Impact of trust and travel experiences on the value of travel time savings for autonomous driving

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Abstract

Autonomous driving is expected to strongly influence the value of travel time savings (VTTS) which is crucial for the assessment of the impact of automated vehicles (AVs). However, no consensus has been reached yet about the size and direction of the effect of AVs on VTTS. This high uncertainty around the VTTS is most likely due to high heterogeneity in preferences for travel time. Our hypothesis is that a key role in the heterogeneity of the VTTS for AVs is played by psychological factors. We focus in particular on *Travel Experiences* (besides individual preference for activities conducted during travelling) and *Trust* in travel time preferences for AVs. For this purpose, an online survey with a stated choice experiment and psychometric scales was conducted. Besides currently available transport modes, also a privately-owned AV (PAV) and a shared AV (SAV) were included in the choice sets. The data was analysed using a hybrid choice model. T-test and confidence intervals of the estimated VTTS are computed to assess if the VTTS are statistically significant and statistically different among user groups. Results confirm that both psychological factors have significant positive effect on VTTS for AVs. Gender, age, level of education and experience with similar systems were found to affect the VTTS directly and indirectly through their impact on the individual attitudes. Significant differences are found among some potential user groups, in particular in terms of trust to technology and anticipated travel experiences. For example, men are found to trust the technology more than women and also to have potentially higher technology affinity. However, our results show that they also perceive higher marginal disutility for travel time in both PAV and SAV. A comparison between a mixed logit model and the hybrid choice model reveals that capturing the indirect effect of the socio-economic characteristics of individuals through the effect of these factors on attitudes allows differentiating between the VTTS for different user groups. Lastly, implications for policy and technology deployment strategies are discussed based on the findings.

Keywords: automated vehicles, autonomous driving, value of travel time savings, willingness to pay, positive utility of travel, hybrid choice model, attitudes

Highlights

- The effect of trust and travel experiences on VTTS for automated vehicles is assessed.
- Privately-owned automated vehicles and shared automated vehicles were considered.
- VTTS for different potential user groups were calculated.
- Individual attitudes were found to influence significantly VTTS for automated vehicles.
- Policy and practice implications are derived from the results.

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1. Introduction

Autonomous driving is expected to strongly affect the preferences for time spent in a vehicle and consequentially, also the value of travel time savings (VTTS), i.e. the willingness to pay for marginal reduction in travel time. As VTTS is a key element of transport cost-benefit analysis, anticipating travel time preferences for travelling in an autonomous vehicle (AV) is crucial for the assessment of the impact of this new technology.

Following a classification proposed by SAE (2019), there are six levels of vehicle automation: no automation (level 0), driver assistance (level 1), partial automation (level 2), conditional automation (level 3), high automation (level 4), and full automation (level 5). While the first three levels represent driver support features, level 3 to 5 are defined as automated driving features (SAE, 2019). It is expected that the higher levels, i.e. from level 3 on, will provide significant benefits to the users as they allow users to take their hand off of the steering wheel and use their travel time for other activities or to relax (Trommer et al., 2016).

The impact of autonomous driving in the preferences for travel time has been extensively discussed in the recent literature, but no consensus has been yet reached about the size and direction of this impact. The majority of the studies (e.g. Gucwa, 2014, Anderson et al., 2014, Childress et al., 2015, Kröger et al., 2016, Wadud et al., 2016) has assumed a significant reduction in VTTS for AV users, i.e. that time is perceived less negative when riding autonomously in a vehicle compared to driving manually. This assumption was confirmed in the few empirical studies on the topic, however, only for certain AV use cases, i.e. for certain trip purposes, vehicle concepts and depending on travel time use preferences (Becker and Axhausen, 2018, Correia et al., 2019, Kolarova et al., 2019b, Kolarova and Steck, 2019). Moreover, there is a small but growing number of researchers suggesting that this reduction will be more modest than expected (Singleton, 2018, Pudāne et al., 2019) or that there will be no reduction (Krueger et al., 2019) or even an increase in VTTS (Rashidi et al., 2020). The high uncertainties regarding size and direction of the VTTS is reflected also in an overview of the results of different studies that used a poll of experts from the transportation field, provided by Singleton (2018): for instance, he cites the work of Willumsen and Kohli (2016), who report that the VTTS impacts of AVs ranged from 50% reduction to 50% increase.

This high uncertainty around the VTTS is most likely due to high heterogeneity in preferences for travel time. However, contrary to the vast literature on “traditional” transport modes, few empirical studies have studied heterogeneity in the preference for travel time on AVs. Moreover, the previous studies on preference heterogeneity in the context of AVs do not relate VTTS differences to individual characteristics but mostly to the vehicle concept (privately-owned AV, shared AV, or first/ last mile mobility solution; Steck et al., 2018, Krueger et al., 2016, Yap et al., 2016, Alonso-González et al., 2020, Moore et al., 2020), trip purpose and/or trip length (Kolarova et al., 2019b, Ashkrof et al., 2019), vehicle equipment (office vs. leisure interior; Correia et al., 2019, De Looff et al., 2018), or spatial characteristics (suburban, urban and rural areas; Zhong et al., 2020).

Both, attitudes and perceptions of potential users have been found to play a crucial role in the user evaluation of riding autonomously (see literature reviews by Becker and Axhausen, 2017, Gkartzonikas and Gkritza, 2019). These include travel experiences (Singleton, 2018, Pudāne et al., 2019), trust in the technology (Ashkrof et al., 2019, Molnar et al., 2018, Yap et al., 2016, Zhang et al., 2019), technology awareness (e.g. Silberg et al., 2013, Schoettle and Sivak, 2014), consumer innovativeness (e.g. Silberg et al., 2013, Haboucha et al., 2017, Schoettle and Sivak, 2014), safety concerns (e.g. Jardim et al., 2013, Yap et al., 2016, Howard and Dai, 2014), environmental concerns (e.g. Jardim et al., 2013, Brown et al., 2014, Haboucha et al., 2017, Bansal et al., 2016), perceived opportunity for productivity or time use and lower stress (e.g. Zmud et al., 2016, Shabanpour et al., 2018), passion for driving or driving related sensation-seeking (e.g. Silberg et al., 2013, Ipsos MORI, 2014), and data privacy concerns (e.g. Zmud et al., 2016, Silberg et al., 2013). Although some factors (e.g. lower stress or trust in the technology) have been discussed in relation to travel perception, these empirical studies focus only on the effect of the psychological constructs on the willingness to use AVs; they do not discuss and even less measure the extent to which attitudinal factors can explain uncertainty around the VTTS for AV users.

In addition, in general in the transportation field, while the impact of psychological variables on mode choices is addressed in various empirical works (e.g. Golob, 2001, Johansson et al., 2006, Kamargianni and Polydoropoulou, 2013, Paulssen et al., 2014), there is only little empirical research on the impact of psychological factors on the value of time. A study conducted by Abou-Zeid et al. (2010) quantifies, according to the authors, for the first time the effect of attitudes on the value of time distribution. The authors looked at cost sensitivity of travellers depending on their attitude toward car use by estimating a parameter for the interaction between this attitude and cost/income which was later used together with the estimated time and cost parameters for the calculation of the value of time. Similar approach for analysing variation in the willingness to pay related to attitudinal factors was applied in forecasting the demand of electric vehicles (Glerum et al., 2014) or the impact of congestion price in the departure time (Thorhauge et al., 2019). Studies addressing travel time sensitivity to psychological factors are, on the other hand, scarce. Bahamonde-Birke et al. (2017) measured the effect of attitudes and perceptions on travel time preferences in a study on interurban public transport, whereas Li and Kamargianni (2020) measured the impact of three attitudinal factors on travel time sensitivity in a recently published research work on preferences for bike- and car-sharing services.

Given the wide range of potential factors that can affect users' preferences for AVs, understanding the sources of variation in travel time preferences for AVs is crucial for developing more realistic and differentiated scenarios about the impact of autonomous driving on mode choices and travel demand. This study aims to contribute to the above literature by discussing the impact of *Travel experiences* (besides individual preference for activities conducted during travelling) and *Trust* in travel time preferences for AVs and providing empirical evidence about the extent to which these factors, and the socio-economic characteristics that explain them, affect heterogeneity around the VTTS for AVs. T-test and confidence intervals of the estimated VTTS are computed to assess if the VTTS are statistically significant and statistically different among user groups. At the best of our knowledge, none of the studies on AVs discussed the statistical significance of the VTTS depending on user characteristics. Only one recent study conducted by Correia et al. (2019) discussed the statistical significance of the VTTS by looking into differences between VTTS in AVs with leisure interior, VTTS in AVs with office interior and VTTS in conventional cars. However, even though the authors consider socio-economic factors as well as respondents' attitudes regarding convenience of automated driving in one of their models, they did not directly measure statistical significance of the VTTS between different user groups depending on these individual characteristics. Other psychological factors mentioned above were found to be related to the intention to use AVs, but these are not directly related to travel time perceptions and are consequentially also not in focus of this study. Passion for driving or driving related sensation-seeking was also found to affect negatively VTTS for AVs, but we did not consider this factor in our study because it is part of the travel experiences in a car and because it is related to the positive utility of manual driving rather than to autonomous driving. Finally, it is worth noting that we focus on perceived travel experiences, besides individual preference for activities conducted during travelling. Despite their strong relation, we consider these factors as separated elements of the AV as recommended in the literature (Mokhtarian and Salomon, 2001, Singleton, 2017). Research found that if people were travelling in an AV they would be more likely to relax than to work (Cyganski et al., 2015, Fraedrich et al., 2016, Roeckle et al., 2018). There is, however, no consensus yet regarding this aspect as working in an AV can indeed be an attractive option for certain population groups (Correia et al., 2019, Kolarova, 2020). The role of trust in travel time perception in an AV is crucial as it is a requirement to consider performing activities in such vehicles.

