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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 traveling as they will be able to undertake other activities while going to work. At the same time, there are still many uncertainties and little 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 with 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 VTTS for commuting trips. It was found that driving autonomously in a privately owned vehicle might reduce the VTTS by 31% compared with driving manually, and is perceived similarly to in-vehicle time in public transportation. Furthermore, riding in a shared autonomous vehicle is perceived 10% less negatively than driving manually. The study provides important insights into VTTS by autonomous driving for commuting trips and could be a base for future research to build upon.

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 (*1*). 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 (*1–3*). Certain user groups might benefit more than others, mainly depending on regular time spent traveling. This is especially the case for people, such as commuters, who routinely make long trips by car, have a limited time budget and therefore 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 (*4*). In recent years, commuting trips in Germany remained unchanged in terms of trip length [57% are shorter than 10 km (6.2 miles)], but increased slightly in terms of trip duration (22% take 30–60 min which corresponds to 4% increase in the share of trips with this duration) suggesting that more commuters are stuck in congestion on the way to and from work (*5*). 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 with users of other modes. Furthermore, time consumption was among the most important subjective stressors for commuters driving on a daily basis (*6*). Therefore, an important benefit of having the opportunity to ride autonomously for commuters might be that they can compensate for time consumption commuting by using the time in a more efficient or more pleasurable way (*7, 8*).

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 (*9*), only Level 4 (the system in charge, some driving use-cases) and Level 5 (the system in charge, all

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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. ARS services are expected to exhibit lower costs per mile at somewhat higher waiting times compared with ACS (*10*). 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 (*11–13*). From a user perspective these services could allow true door-to-door trips for individuals who do not currently have access to a car (*14*).

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 (*15–17*). 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 vehicles (SAVs), which combine (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 into 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 microeconomic theory, individuals are supposed to make transportation decisions under the assumption that the daily time budget is constrained. Therefore, people choose whether they spend their time on one activity compared with another, or how much are they willing to pay to save the time spent in one particular activity (*18*). The subjective VTTS can be defined, therefore, as the WTP to reduce the travel time (*19*). 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 (*20, 21*). In addition, the VTTS for commuting by car are lower in some studies, but in others higher, than for public transportation, and car passengers tend to have lower VTTS compared with car drivers (*20–22*). Furthermore, various empirical studies found that the VTTS of business travelers and commuters is higher in congestion than in free-flowing traffic (*18, 21, 23*). 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 might 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 (*7, 24, 25*). 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 could 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. Therefore, while attempting a detailed analysis of groundbreaking mobility options might prove difficult, focusing the analysis on potential reductions in the VTTS appears a more plausible task for respondents. To our knowledge, only a few stated-choice studies addressing this topic have been conducted to date.

Yap et al. 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) (*11*). 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 to in-vehicle time is higher in autonomous compared with manually driven vehicles, resulting in higher VTTS, which the authors attribute to attitudinal and perceptual concerns about the technology. Along these lines, the results by Winter et al. 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 (*26*). The results of Krueger et al. on the adoption of SAVs show a similar trend (*27*). The authors found that service attributes including travel time, waiting time, and fares, had a strong impact on mode choices, and individual-specific characteristics, such as age and an individual's modality style also had a significant effect.

All three studies, while providing initial empirical insights into user preferences regarding AVs, focus on the introduction of SAVs as an alternative to current modes of transportation. In doing so, they ignore nonmotorized alternatives, such as walking or cycling, but also the option of privately owned AVs. Therefore, it is not possible to gain from these

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 km/h and 68 km/h, distance dependent]
	Waiting time	2 min | 5 min | 10 min
	Cost	−30%|−10%|+20% current costs [€0.20/km]
Shared autonomous vehicle (SAV)	Time	−30%|−10%|+20% reference Time [Speed: between 26 km/h and 68 km/h, distance dependent]
	Waiting time	2 min | 5 min | 10 min
	Other passengers	alone/other passengers
	Cost	−30%|−10%|+20% reference costs "alone" [€0.20/km] -30%|−10%|+20% reference costs "other passengers" [€0.20/km]
Public transportation	Time	−30%|−10%|+20% reference Time [Speed: between 18 km/h and 51 km/h, distance dependent]
	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, distance dependent]

