and public transportation, but still 10% lower than for driving a car by oneself. Hence, using an SAV may be deemed more attractive than driving manually to work (although relying on SAVs may also involve waiting time).

CONCLUSIONS

The main aim of this study was to analyze how autonomous driving may affect the subjective value of travel time savings for commuting trips. For this purpose, a discrete choice experiment was conducted and the data were analyzed using a mixed logit model.

First, the results provide empirical evidence supporting the assumption that autonomous driving will potentially reduce the VTTS for commuting trips, i.e. it will be an attractive function for people making regular commuting trips. Moreover, the VTTS for two different possible uses of autonomous driving, namely privately owned AVs and SAVs, were estimated for different income classes and contrasted with alternative modes of transportation. Our results suggest that driving autonomously leads to a reduction of 31% in the VTTS compared with driving manually, and is perceived similarly to the VTTS of in-vehicle time in public transportation (waiting and access/egress time is perceived more negatively in public transportation).

Second, when considering the preferences toward SAVs, we found that travel time spent in SAVs is perceived less negatively than driving manually by 10%. However, riding autonomously privately owned AVs seems to be more attractive than using SAVs. In general, the preference for using privately owned vehicle in the sample seems to be higher than using shared vehicles; at least for regular commuting trips. Even though the VTTS in SAVs seems to be a little higher than the in-vehicle VTTS for public transportation, it does not include larger waiting and access/egress time associated with public transportation (and the fact that the travel time in public transportation is usually greater than by car). This suggests potential for SAVs as an alternative (or complementary service) for public transportation.

Regarding different user perceptions towards autonomous ridesharing compared to autonomous carsharing, our study does not offer conclusive results. However, users´ concerns about sharing a ride with strangers are possible. Thus, attitudes towards sharing a ride have to be considered in future works, for instance using a sample of people with ridesharing experience, such as users of uberPOOL or of private-organized ridesharing.

The main limitation of the study is related to possible hypothetical bias as AVs are not currently available. Therefore, providing realistic answers may be difficult for the respondents, as they do not have direct experience with the technology. Therefore, while acknowledging the limitations of the technique, we have centered the analysis on a high-level feature, the VTTS, which may be easier for the respondents to internalize.

In all, the study provides important empirical evidence and insights into how autonomous driving might affect mode choices and valuation of travel time for commuting trips. This study thus lays groundwork on the possible impacts of introducing AVs on the valuation of travel time, which future research can build upon. Along the same lines, the study provides empirical evidence sustaining the reduction of the VTTS considered by many authors in simulations exercises.

Future research should focus on other relevant determinants of mode choices, and also on understanding the perception of in-vehicle time for autonomous driving, which has not been covered in this study. In any case, caution is required, as respondents may be overwhelmed when confronted with groundbreaking technologies they are not familiar with. Thus, the analyst should focus their efforts on aspects the respondents can deal with. Another avenue for future research may be understanding determinants behind user preferences and perception. Hence, further work on users' attitudes and needs as well as perceived individual benefits of automation might be crucial in understanding commuters' decision-making processes.

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