The paper is organised as follows: in section 2 we discuss the role of travel experiences and trust in the VTTS; in section 3 we describe the methodology used to collect the data (section 3.1), to estimate the demand model (section 3.2) and to compute the VTTS (section 3.3). In section 4 we present and discuss the results of the models´ estimated, while in section 5 we discuss the distribution of VTTS among users depending on their socio-economic characteristics and attitudes and the implications for the development of the AV technology. Finally, in section 5 we summarise the conclusions derived from this study as well as future research.

2. Impact of travel experiences and trust in an AV on the preferences for autonomous driving

In the following, we give a brief overview of the state of the art and knowledge on potential determinants and elements of the value of time for AVs, focusing on the two selected psychological factors for this study.

2.1. Travel experiences and activities conducted during travelling

One theoretical justification of the changes in travel time preferences due to vehicle automation can be derived from conceptual and empirical works on the positive utility of travel. It is an extension to the assumption that travel is a derived demand and is theoretically postulated by Mokhtarian and Salomon (2001). These authors suggest that travel can also be desired for its own sake, i.e. travel time can have a positive utility for an individual. Thus, they conceptualize three elements of the utility of travel: (i) activities conducted at the destination, (ii) activities that can be conducted while travelling, and (iii) the activity of travelling itself. The first element won´t change due to vehicle automation, whereas the second one, i.e. feasibility of new activities during travelling, as well as the third one, i.e. the activity of travelling itself, potentially will. In other words, there are two potential improvements, because people will be able to perform other activities and because the travelling itself will change due to the potential improvement of the travel experiences in terms of stress relief or increased comfort level (Mokhtarian, 2018, Singleton, 2018). This assumption is supported also by the results of a naturalistic experiment where people were projected into a world with autonomous vehicles by providing them with free chauffeur service (Harb et al., 2018). In this study, the main reasons behind more travel by car, mentioned by the participants, was being able to multitask as well as enjoy their commute. Although these two elements – performing activities while travelling and enjoying the trip - are strongly interrelated with each other, theoretical and empirical works suggest that it is useful to consider them as separate elements of the travel utility (Mokhtarian and Salomon, 2001, Singleton, 2017) as they have different determinants and implications for travel demand (Pudāne et al., 2019).

Previous studies for currently available modes of transport found that commute well-being (e.g. Smith, 2017, Ettema et al., 2013) as well as conducting activities while travelling (e.g. Molin et al., 2020, Malokin et al., 2019) influence mode choices and VTTS. However, there are contradictory empirical findings, some suggesting lower VTTS for AVs with an office interior than for a conventional vehicle or an AV with a leisure one (Correia et al., 2019). These authors stress that the results are not intuitive and in line with the expectation of several experts and recommend further research on the role of leisure activities on travel time perception in an AV. In a follow-up comment published by Pudāne and Correia (2020), the authors discuss potential explanation of the findings suggesting the additional consideration of the facilitation-level of on-board activities, i.e. whether the AV provides the same work or leisure experience as out-of-vehicle locations. If this is the case, they suggest that the value of time in an AV corresponds to the intrinsic cost of travel which is smaller than the VTTS in conventional cars. Again, the authors suggest further research in this field, among others, accounting for various types of work and leisure activities. Along these lines, context-related characteristics can shape the utility of giving up the driving task (see also Kolarova et al., 2019a). For example, performing different activities while travelling can become relevant on longer trips as some of them might require certain minimal time (e.g. reading, watching movie, etc.). Also Malokin et al. (2019) analysed the effect of activities during travelling on mode choices and looked at potential AV scenarios. The authors found that the propensity to engage in productive activities influence the VTTS.

The role of both feasibility of activities performed while travelling and improvement of travel experiences together, is discussed so far in theoretical works (Mokhtarian, 2018, Singleton, 2018) or in explorative qualitative studies (Pudāne et al., 2019, Kolarova, 2020). These studies suggest that VTTS for AVs might change mainly because of advantages related to reduced stress of driving and ability to relax during the trips rather than of being able to use the travel time in a productive way, which is often postulated in the literature as an important benefit of vehicle automation (Singleton, 2018).

In line with this discussion, the results of a study conducted by Cyganski et al. (2015) on the desirable activities performed during travelling in an AV, suggest that, in contrast to the theoretically assumed productivity benefits of vehicle automation (Clements and Kockelman, 2017, Montgomery et al., 2018, Anderson et al., 2014), working is among the least preferred activities in an AV. Indeed, desirable activities performed in an AV are more likely to be those also currently performed while travelling (Cyganski et al., 2015, Fraedrich et al., 2016, Pudāne et al., 2019) and in particular rather passive activities, such as enjoying the trip and the landscape and/or relaxing (Cyganski et al., 2015, Fraedrich et al., 2016, Roeckle et al., 2018). These results are not confirmed in all empirical studies as indeed a study conducted by Correia et al. (2019) found, for instance, that the VTTS in an AV with an office interior is lower than in an AV with leisure interior on commuting trips. A qualitative study also conducted by Kolarova (2020) indicates that working in an AV is perceived as an attractive option by some users. However, the empirical insights regarding this aspect are rather scarce. This supports our choice to focus on the travel experiences in terms of how people feel when travelling in a car rather than on how the time inside the car is used. So far, this discussion lacks quantitative empirical evidence especially for the impact of travel experiences on travel time valuation of AV users.

Summarising the discussion in this section, findings in the current literature point out that improvement of travel experiences (in terms of reduced stress when riding autonomously is discussed to play an even more important role for travel time valuation in an AV than using travel time for other (productive) activities.

2.2. Trust in the automated technology

Among the several psychological factors discussed in the AV literature, trust in the technology is (one of) the most relevant psychological determinants of the willingness to ride autonomously (e.g. Zmud et al., 2016, Molnar et al., 2018, Ashkrof et al., 2019). Furthermore, trust has been proven to play in general a key role in the adoption of new technologies (e.g. Gefen et al., 2003, Pavlou, 2003).

Research in the context of AVs has focused on the effect of trust on the willingness to use an AV. Across different types of studies, trust in AVs is found to influence: user acceptance in terms of intention to use an AV (e.g. Choi and Ji, 2015, Kaur and Rampersad, 2018), mode choice preferences for AVs (e.g. Yap et al., 2016, Ashkrof et al., 2019), willingness to purchase an AV (Jardim et al., 2013), as well as the extent to which participants in a simulated driving study chose to engage with the automated driving mode (Molnar et al., 2018). It is noteworthy, however, that there is neither standardized definition nor standardized measurement instrument of trust in AVs. The term "trust" in the context of AVs is used mainly in relation to vehicle safety, reliability of the system, or to describe affective reactions, such as being nervous or being afraid of using an AV. For instance, Yap et al. (2016) and De Looff et al. (2018) measured "trust in AVs" with items or indicators, such as *"I trust that a computer can drive my car with no assistance from me"*, which were borrowed from a study conducted by Jardim et al. (2013), where the authors called the same construct "safety". In this sense, measuring trust in the system include also various related aspects which are found to be crucial in choosing riding autonomously (e.g. safety concerns; Gkartzonikas and Gkritza, 2019).

The above brief literature review stresses that the studies in the context of AVs so far have measured the effect of trust on the intention to use AVs (Choi and Ji, 2015, Yap et al., 2016, Ashkrof et al., 2019, Zhang et al., 2019, Keszey, 2020). Trust has, however, been also discussed to be a necessary condition to consider using an AV and/or to perceive the benefits of time spent riding autonomously. For instance, Yap et al. (2016) comment that lack of trust in the technology contribute that "passengers do not fully perceive theoretical advantages of AVs regarding travel time valuation". Wadud and Huda (2019) suggest that preferences to watch the roadway instead of performing other activities in an AV indicate lack of trust in the system. This aspect was pointed out also by Fraedrich et al. (2016): willingness of potential AV users to focus their attention towards traffic and to remain in the traditional upright seating position was attributed by the authors to low level of trust, although also further factors might play a role, such as potential motion sickness when concentrating on other tasks or changing sitting position. In other words, lack of trust in AVs, among other factors, potentially will make people feel uncomfortable when riding autonomously and limit the utility of travel time in an AV. But none of the studies so far measured the impact of trust on the travel time preference while driving in an AV, and hence on the VTTS.

Last but not least, regarding determinants of trust in AVs, experience with advanced driving assistance systems (ADAS) was found to play an important role: people who are using or have tested ADAS seem to be more likely to trust the technology (e.g. in Rödel et al., 2014, Kolarova, 2020). Experiences with similar technologies have been also found to influence directly the willingness to use an AV (Kyriakidis et al., 2015, Zmud et al., 2016). None of these studies, however, has analysed quantitatively both the direct effect of previous experiences on choosing an AV and their indirect effect on this choice trough increasing trust in the technology simultaneously. Given the potential impact of trust on VTTS which we discussed above and the important role of previous experiences with ADAS as a determinant of trust, we suggest that it is necessary considering this factor in the estimation of VTTS depending on individual attitudes.