Note: 1 kilometer = 0.62 miles; 1 euro = US$1.10 (exchange rate during study period: May 5, 2017).

studies' insights on the willingness to use privately owned AVs compared with 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 and Axhausen used a stated choices approach to assess the impact of SAVs and privately owned AVs on mode choices (*28*). 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 the 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 (*29*). However, the study focuses more on long-term choice decisions than on influencing factors on trip mode choices.

In summary, no studies were identified that focused on the evolution of VTTS related to the introduction of AVs, nor studies that addressed both privately owned AVs and SAVs simultaneously, and compared with all other relevant modes of transportation.

Methods

Study Design

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), a 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 sociodemographics.

The study design was based on an earlier methodological approach that combines revealed and stated preference data (*30, 31*). 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 costs 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" 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. Therefore, access and egress time for the AVs were excluded as attributes and waiting time was considered.

To present realistic alternatives to the study participants, "average speeds" and "cost per transportation mode" were used for the German case. Average speeds were estimated using the German national household travel survey from 2008, called MiD 2008 (*4*). The costs per kilometer for the private car were drawn from the Allgemeiner Deutscher Automobil-Club (*32*). Only fuel and maintenance cost were taken into account. Costs related to the purchase of the vehicle or parking cost were not considered. The kilometer price for the SAVs followed existing analysis (*10*). The cost for public transportation was drawn from existing rates for public transportation systems in Germany. Fixed costs were used for different distance classes with a minimal price of €1.50. Season, annual or student tickets for public transportation were not considered.

To enhance the data quality of the experiments by maximizing the information obtained from each choice situation, a Bayesian efficient design was created, using the software Ngene (*33*). An efficient design is recommended 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 (*34*). In the current study, the prior values for the estimation of the efficient design were drawn from a pretest with 30 respondents. The design was optimized for short, and medium, and long trips so as 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 preprogrammed destination, gets out of the car on arrival, and the vehicle continues to drive autonomously and parks itself. During the trip she can decide whether she prefers to drive manually or ride autonomously. 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 then drives on to collect its next passenger(s). The main difference between the two introduced concepts was that, in the privately owned vehicle, there was an option to switch off the autopilot. In the SAV there was no steering wheel or brakes, it could not be driven manually. The two concepts were presented as neutrally as possible (without using evaluative adjectives) so as to influence the preferences toward autonomous driving as little as possible.

To find out if respondents preferred to drive their hypothetical privately owned vehicles autonomously or manually, an additional question was added with a Likert scale related to this preference after the choice experiment. Based on the responses, two dichotomous variables were created that indicated whether they preferred 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 (*35*). Survey participants were recruited using a professional panel service. A sample of 485 respondents representative of Germany by age and gender was recruited. The sample included car users as well as noncar users and was limited to participants older than 18 years. The duration of filling in the online survey was 13 min 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 as the rest of the sample reported trips other than commuting.

A comparison between the reported commuting trips of our sample and commuting trips from MiD 2008 (*4*) 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, by using trip length and trip duration as reference parameters of the presented choice experiments, the existing data seem to be suitable.

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 (*36*). The MNL model developed and described by McFadden estimates the probability of each individual n selecting alternative i (*37*). 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. Assuming additive linearity, the expected utility is given by the following expression:

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

Here $X_{n,i}$ is a vector of explanatory variables including the attributes of the alternatives as well as socioeconomic characteristics of the respondent, and β_i are parameters to be estimated. The error term $\varepsilon_{n,i}$ represents 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 distributed (iid) extreme value type 1 distribution (*37*). However (and because of the restriction imposed upon the distribution of the stochastic elements), the MNL does not allow for consideration of heterogeneity among respondents, nor for capturing the pseudo-panel nature of our data, that is, eight choice sets per person. Thus, an ML was employed to relax the assumptions that the coefficients are the same for all individuals (*38, 39*) and to allow correlation across choice situations (*36, 40*). The utility function of an ML with panel data can be extended as follows:

Table 2. Comparison of the Commuting Trips between the German National Travel Survey, MiD 2008 (*4*), 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

Note: 1 kilometer = 0.62 miles.