3. Methodology

3.1. Survey design and sample

In order to analyse the effect of travel experiences and trust on the marginal utility of travel time and hence on the VTTS, an online survey was conducted among commuters aiming to control in this way for the effect of trip purpose on the VTTS. Having a regular commuting trip (to work or to professional school/ university) was then a requirement to participate in the survey[2]. Respondents were recruited by a professional online panel provider. The sample was selected in a way to represent the age and gender distribution in the population in Germany of the age group between 18 and 69 years old. After data cleaning, the final sample for the analyses consists of 484 respondents.

The questionnaire contained the following five parts: (i) information about the current commuting trip, (ii) a SP experiment on mode choices for the reported commuting trip, (iii) attitudes related to the use of autonomous driving, (iv) an individual evaluation of the commuting trip in terms of experiences and time use and (v) questions about socio-demographic and travel behaviour-related characteristics of the respondents. The SP experiment and the videos that present the two AV concepts are the same used in Steck et al. (2018) and Kolarova et al. (2019b). The individual attitudes of potential users have been collected specifically for the present study.

The information about the current commuting trip included questions about trip length, duration, mode of transport usually used for the trip, level of congestion experienced (for the car users only), satisfaction with the trip, and activities conducted during the trip.

The SP experiment included eight decision situations in which respondents had to choose between five modes of transport for their commuting trip, assuming that all of these alternative modes are available in the market. The alternatives were: walk, bike, public transport and two concepts of AVs: a privately-owned automated vehicle (PAV), and a shared automated vehicle (SAV). The alternatives were described with the following characteristics (attributes): (in-vehicle) travel time, access/ egress time (only public transport), waiting time (public transport, PAV and SAV), cost for the trip (public transport, PAV and SAV), and only for the SAV whether the vehicle was going to be used individually or in a ride-sharing arrangement. The attributes and their levels are presented in Table 1. The study design for

[2] Besides the insights from previous works that automated driving is considered as an attractive option for commuting, certain characteristics of this type of trip makes it relevant to look at when considering the travel time preferences change due to AVs. These are, among others, the regular nature of the trip, role of habit, higher time pressure on working days, and the higher probability of driving in congestion while commuting because of peak hours.

the stated choice experiments was based on a value of time study for Germany conducted by Axhausen et al. (2014). Information about the current commuting trip was collected in the first part of the questionnaire and used to customise the values of the attributes by pivoting time and cost around a computed base level. We used the same levels, i.e. same amount of reduction or increase in the reference values as in Axhausen et al. (2014). A Bayesian efficient design was created using the software Ngene (ChoiceMetrics, 2012). The design was optimized for two trip distances, a short and a long trip, in order to consider the effect of trips distance on mode choices.

Table 1: Attributes and levels of the SP experiment

Mode of transportation	Attribute	Levels
Walk	Travel time	-30%|-10%|+20% from the reference time[1]
Bike	Travel time	-30%|-10%|+20% from the reference time
Privately-owned automated vehicle (PAV)	Travel time	-30%|-10%|+20% from the reference time
	Waiting time	2 Min. | 5 Min. | 10 Min.
	Cost	-30%|-10%|+20% from the reference cost
Shared automated vehicle (SAV)	Travel time	-30%|-10%|+20% from the reference time
	Waiting time	2 Min. | 5 Min. | 10 Min.
	Individual use vs. ride-sharing	Dummy variable
	Cost	-30%|-10%|+20% from the reference cost "individual use" -30%|-10%|+20% from the reference costs"ride-sharing"
Public Transport (PT)	Travel time	-30%|-10%|+20% from the reference time
	Access/ egress time	2 Min. | 5 Min. | 10 Min.
	Waiting time	2 Min. | 5 Min. | 10 Min.
	Travel cost	-30%|-10%|+20% from the reference cost

1. The reference time and cost are the values of the current trip described by each respondent at the beginning of the survey.

Before showing the SP experiment, two concepts of AVs were presented to the respondents using short videos that showing how a trip with a PAV or a SAV can look like. For the SAV, two options were shown: (i) an individual trip in a SAV, i.e. the user ride alone in the vehicle and (ii) a trip in a ride-sharing arrangement, i.e. the user share the ride with other users with the benefit of reducing the trip cost. The PAV was presented as a vehicle that is able to drive fully autonomously and, on request, can be driven manually[3]. In contrast to this, the SAV was presented as a vehicle that can only drive fully autonomously and cannot be overridden by the user. The storyboard of the videos including example pictures is reported in Annex 1. Following the SAE (2019) classification, both AV concepts presented in the study are level 5 (i.e. full automation), which makes it also clear the importance of study the impact of trust. The PAV in particular was presented as a vehicle that can be also overridden at any time by the users – an option which is not described in the SAE (2019) classification, but which was important to add because of the study design[3].

The next part of the survey included the measurement of the selected psychological factors. The constructs were operationalized using psychometric scales: for the construct trust, a set of items measured on a five-point Likert scale were used; the construct travel experiences[4] was measured instead using a semantic differential (Osgood et al., 1957). The constructs were operationalized relying on existing scales from the literature; they were adapted to the research focus and translated into German. To ensure the quality of the scales after the adaptation and translation, a two-step pre-test was conducted

[3] The reason behind the choice to make the use of PAV on request, similarly to a conventional vehicle, was mainly to focus on the willingness to use automation as a feature, and to avoid mixing a purchase decision for an AV with a mode choice decision.
[4] The measured construct represents the subjective evaluation or satisfaction of travelling in an AV and covers the affective components of the construct commute well-being (see Ettema et al., 2011, Smith, 2017).

and the items were adjusted based on the results from the test. Trust in an AV, or in the reliability/ safety of an AV, was measured using indicators for the construct developed in a study by Jardim et al. (2013) and used also in Ashkrof et al. (2019). The travel experiences in an AV was measures using indicators adapted from the Satisfaction with Travel Scale (STS) developed by Ettema et al. (2011) and from the scale used by Smith (2017) that builds upon the STS. We considered in this study only affective components[5], i.e. feelings during a commute with AV. Note that the STS was developed and used to evaluate commute well-being and travel satisfaction with currently available modes of transportation. In this study, it measures the *expected* travel experiences in an AV or the subjective evaluation of how people imagine a commuting trip to be if they were using an AV. Table 2 gives an overview of the measured constructs, their indicators and *Cronbach´s α* for each scale.

Table 2: Overview of the latent variables and their indicators

Latent variables	**Indicators/ Items**	**M**	**SD**	**Cronbach´s α**
Trust[a]	I trust that a computer can drive my car with no assistance from me. *(trust_01)*	2.88	1.34	.900
Trust[a]	I would be comfortable entrusting the safety of a close family member to an automated vehicle. *(trust_02)*	2.90	1.37	
Trust[a]	I think that the automated driving system provides me more safety compared to manually driving. *(trust_03)*	2.80	1.28	
Travel experiences[b]	My commuting trip would be very … 1 = ... displeasing.; 5 = ... enjoyable. *(travel_experiences_AV_01)*	3.57	1.28	.872
Travel experiences[b]	I would be very … 1 =... stressed.; 5 = …calm. *(travel_experiences_AV_02)*	3.49	1.35	
Travel experiences[b]	My commuting trip would be … 1 =... monotonous and boring.; 5=... very exciting. *(travel_experiences_AV_03)*	3.10	1.23	

[a] All indicator statements were measured on a 5-point Likert scale (1 = strongly disagree;5 = strongly agree)
[b] Indicator statements 5-point semantic differential

As part of the individual evaluation of the commuting trip, respondents were asked to report which activity they would have most likely performed while travelling in an AV (Question: *"Which of the following activities are likely to apply to your trip to work if you were using an autonomous vehicle on your commuting trip?"*). Figure 1 shows the share of the answers for the willingness to perform a certain activity in the AV. The list of activities that can be performed in the AV was borrowed from a study on acceptance of different use-cases of autonomous driving conducted by Fraedrich et al. (2016). Results are in line with previous studies (among others Fraedrich et al., 2016, Cyganski et al., 2015), though as we discussed in the literature review, some studies found opposite results. However, at least in our application, these results show that a higher share of potential users would rather prefer relaxing or enjoying the ride and the landscape when riding in an AV, whereas a small share of people (19%) would prefer using the trip for working. These results underline additionally that improvement in travel experiences in terms of reduced stress or being able to relax or perform more passive activities are perceived as more important benefits of autonomous driving than active or productive time use. This justifies focussing on travel experiences and their impact on VTTS in this study.

[5] The STS measure affective responses to the commute (i.e. feelings during the commute, such as enjoyment, excitement) and cognitive responses (i.e. evaluation of the commute afterwards, such as "worked well", "was high standard") (see Ettema et al., 2011, Smith, 2017).