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

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 0) and density to be estimated. This allows for 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 situations t, taking the pseudo-panel effect into account (i.e., the valuation of the attributes 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 the distribution of η.

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

In Equation 3 the choice probability $L_{n,i}$ represents 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:

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

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, socioeconomic variables were introduced (solely significant socioeconomic variables were ultimately included in the models). The final specification of the model considered the following explanatory variables:

TT_i*: travel time of mode i (in min)*

TC_i*: travel cost of mode i (in €)*

SR*: dummy for shared ride for driverless taxi*

MAN*: dummy for individual who prefers driving privately owned AV manually*

AUT*: dummy for individual who prefers driving privately owned AV autonomously*

LH*: dummy for license holder*

PT_CARD*: dummy for holder of a public transport pass*

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

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

WT*: waiting time for mode i (in min)*

INC*: dummy for income class [low: up to €1.500 (US$1.650), middle: €1.500–€3.000 (US$1.650–US$3.630), high: more than €3.000 (US$3.630)]*

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 β parameter associated with the cost of the alternatives is assumed to exhibit variation among income classes.

To consider a decreasing marginal utility of time and cost on mode choices, a Box-Cox transformation was used (*41*). 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.

$$\beta_{\text{Time},i} \cdot \frac{(\text{TT}_i + \beta_{\text{Acc}} \cdot \text{AT}_i + \beta_{\text{Wait}} \cdot \text{WT}_i)^{\lambda_{\text{Time}}} - 1}{\lambda_{\text{Time}}}$$
$$\text{and } \beta_{\text{Cost}} \cdot \frac{(\text{TC}_i)^{\lambda_{\text{Cost}}} - 1}{\lambda_{\text{Cost}}} \quad (5)$$

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, so as to avoid problems with negative values inside the Box-Cox transformation.

Finally, two ML models were estimated, one of which did not consider nonlinearity, and the other considered the Box-Cox transformation. As previously mentioned, parameter variability across individuals was 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 (*42*). The distributions of the random parameters were simulated by using 5,000 modified Latin hybercube sampling draws (*43*).

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. A significantly better model fit was obtained by modeling possible nonlinearity for the time and cost parameters, χ^2 (2, N = 172) = 9.65, p < .01. Therefore, our results confirm the existence of decreasing marginal utilities.

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 were higher than in Model 1 but had similar relations to each other, suggesting stable tendencies.

The generalized time coefficients show differences between the modes. Travel time in privately owned AVs was perceived less negatively by people using the automation function on commuting trips compared with people driving manually. The segmentation of the respondents into the two groups was based on two dichotomous variables, which specify if a person prefers to drive manually or ride autonomously. The across-population variability of the estimated coefficients suggests a wider heterogeneity between driving AVs automatically than manually. Moreover, riding autonomously to work was perceived less negatively than the travel time of any of the other available motorized alternatives. However, the differences were not statistically significant.

When considering the ASCs, the general preference for SAVs was significantly lower compared with privately owned vehicles; however the mode was more attractive than public transportation. At the same time, exploration of the travel time coefficients suggests that riding autonomously in an SAV was perceived less negatively than driving, but was 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 were no major differences between access and in-vehicle travel time (access time was perceived as slightly more negative), waiting time was perceived 2.12 to 3.28 times more negatively (depending on the model) than the in-vehicle time.

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

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

Regarding the impact of sociodemographic factors, only the variables found to exhibit a statistically significant effect were included in the final model. No significant effect of gender on mode preferences in the final estimations was found. On the subject of age, the analysis shows that middle-aged people (between 30 and 50 years old) were less inclined to walk or cycle to work than younger or older people. Possession of a public transportation pass positively influenced preferences for that mode. Furthermore, people who possess a driver's license were less inclined to walk to work. No socioeconomic variables that directly related to preferences toward AVs were found.