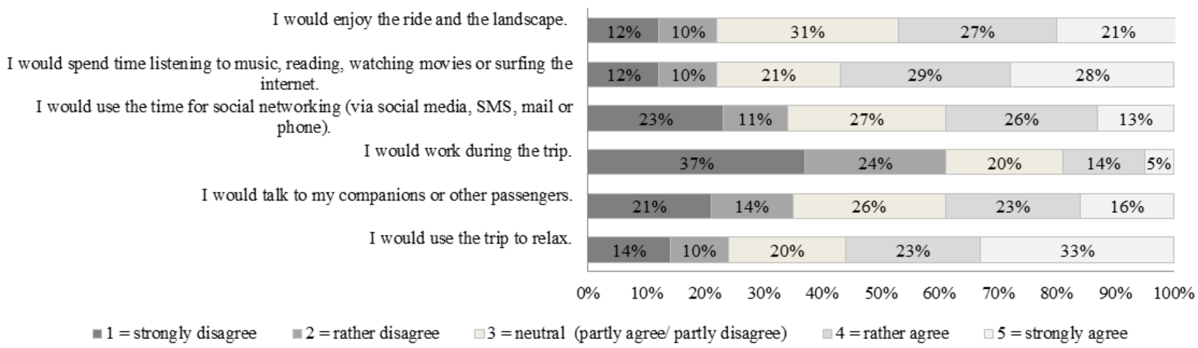


Figure 1: Distribution of how likely will various types of activities be performed in an AV on the commuting trip according to respondents

The final part of the survey was dedicated to collect the following socio-demographic and travel behaviour-related characteristics of the respondents: age, gender, educational level, household income, possession of a driving license and/or public transport pass, car availability in the household, and experiences with advanced driving assistance systems (ADAS). Table 1 summarizes the descriptive statistics for these variables. As the study focuses on commuting trips, we compared the descriptive statistics with representative statistics for the German working population. This comparison shows that the values for the most socio-demographic characteristics in the sample are in the range of the target population. Some differences can only be seen for the age distribution (lower share of people between 30 and 50 years and higher share of over 50 years old people in the sample) as well as in the share of possession of driving licence and car availability in the household (both higher in the sample compared to the reference values).

Table 3: Descriptive statistics of the socio-demographic and mobility-related characteristics

Variable	**Category**	**Relative frequency in the sample (N=484)**	**Relative frequency in the German working population**
Gender	Male Female	50.2% 49.8%	50.8% 49.2%
Age	18-29 years old 30-50 years old over 50 years old	17.4% 42.1% 40.5%	19.1% 48.8% 32.1%
Educational level	Lower than university University or higher	65.7% 34.3%	68.8% 31.2%
Household income	Low (< 1.500 Euro/ month) Medium (1.500 – 3.000 Euro/ month) High (> 3.000 Euro/ month)	14.5% 41.7% 43.8%	13.9% 41.6% 44,5%
Possession of driving license	No Yes	6.0% 94.0%	15.8% 84.2%
Possession of public transport pass	No Yes	68.0% 32.0%	73.0% 27.0%
Car availability in the household	No Yes	11.2% 88.8%	17.2% 82.8%
Experiences with ADAS	No *(= no experiences)* Yes *(= use them or have tested them)*	63.4% 36.6%	*no information*

3.2. Demand Model specification

In the *first* step, the data was analysed using a multinomial logit (MNL) model (McFadden, 1974, Ortúzar and Willumsen, 2011) and a mixed logit (ML) model (Train, 2009, Hensher and Greene, 2001). The ML model outperforms, as expected, the MNL model as it considers agent effects (i.e. the correlation among responses from the same individual in the eight choice situations that s/he faces in the choice experiment). Therefore, the baseline model chosen for this study was an ML. The final estimated ML model includes a set of error components to measure correlation across decision situations (i.e. the correlation among choices of the same individual) and a set of interactions between socioeconomic characteristics and travel times to measure systematic heterogeneity in valuation of travel time.

The utility function of the baseline ML model is formulated as follows:

$$U_{int} = \beta_x \cdot X_{int} + \beta_s \cdot SE_n + \beta_{s,TT} \cdot (SE_n \cdot TT_{int}) + \eta_{in} + \varepsilon_{int} \tag{1}$$

In equation 1, the utility U_{int} associated with alternative i as evaluated by the individual n in the choice situation t. is represented by (i) a vector of explanatory variables X_{int} (characteristics of the alternatives, including travel time TT) and SE_n (socio-economic characteristics of the individuals), (ii) a vector of parameters associated to these variables (β_x, β_s, $\beta_{s,TT}$) that includes also parameters for the interaction between the socio-economic variables and travel time, and (iii) two additive stochastic terms: a random term η_{in} normally distributed with a zero mean and standard deviation σ_t to be estimated (capturing the correlation across the multiple choice situations) and a random term ε_{int} distributed iid extreme value type 1.

In the *second* step, a hybrid choice model (HCM) was estimated, to test the effect of the latent attitudes (Ben-Akiva et al., 2002, Walker and Ben-Akiva, 2002). Differently from the common HCM applications, in this paper we interact the latent attitudes with the travel times, to account for systematic and random heterogeneity in travel time due to respondents' attitudes toward trust and perceptions of travel experiences. The utility of the HCM is formulate as follows:

$$U_{int} = \beta_x \cdot X_{int} + \beta_s \cdot SE_n + (\beta_{s,TT} \cdot SE_n + \beta_{LV,TT} \cdot LV_{in}) \cdot TT_{int} + \eta_{in} + \varepsilon_{int} \tag{2}$$

where $\beta_{LV,TT}$ is a vector of parameters associated to the interaction between the LV and TT, to be estimated; all other terms are the same as in equation (1). Figure 2 reports the diagram of the model, where we have explicitly represented the interactions between the two LVs and travel time. Other interactions with SE are not explicitly reported.

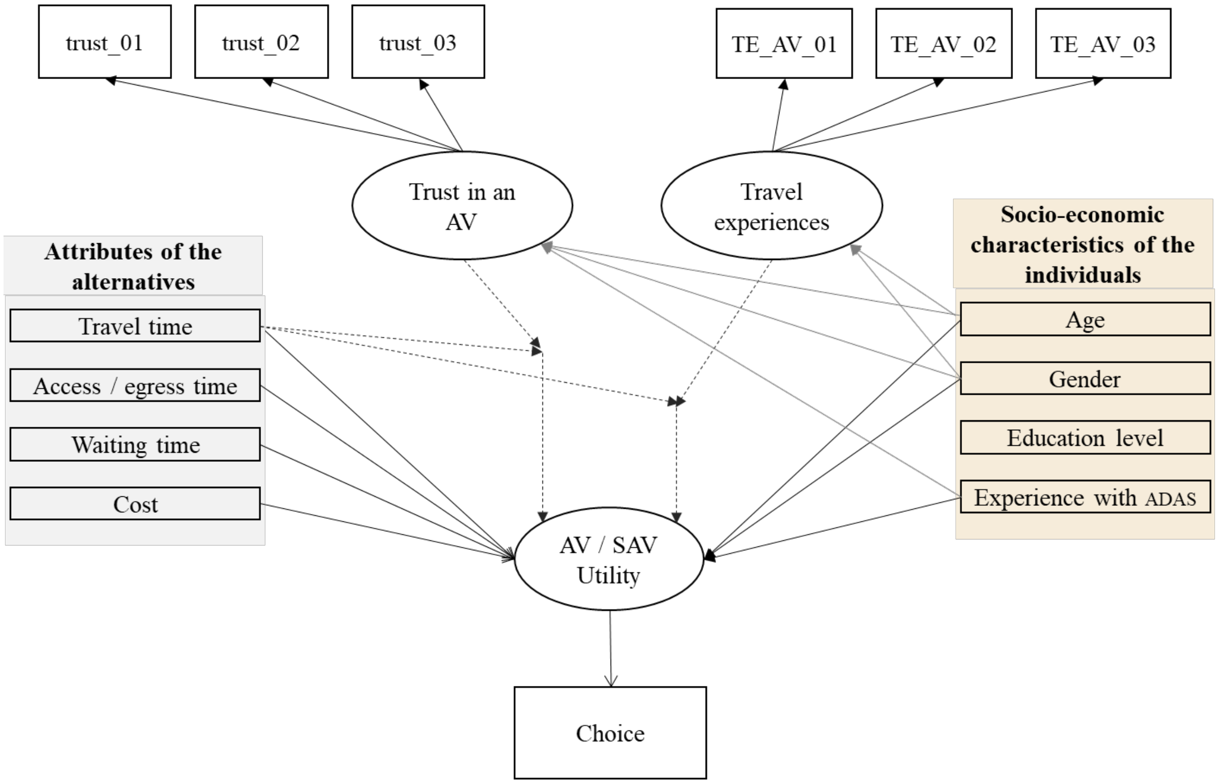


Figure 2: Diagram of the HCM, with highlighted explicitly the interactions between the LVs and TT

The LVs cannot be directly measured as other variables, but information about them can be inferred from observable (measurable) indicators, such as the answers on the Likert scale questions. The latent variables are explained by observed explanatory variables (typically characteristic of the individual SE_n) through *structural equations,* which take the following form:

$$LV_{nl} = \alpha_l + \alpha_{l,LV} \cdot SE_n + \nu_{nl} \qquad l = 1,2 \tag{3}$$

Where, in our case, l=1,2 as we have two LV (trust and travel experiences), α_l is the intercept, $\alpha_{l,LV}$ is a vector of coefficients associated to the explanatory attributes and ν_{nl} is a random term normally distributed with a zero mean and standard deviation $\sigma_{\nu l}$ to be estimated.

On the other hand, the latent variable explains the indicators I_{nlp} through *measurement equations,* formulated as follows:

$$I_{nlp} = \gamma_{lp} + \gamma_{lp,LV} \cdot LV_{nl} + \zeta_{nlp} \qquad p = 1,...,P_l \quad \& \quad l = 1,2 \tag{4}$$

P_l is the number of indicators for each latent variable l, γ_{lp} is the intercept, $\gamma_{lp,LV}$ is the coefficient associated to the latent variable and ζ_{nlp} is a random terms normally distributed with zero mean and standard deviation σ_ζ to be estimated.

Let P_{int} be the multinomial logit probability of individual *n* choosing alternative *i* in the choice situation *t*. The conditional probability of individual *n* choosing *alternative i* in the sequence of choices **t**=(1,..., *T*) is given by:

$$P_{in}(LV(\nu_n), \eta_n) = \prod_{t=1,...T} P_{int}(LV(\nu_n), \eta_n) \tag{5}$$

The unconditional probability of individual *n* choosing the sequence of choices **t** is the integral of P_{in} over the density functions of ν and η. The LVs are treated as two independent factors, i.e. potential relationship between both variables was not considered.

The log-likelihood function for the HCM can be expressed as follows:

$$L = \int_{\eta,\nu} P_{in}(LV(\nu_n),\eta_n) \prod_{l=1,2} f_{LV}(\nu_{nl}) \prod_{p=1,..,P_l} f_I(I_{lnp} \mid LV(\nu_{nl})) f(\nu) f(\eta) d\eta d\nu \qquad (6)$$

Where f_{LV} is the probability density function of the latent variables, and f_I is the probability density functions on the indicators. The log-likelihood function is given by the log of the product across the sample of the unconditional probabilities in equation (6).

All model estimations were performed using the software package PythonBiogeme (Bierlaire and Fetiarison, 2009). The HCM were estimated simultaneously; Monte Carlo integration is used and random numbers are generated using 2.000 modified Latin hypercube sampling (MLHS) draws (Hess et al., 2006) [6].

3.3. VTTS simulation

The value of travel time savings (VTTS) represents the individual willingness to pay for saving travel time. It can be directly calculated from the estimated models as the ratio between the marginal utility of travel time and the marginal utility of cost. In case of utility linear in the attributes, the marginal utility equals the coefficient estimated. In case of utility non-linear in the attributes, the marginal utility needs to be computed as the partial derivative of the utility with respect to the attribute of interest. In our models, the utility is linear in the cost but not linear in travel time.

For the ML in equation (1), the average VTTS takes then the following expression:

$$VTTS_{SE_n} = \frac{(\beta_{TT} + \beta_{s,TT} \cdot SE_n)}{\beta_{\cos t}} \cdot 60 \quad \left[\frac{Euro}{hour}\right] \qquad (7)$$

For the HCM in equation (2), the average VTTS takes the following expression:

$$VTTS_{SE_n} = \frac{(\beta_{TT} + \beta_{sTT} \cdot SE_n + \beta_{LV,TT} \cdot LV_{in})}{\beta_{\cos t}} \cdot 60 \quad \left[\frac{Euro}{hour}\right] \qquad (8)$$

As shown in equation (3), the two LVs, trust and travel experiences, follow a Normal distribution. Confidence intervals for the VTTS with both models (ML and HCM) were computed considering the mean values of the LV. To reproduce the distribution of the coefficient estimated, we used Monte Carlo simulation with 5,000 draws from a multivariate truncated Normal distribution[7].

Let be $VTTS_g(r)$ the value of time for the potential user group *g* (with g=1,…,G) and draw r (with

[6] The HCM model was estimated with 27 parallel threads and using as starting point the coefficients estimated with the ML model. The run time to convergence it took 10 hours and 35 minutes. The ML run time was 3 hours and 10 minutes. While the run time of the HCM with different starting points took up to 20 hours, but it is worth mentioning that the value of the estimates were not too different depending on the starting point.

[7] As suggested by one reviewer, given that structural equations are often weak, i.e. sociodemographic variables are poor predictors of the LVs, a better option would be to use the measurement equations to simulate the LVs. However, this is not straightforward because it requires computing for each individual in the sample the optimal LV value, given the parameters of the measurement sub-model estimated previously, and given the responses to the measurement indicators for that individual.

r=1,…,R), where each group is defined as a function of socio-economic characteristics g(SE_n) the population average and standard deviation for the value of time were computed as:

$$E(VTTS) = \frac{1}{R}\sum_{r=1}^{R}\sum_{g=1}^{G}\left(VTTS_g(r)\times w_g\right) \tag{9}$$

$$st.dev(VTTS) = \sqrt{\frac{1}{R-1}\sum_{r=1}^{R}\sum_{g=1}^{G}\left[\left(VTTS_g(r)-E(VTTS)\right)^2\times w_g\right]} \tag{10}$$

where w_g is the weight of each user group g. Analogously, the average value of time and standard deviation in each group was computed as:

$$E(VTTS_g) = \frac{1}{R}\sum_{r=1}^{R} VTTS_g(r)\times w_g \tag{11}$$

$$st.dev(VTTS_g) = \sqrt{\frac{1}{R-1}\sum_{r=1}^{R}\left[\left(VTTS_g(r)-E(VTTS_g)\right)^2\times w_g\right]} \tag{12}$$

The t-test of the VTTS were then computed as the ratio between the mean and the standard deviation (H0: VTTS=0) and the confidence intervals were then computed as the 0.025 and 0.975 percentiles.

Finally, the distribution of the VTTS around the mean LVs was also computed for each of the defined groups in the sample using Monte Carlo simulation (5,000 draws were used for each LV). The 95% range of variation of the VTTS due to the latent variables, was then computed as the 0.025 and 0.975 percentiles.

4. Models Results and discussions

Table 4 summarized the results of the models estimated. Overall, the parameters estimated in both models are statistically significant at 5% level of significance and they are the same in the ML and the HCM with the exception of travel time by PAV and SAV because in the HCM these are interacted with the LV. We also note that the parameters of all the attributes that have a linear effect in the utility have the right sign in agreement with the microeconomic theory. Moreover, the agent effect, captured with the estimated error components σ_i, is also highly significant. The comparison between the travel time parameters in the ML and HCM and the microeconomic conditions for the attributes with non-linear effects will be discussed in the next section, when we will discuss the VTTS.

Different potential effects due to SE characteristics were considered: (i) direct effect of SE, and (ii) interaction effect between SE and travel time. In both the ML and the HCM, results show that gender and age significantly affect directly the choice of PAV, SAV, and walking. Specifically, men have a higher preference than women for the AVs, but have also a higher marginal disutility for travel time spent while travelling within an AV. Respondents 50 years or older prefer other modes of transport than AV and walking. Furthermore, in line with results on inertia effect (Gärling and Axhausen, 2003), possession of a public transport card increases the probability to choose public transport.

As discussed in the literature, previous studies on qualitative (Silberg et al., 2013) and quantitative user acceptance (Rödel et al., 2014, Schoettle and Sivak, 2014, Kyriakidis et al., 2015) found that the autonomy level of the respondents current vehicle positively affects the stated intention to use an AV. Our results from the ML model confirm this effect. In the ML model, we found that having experience with ADAS has a positive effect on the preference for both PAV and SAV. However, the results from the HCM show that this is indeed a spurious effect. In fact, in the HCM, where the experience with

ADAS is specified to affect the utility of PAV and SAV also indirectly through the trust on the technology, the direct effect is significant only in PAV but not in SAV. This is correct, because in the SAV drivers cannot take control of the vehicle, hence having experience with ADAS has also an indirect impact on the use of SAV as increases the trust on the technology.

Results also show that almost all these SE have also a significant impact in explaining heterogeneity in the preference for travel time, though interestingly, this interaction effect is generally more significant in the HCM than in the ML, due to the fact that in the HCM we are accounting for the role of attitudes in explaining the heterogeneity in travel time preferences. Specifically, results show that male, with experience with ADAS and a high education have lower marginal utility of travel time by PAV, while being 50 years or older decreases the marginal utility of walking time, as expected.

Looking at the impact of *trust* and *travel experiences* on the preference for travel time, results from the HCM model show a significant positive interaction effect between the two psychological variables and travel time in both PAV and SAV. Confirming our initial assumptions that the disutility of travel time by AV would depend on the individual attitudes. Firstly, we note that the expectation of positive travel experiences when riding autonomously (or anticipated subjective commute well-being in relation to the use on an AV) influences positively the preference for time spent in an AV. This result provides empirical evidences that potentially improved travel quality and increased comfort are crucial determinants of the willingness to use AVs and preferences for travel time. Moreover, they underline the important role of well-being benefits in the context of autonomous driving, discussed in previous theoretical and qualitative works (e.g. Singleton, 2018, Kolarova, 2020, Mokhtarian, 2018). Secondly, trust in the technology of AVs influences the marginal utility of travel time that is potentially spent in an AV. People who stated to entrust the driving system perceive travel time in an AV less negatively than those who do not. These results are in line with previous qualitative studies which found that trust is an important component of the acceptance of AVs, i.e. willingness to use such vehicles (e.g. Molnar et al., 2018, Ashkrof et al., 2019). Our results quantify this effect allowing for these effects to be correctly included in the estimation of the VTTS and the welfare measures.

Regarding the factors that influence respondents' attitudes, as discussed previously, results show that experience with ADAS affects strongly the trust in the AV technology. Specifically, people who have used such systems or at least have tested them trust more the AV technology. These findings are in line with previous qualitative and quantitative researches on the impact of trust on user acceptance of AVs (Rödel et al., 2014, Kolarova, 2020). Moreover, men are found to trust the technology more than women; also, people who are between 18- and 30-years old trust the technology more than people who are older than 30 years. Our findings align with the results of the few qualitative studies that found that men (Schoettle and Sivak, 2014, Schoettle and Sivak, 2015) as well as young respondents (Schoettle and Sivak, 2015, Seapine Software, 2014) are less concerned or worried about riding in a fully automated vehicle. The age of potential users plays also an important role in the evaluation of the travel experiences in an AV. Again, people under 30 years old have more positive expectations regarding the commuting time spent riding autonomously compared to people older than 30 years.