Estimation of VTTS

As previously mentioned, the main objective of the analysis is to establish the differences among the VTTS according to transportation mode when AVs are available. This would allow us to establish the extent to which relieving users from the task of driving might impact on perceptions of time.

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

$$\mathrm{VTTS} = \frac{\partial U_i / \partial \mathrm{TT}_i}{\partial U_i / \partial \mathrm{TC}_i} = \frac{\beta_{\mathrm{Time},i}}{\beta_{\mathrm{Cost},n}} \tag{6}$$

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:

Table 3. Results of the Two Mixed Logit Model Estimation

Coefficient	Model 1: Mixed logit		Model 2: Mixed logit with a Box-Cox transformation for time and cost	
	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	1,376		1,376	

Note: * The *t*-values refer to the bottom level of the uniform distribution.

$$\mathrm{VTTS} = \frac{\partial U_i / \partial \mathrm{TT}_i}{\partial U_i / \partial \mathrm{TC}_i} = \frac{\beta_{\mathrm{Time},i} \cdot (\mathrm{TT}_i + \beta_{\mathrm{Acc}} \cdot \mathrm{AT}_i + \beta_{\mathrm{Wait}} \cdot \mathrm{WT}_i)^{\lambda_{Time}-1}}{\beta_{\mathrm{Cost},n} \cdot (\mathrm{TC}_i)^{\lambda_{Cost}-1}} \tag{7}$$

Therefore, it was 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 4.

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

Note: 1 euro = US$1.10 (exchange rate during study period: May 5, 2017).

The results for the VTTS reflect the results from the estimations presented above. People with a high income had a higher WTP for saving commuting travel time. Here, again, the VTTS for people who prefer autonomously driving privately owned AVs was 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 more meaningful. The VTTS for driving autonomously was in the range of VTTS for in-vehicle time in public transportation, suggesting a similar perception for both modes of transportation. However, it did not include waiting and access/egress time, which can be, as estimated above, up to two or three times more negative than in-vehicle time (this phenomenon negatively affects the perception of public transportation). At the same time, the VTTS for SAVs was slightly higher than autonomously driven vehicles and public transportation, but still 10% lower than for driving a car by oneself. Therefore, 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 VTTS for commuting trips. For this purpose, a DCE was conducted and the data were analyzed using an ML model.

First, the results provide empirical evidence supporting the assumption that autonomous driving will potentially reduce the VTTS for commuting trips, that is, 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 are perceived more negatively in public transportation).

Second, when considering the preferences toward SAVs, we found that travel time spent in SAVs is perceived 10% less negatively than driving manually. However, riding privately owned AVs seems to be more attractive than using SAVs. In general, the preference for using a 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 seem to be a little higher than the in-vehicle VTTS for public transportation, the calculation does not include the longer waiting and access/egress times associated with public transportation (and the fact that the travel time in public transportation is usually greater than by car). This suggests there is potential for SAVs to be an alternative (or complementary service) for public transportation.

Regarding different user perceptions toward autonomous ridesharing compared with autonomous carsharing, our study does not offer conclusive results. However, we suggest that users' concerns about sharing a ride with strangers are possible. Thus, attitudes toward sharing a ride have to be considered in future work, for instance using a sample of people with ridesharing experience, such as users of uberPOOL, or of privately 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 centered the analysis on a high-level feature, the VTTS, which may have been 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 the groundwork for 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 supporting the reduction of the VTTS, considered by many authors in simulation exercises.

Future research should focus on other relevant determinants of mode choice, and also on understanding the perception of in-vehicle time for autonomous driving, which has not been covered in this study. For instance, geographic variables can play an important role in mode-choice decisions and should be explored in future research. 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 in understanding the determinants behind user preferences and perceptions. Therefore, 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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