The results of the measurement equations are also in line with the expectation that the selected indicators are positively associated with the LVs: higher agreement with the statements indicates that people hold the corresponding attitude. The structural equation models for both LVs were also estimated separately in order to analyse their goodness-of-fit. Results confirm that all goodness-of-fit measures meet the criteria for a good fit except of one for the model of the LV travel experience.

Finally, results show also that the travel time coefficient values for the active modes of transport (walk, bicycle) are higher than for the motorized modes of transport, which appears a plausible finding given the differences in comfort level and speed between motorized and non-motorized alternatives.

Table 4: Discrete choice models results

	Mixed Logit model		Hybrid choice model	
Coefficients	**Est. value**	***t*-stat.**	**Est. value**	***t*-stat.**
ASC $_{walk}$	5.830	*4.54*	5.110	*4.80*
ASC $_{bicycle}$	-1.060	*-1.62*	-0.557	*-1.09*
ASC $_{PT}$	-2.110	*-4.35*	-2.060	*-5.05*
ASC $_{SAV}$	-0.746	*-2.44*	-0.694	*-2.4*
ß $_{\text{travel time walk [time in minutes]}}$	-0.295	*-7.37*	-0.264	*-7.48*
ß $_{\text{travel time bicycle [time in minutes]}}$	-0.123	*-13.42*	-0.128	*-14.60*
ß $_{\text{travel time PT [time in minutes]}}$	-0.058	*-8.79*	-0.060	*-9.28*
ß $_{\text{travel time PAV [time in minutes]}}$	-0.035	*-3.08*	-0.191	*-10.12*
ß $_{\text{travel time SAV [time in minutes]}}$	-0.042	*-5.09*	-0.204	*-9.50*
ß $_{\text{access/egress time (PT) [time in minutes]}}$	-0.057	*-2.77*	-0.050	*-2.47*
ß $_{\text{waiting time (PT, PAV, SAV) [time in minutes]}}$	-0.072	*-8.27*	-0.071	*-8.17*
ß $_{\text{ridesharing (SAV) [time in minutes]}}$	-0.593	*-4.64*	-0.609	*-4.78*
ß $_{\text{cost (PT, PAV, SAV) [cost in euro]}}$	-0.662	*-18.63*	-0.643	*-18.54*
$\tau_{\text{travel time PAV * travel experiences}}$			0.029	*4.64*
$\tau_{\text{travel time SAV * travel experiences}}$			0.031	*4.46*
$\tau_{\text{travel time PAV * trust}}$			0.017	*2.98*
$\tau_{\text{travel time SAV * trust}}$			0.014	*2.54*
ß $_{\text{pt pass (PT)}}$	3.160	*6.95*	3.040	*9.23*
ß $_{\text{male (PAV)}}$	0.627	*2.01*	0.596	*1.96*
ß $_{\text{male * travel time (PAV)}}$	-0.022	*-1.94*	-0.028	*-2.41*
ß $_{\text{50+ years old (PAV)}}$	-0.468	*-2.41*	-0.386	*-2.09*
ß $_{\text{50+ years old (walk)}}$	-12.60	*-5.35*	-12.40	*-6.11*
ß $_{\text{50+ years old * travel time walk}}$	0.247	*5.81*	0.227	*6.26*
ß $_{\text{university education level * travel time (PAV)}}$	-0.033	*-3.39*	-0.032	*-3.46*
ß $_{\text{university education level * travel time (SAV)}}$	-0.020	*-1.84*	-0.021	*-2.11*
ß $_{\text{experience with ADAS (PAV)}}$	1.440	*3.08*	0.927	*2.37*
ß $_{\text{experience with ADAS (SAV)}}$	0.814	*2.04*	0.130	*0.42*
ß $_{\text{experience with ADAS * travel time (PAV)}}$	-0.013	*-1.13*	-0.024	*-2.05*
σ_{walk}	4.890	*6.11*	-5.170	*-7.12*
$\sigma_{bicycle}$	-4.820	*-11.4*	-4.160	*-11.67*
σ_{PT}	-3.850	*-13.6*	-3.150	*-15.42*
σ_{PAV}	-1.030	*-4.06*	-1.110	*-7.83*
σ_{SAV}	-1.110	*-4.76*	1.030	*6.90*

Table 4 (Ctd'): Discrete choice models results

		Hybrid choice model	
Structural equations - coefficients		**Est. value**	***t*-statistic**
LV: Trust in the technology of automated vehicles			
Intercept $_{trust}$		2.390	*30.38*
α_{male}		0.450	*4.59*
$\alpha_{18\text{-}30\ years\ old}$		0.409	*2.61*
$\alpha_{experience\ with\ ADAS}$		0.470	*4.73*
σ_{trust}		1.210	*27.67*
LV: Travel experiences (for riding autonomously)			
Intercept $_{travel\ experiences}$		3.720	*24.58*
α_{male}		0.133	*1.26*
$\alpha_{30\text{-}50\ years\ old}$		-0.393	*-2.33*
$\alpha_{50+\ years\ old}$		-0.434	*-2.59*
$\sigma_{travel\ experiences}$		1.190	*24.82*
Measurement equations - coefficients			
LV: Trust in the technology of automated vehicles			
Intercept $_{trust\_01}$		0	*fixed*
Intercept $_{trust\_02}$		0.398	*3.24*
Intercept $_{trust\_03}$		0.090	*0.91*
γ_{trust_02}		1.000	*fixed*
γ_{trust_02}		0.869	*21.77*
γ_{trust_03}		0.941	*28.84*
ζ_{trust_01}		0.525	*14.78*
ζ_{trust_02}		0.861	*26.47*
ζ_{trust_03}		0.556	*18.56*
LV: Travel experiences (for riding autonomously)			
Intercept $_{travel\_experiences\_AV\_01}$		0	*fixed*
Intercept $_{travel\_experiences\_AV\_02}$		-0.316	*-2.23*
Intercept $_{travel\_experiences\_AV\_03}$		2.240	*11.77*
$\gamma_{travel\_experiences\_AV\_01}$		1.000	*fixed*
$\gamma_{travel\_experiences\_AV\_02}$		1.070	*27.67*
$\gamma_{travel\_experiences\_AV\_03}$		0.285	*5.60*
$\zeta_{travel\_experiences\_AV\_01}$		0.515	*14.03*
$\zeta_{travel\_experiences\_AV\_02}$		0.512	*11.99*
$\zeta_{travel\_experiences\_AV\_03}$		1.250	*30.91*

Model fit		
Cte log likelihood	-5383.23	-5383.23
Log-likelihood (final)	-2863.43	-8963.672
Log-likelihood (final) DCM part		-3122.418
Nr. of estimated parameters	29	82
AIC	5785	13980
BIC	5831	14071
Sample size / Nr. of individuals	3872 / 484	3872 / 484
Nr. of draws	2000	2000

5. Calculated VTTS for PAV and SAV

5.1. VTTS distribution

Table 5 reports the average VTTS, along with the statistics, computed using the estimated coefficients in the ML and the HCM, and Monte Carlo simulation (equations (9) and (10)), where marginal utilities of travel time for PAV and SAV account for systematic heterogeneity due to (i) the effect of SE and (ii) the effect of the psychological factors travel experiences and trust (only for the HCM). The statistics for the hybrid choice model were computed considering the average values of the latent constructs. We will discuss later the distribution of the LV. Draws were taken from a MVN, however only the covariance between the estimated parameter for the TT_SAV and the estimated parameter for the interaction TT_SAV*TE was significantly different from zero. We made then the assumption to set to zero all other covariance elements. Since the VTTS is a ratio between estimated coefficients, differences in VTTS between the ML and the HCM are not attributable to difference in scale but only to the effect of the heterogeneity of the sample. We also note that for all the observations in the sample the VTTS is always positive. Considering the simulated distribution, we found negative VTTS for only 3% of the population in the ML model and for 5% in the HCM, which is negligible.

A comparison with existing values from the literature shows that they are in the expected range. For instance, in the representative study on value of time for Germany, the VTTS for a conventional car on commuting trips (i.e. trips to work or education) are 4,44 Euro per hour and those for public transport 4,23 (Axhausen et al., 2014). In a previous study, which uses the same choice experiment, the calculated VTTS for an AV (using in an automated driving mode) was between 3,74 and 8,66 Euro per hour, for an SAV between 4,85 and 11,27 Euro per hour, and for public transport between 3,93 and 9,12 Euro per hour - all depending on the income class the person belongs to (Steck et al., 2018). Also, Correia et al. (2019) in a study conducted in Netherlands calculated average VTTS for AVs between 6,41 and 9,10 Euro per hours over different types of estimated models and depending on interior design of the AV.

Table 5 shows that in both models (the ML and HCM) the average VTTS for SAV is lower than for PAV; this difference is about 28% in the ML and 18% in the hybrid choice model. However, it is important to note that our results show also that in both cases, the difference is not statistically significant (in the ML *t-test*[8]$=0.54$, $p>0.05$; in the HCM *t-test*$=0.24$, $p>0.05$). The t-test of the VTTS are significant at 95% (one tail, because VTTS>0) in both models. The confidence intervals of the VTTS in the HCM is wider than in the ML, which seems to reflect the additional heterogeneity in the attitude toward trust and travel experiences. But the confidence interval estimated with the HCM includes the mean value estimated with the ML model and vice versa. For comparison, Table 5 includes also the VTTS for the other modes included in the models: Public Transport, Bicycle and Walk. All VTTS are significantly different from zero and from one each other. The only exception is the VTTS for PT that in the ML model is not significantly different from the VTTS for PAV (*t-test*$=0.49$, $p>0.05$) and from the t-test for SAV (*t-test*$=0.84$, $p>0.05$). This means that all three modes are perceived similarly by respondents according to the results of the ML. Interestingly, in the HCM, that properly accounts for the latent effect of trust and travel experience, the VTTS for PT is significantly different from the VTTS for PAV (*t-test*$=2.40$, $p<0.01$). This is a correct result, because it is plausible to assume that SAV is closer to a PT, while PAV is closer to a private car.

Table 5: Simulated value of travel time savings (VTTS) in euro per hour

Mode of transport		**Mixed Logit Model**	**Hybrid Choice Model**
Privately-owned automated vehicle (PAV)	Average t-test confidence interval	5.65 2.25 [0.73,10.58]	7.35 1.88 [-0.29,14.99]
Shared automated vehicle (SAV)	Average t-test confidence interval	4.42 3.42 [1.87,6.96]	6.23 1.70 [-1.04,13.32]
Public Transport (PT)	Average t-test confidence interval	5.28 7.93 [3.97,6.58]	5.63 8.27 [4.29,6.96]
Bicycle	Average t-test confidence interval	11.16 10.83 [9.14,13.18]	11.96 11.38 [9.90,14.02]
Walk	Average t-test confidence interval	26.79 6.86 [19.13,34.44]	24.70 15.82 [21.26,27.77]

[8] This is the t-test for generic coefficients that accounts for the simulated covariance between VTTS-PAV and VTTS-SAV, that is equal to 1.33 in the ML and 3.34 in the HCM.

More interesting results are obtained looking at the VTTS for specific user group. Based on the SE characteristics included in the structural equation of the LVs, we were able to identify 24 user groups. Table 6 provides a description of these user groups, along with the simulated mean VTTS for each group and its statistics, (t-test against zero) and [confidence interval]. In terms of the distribution of the sample among groups, groups 2, 3, 5 and 6 account for 37.5% of the sample. The remaining 62.5% is relatively evenly distributed among the other 21 groups. Unless differently specified all the VTTS in this section are computed using the HCM and the average value of the LV.

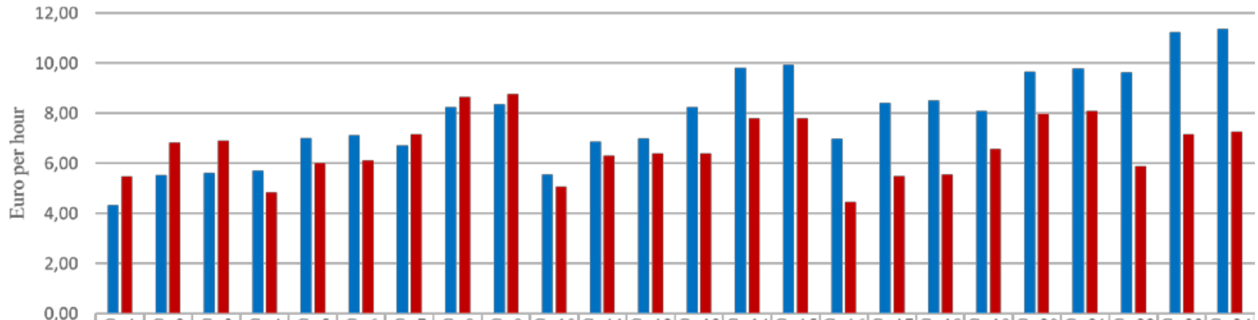
Figure 3 visualizes the mean VTTS reported in Table 6. As mentioned above, the population VTTS for PAV are higher than for SAV, but not significantly different. If we look at each group, even though the mean VTTS is quite different between PAV and SAV (see e.g. groups 16, 17, 18, 22, 23 and 24) none of them is significantly different. This result can be affected by the low significance of the SAV VTTS in groups 16, 17, 18 and 22. However, in groups 23 and 24 the SAV VTTS is significant. Differently from previous funding (e.g. Kolarova et al., 2019b), our results suggest that there is not indeed a difference in the VTTS between PAV and SAV.

5.2. VTTS distribution among user groups

We now turn our attention to the difference among SE groups. Looking at the effect of single SE, we see a trend that indicates higher VTTS (for both PAV and SAV) as age increases, higher for people with university degree than for those without, lower for people who had experience with ADAS than for those without and higher for men than for female (for the last one, this applies especially in the case of PAV). Some of these effects (such as age and university degree) might be related also to the level of income (we do not have this information to control for it), but can also reflect a different propensity to accept new technology (for instance in the case of men as it is plausible to assume that they have on average higher income than women).

Table 6: User group-specific VTTS estimated with the HCM

Group		Characteristics of the user group				PAV - VTTS			SAV - VTTS		
	Distr.	Gender	Age	Univ or higher	ADAS exp.	Mean	t-test	Confidence interval	Mean	t-test	Confidence interval
1	3.7%	Female	18-30	No	No	4.34	1.23	[-2.57,11.24]	5.47	1.51	[-1.63,12.56]
2	10.5%		30-50			5.54	1.81	[-0.47,11.24]	6.82	2.08	[0.38,13.26]
3	10.5%		50+			5.62	1.85	[-0.32,11.57]	6.90	2.12	[0.51,13.30]
4	3.1%	Male	18-30	No	No	5.71	1.52	[-1.65,13.07]	4.84	1.22	[-2.92,12.60]
5	8.1%		30-50			7.03	2.06	[0.35,13.70]	6.01	1.72	[-0.83,12.85]
6	8.7%		50+			7.14	2.11	[0.51,13.77]	6.11	1.77	[-0.67,12.09]
7	1.9%	Female	18-30	Yes	No	6.72	1.99	[0.09,13.36]	7.18	1.98	[0.06,14.29]
8	4.1%		30-50			8.24	2.62	[2.08,14.40]	8.64	2.58	[2.08,15.20]
9	3.7%		50+			8.36	2.68	[2.24,14.48]	8.76	2.61	[2.17,15.35]
10	2.1%	Female	18-30	No	Yes	5.55	1.52	[-1.60,12.70]	5.07	1.33	[-2.43,12.56]
11	3.7%		30-50			6.88	2.08	[0.41,13.34]	6.31	1.85	[0.38,12.99]
12	3.7%		50+			6.99	2.13	[0.57,13.41]	6.39	1.89	[-0.23,13.00]
13	1.0%	Male	18-30	Yes	No	8.24	2.21	[0.94,15.55]	6.39	1.66	[-1.14,13.92]
14	3.3%		30-50			9.81	2.80	[2.95,16.66]	7.79	2.21	[0.89,14.68]
15	4.8%		50+			9.93	2.85	[3.11,16.76]	7.79	2.26	[1.04,14.54]
16	1.9%	Male	18-30	No	Yes	6.98	1.77	[-0.74,14.70]	4.46	1.06	[-3.75,12.66]
17	5.4%		30-50			8.41	2.30	[1.26,15.56]	5.50	1.53	[-1.56,12.55]
18	4.3%		50+			8.52	2.35	[1.41,15.63]	5.57	1.57	[-1.39,12.52]
19	1.7%	Female	18-30	Yes	Yes	8.10	2.23	[0.99,15.21]	6.57	1.78	[-0.65,13.79]
20	2.3%		30-50			9.67	2.84	[3.00,16.33]	7.99	2.35	[1.32,14.66]
21	1.9%		50+			9.78	2.89	[3.16,16.41]	8.09	2.40	[1.48,14.70]
22	2.1%	Male	18-30	Yes	Yes	9.63	2.43	[1.86,17.41]	5.87	1.49	[-1.86,13.60]
23	4.8%		30-50			11.24	2.99	[3.88,18.60]	7.17	2.00	[0.13,14.21]
24	2.9%		50+			11.37	3.04	[4.04,18.70]	7.26	2.04	[0.28,14.23]



	Gr.1	Gr.2	Gr.3	Gr.4	Gr.5	Gr.6	Gr.7	Gr.8	Gr.9	Gr.10	Gr.11	Gr.12	Gr.13	Gr.14	Gr.15	Gr.16	Gr.17	Gr.18	Gr.19	Gr.20	Gr.21	Gr.22	Gr.23	Gr.24
VTTS-PAV	4,34	5,54	5,62	5,71	7,03	7,14	6,72	8,24	8,36	5,55	6,88	6,99	8,24	9,81	9,93	6,98	8,41	8,52	8,10	9,67	9,78	9,63	11,24	11,37
VTTS-SAV	5,47	6,82	6,90	4,84	6,01	6,11	7,18	8,64	8,76	5,07	6,31	6,39	6,39	7,79	7,79	4,46	5,50	5,57	6,57	7,99	8,09	5,87	7,17	7,26

Figure 3: Average VTTS for different user groups in euro per hour

However, despite the difference in the average values, the VTTS is significantly different only between few groups. Table 7 reports t-test for the difference in the PAV-VTTS between groups[9]. Comparing all groups that have the same characteristics except for a particular SE, results suggest that the main differences in the VTTS for PAV between groups depends, with few exceptions, on the education level of the potential users (higher education level is associated with higher VTTS). The VTTS for people with university or higher education level (groups 8, 9, 14, 15, 20-24) is higher and statistically different from the VTTS for people with lower education level (groups 1-6, 10-12, 16-18). This is a consequence of the fact that higher educated people have higher marginal disutility for travel time, hence they seem to be more reserved when it comes to AV. Theories on adoption and diffusion of innovations suggest that innovators and early adopters of innovations have usually high education level (Rogers, 1995). This is also confirmed by empirical studies on the early adopters of electric vehicles (for instance Giffi et al., 2011, Hagman et al., 2011, Hidrue et al., 2011, Trommer et al., 2015). People with higher education are probably able to understand better complex new technologies and their benefits and they might be more prone to gather new information about current developments (Lüthje, 2006). Because of that, it is also likely that this group is more aware of the technological issues related to AVs, including some accidents with autopilot systems.

Among people with the same level of education, youngers have VTTS significantly different from medium age and older people. Compare group 7 (young) with groups 8 (medium age) and 9 (50+), which are equal in all other characteristics (female with university education and no ADAS experience); compare also group 13 (young) with groups 23 (medium age) and 24 (50+ years old), which are all male with university education and ADAS experience.

Gender alone seems not to play overall an important role. However, our results show that this is due to the sum of two opposite effects. In line with previous literature (Schoettle and Sivak, 2014, Schoettle and Sivak, 2015, Kyriakidis et al., 2015, Sweet and Laidlaw, 2019), men are found to trust the technology more than women. However, our results show that they also perceive higher marginal disutility for travel time. Hence, overall the VTTS for PAV is not statistically different between male and female. For similar reasons, ADAS does not seem to have either a significant impact in the VTTS for PAV. In fact, both male and ADAS have a negative direct impact on the marginal utility of travel time for AV but also a positive impact on trust, which in turn affects positively the marginal utility of travel time.

We performed the same analysis for the VTTS computed using the ML model (i.e. without accounting for the latent effect of trust and travel experiences). Table 8 report the VTTS for the various groups. Results are very different and clearly confirm the importance of accounting for the above latent effects. In the ML model, we found in fact that the VTTS for PAV is significantly different only between female

[9] The table reports only the cases where the H0 that the VTTS of two groups is equal was rejected at 5% level of significance The t-test between almost all other groups is lower than 1.00

without high education and without ADAS experience (groups 1, 2 and 3[10]) and male with higher education without (groups 13, 14, 15) (*t-test = 2.32, p<0.01)* or with ADAS experience (groups 22, 23 and 24) (*t-test = 2.45, p<0.01)*. We also found that the t-test between the VTTS for female without high education and without ADAS experience (groups 1, 2, 3) and female with high education and ADAS experience is equal to 1.89 (*p=0.03)*. The t-test for difference between all other groups can be rejected with *p >0.05*. As we can see, the ML does not capture differences in the VTTS due to age, and it does not allow differentiating the difference in VTTS due to gender and experience with ADAS.

Table 7: T-test for differences between PAV-VTTS

	Group 8	Group 9	Group 14	Group 15	Group 20	Group 21	Group 22	Group 23	Group 24
Group 1	-2.09	-2.15	-2.51	-2.55	-2.49	-2.54	-2.16	-2.83	-2.87
Group 2	-2.49	-2.24	-2.67	-2.52	-2.68	-2.54	-1.90	-2.90	-2.80
Group 3	-2.10	-2.57	-2.44	-2.71	-2.44	-2.73	-1.87	-2.73	-2.93
Group 4			-2.61	-2.68	-1.81	-1.87	-2.13	-2.94	-2.99
Group 5			-2.76	-2.42				-2.83	-2.66
Group 6			-2.27	-2.84				-2.56	-2.87
Group 7	-1.82	-1.95	-2.25	-2.31	-2.22	-2.30		-2.58	-2.63
Group 10			-1.90	-1.95	-2.61	-2.68	-2.14	-2.94	-2.98
Group 11					-2.75	-2.41		-2.80	-2.63
Group 12					-2.31	-2.88		-2.58	-2.87
Group 13			-2.06	-2.19				-2.33	-2.41
Group 14							-2.09	-3.10	-3.17
Group 16								-2.95	-2.55
Group 17								-2.38	-3.00
Group 18					-2.05	-2.17		-2.36	-2.42
Group 19			-1.90	-1.95	-2.61	-2.68	-2.14	-2.94	-2.98
Group 23								-2.21	-2.34
Group 24									-2.49

Table 8: User group-specific VTTS estimated with the ML model

Group					PAV - VTTS			SAV - VTTS		
	Distr.	Gender	Edu: Univ or higher	ADAS exp.	Mean	t-test	Confidence interval	Mean	t-test	Confidence interval
1-3	24.8%	Female	No	No	3.18	3.06	[1.14, 5.21]	3.80	4.88	[2.27, 5.32]
4-6	6.6%	Male	No	No	5.19	3.51	[2.29, 8.09]			
10-12	9.5%	Female	No	Yes	4.34	2.96	[1.46, 7.22]			
16-18	11.6%	Male	No	Yes	6,36	3.51	[2.81, 9.91]			
7-9	3.2%	Female	Yes	No	6.17	4.42	[3.43, 8.91]	5.60	4.43	[3.12, 8.07]
13-15	9.1%	Male	Yes	No	8.18	4.64	[4.73,11.64]			
19-21	5.8%	Female	Yes	Yes	7.33	4.22	[3.93, 10.74]			
22-24	9.7%	Male	Yes	Yes	9.35	4.57	[5.34, 13.36]			

The t-test between groups was also computed for the VTTS for SAV. We do not report the table, but we found that the VTTS was statistically significant only between groups 8, 9 (women over 30 years old, without experience with ADAS and higher education level) and groups 1, 4, 10, 17, 18, and 19 (mostly younger women under 30 years old or people with ADAS experience). Group 8 is additionally statistically significantly different from groups 5 and 10, and group 9 from group 6. There is not a clear pattern in these results with small exceptions. Groups 8 and 9 are the user groups with the highest VTTS for SAV in the sample and significantly higher than the VTTS of group 19, which represents women

[10] Note that in the ML model, the interaction between age and Travel Time was not significant and hence it does not affect the VTTS. The VTTS is then the same among groups 1, 2 and 3, as well as among groups 22, 23 and 24 and so on.

under 30 years old, which have higher education level, but also experience with ADAS.

Given that (i) the SAV is introduced as a vehicle that drive fully autonomously while the PAV can be driven manually and (ii) the strong positive effect of ADAS experience on trust in the technology of AVs, our results underline the impact of experiences with similar technology on the VTTS for AVs.

5.3 Impact of Trust and Travel experiences distribution on VTTS

Since the latent variables, trust and travel experiences, are random variables distributed Normal (see equation 3), the VTTS is also distributed Normal. We first looked at the simulated average values and the distribution characteristics of both LVs, then at the impact of the LV distribution on the VTTS. The average values for the sample are summarized in Table 8. Figure 4 displays the average values for each user groups.

Table 8: Average values for the LVs travel experiences and trust in the sample

				Percentiles			
Latent variable	**Mean**	**t-test**	**Confidence interval**	**10%**	**25%**	**75%**	**90%**
Travel experiences	3.44	12.24	[2.89;3.99]	3.20	3.32	3.57	3.68
Trust in an AV	2.86	7.16	[2.07;3.64]	2.73	2.79	2.93	2.99

Generally speaking, the higher the average values of the LVs, the more respondents hold positive attitude toward AVs, i.e. evaluate travel experiences (TE) more positively or trust the technology more compared to people with lower LV values. Trust is significantly different (at less than 5% significance) among almost all groups (with few exceptions), but it is not possible to recognise a pattern. In the travel experiences instead, there is a striking difference between groups with young respondents (less than 30 years old) and the groups with respondents older than 30.

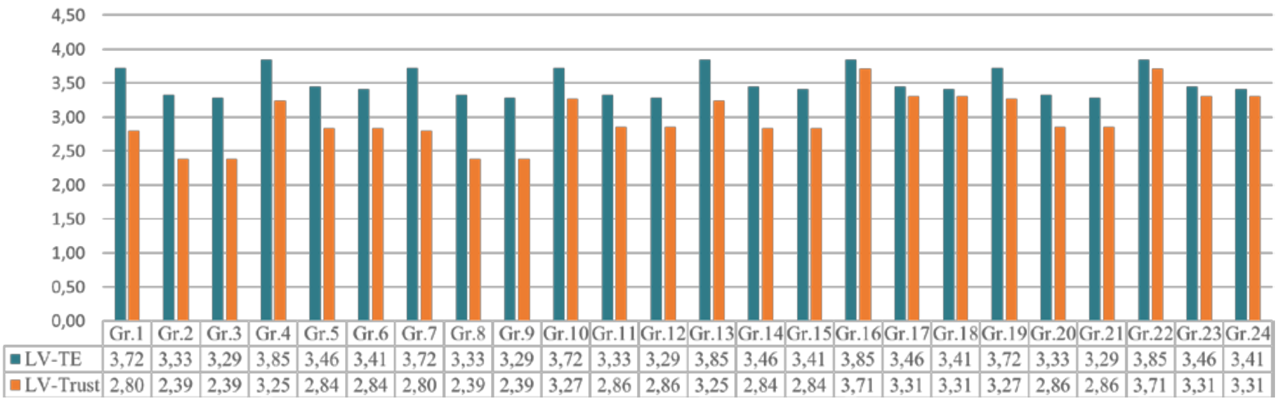


Figure 4: Average values of the latent variables Travel experiences (TE) and Trust for different user groups.

Finally, we analyzed the impact of trust and travel experiences on the VTTS. Table 9 summarizes the mean VTTS values for PAV and SAV using the LV values that define the different percentiles of the distribution of the LVs (see the values in Table 9). Simulation was used to build the distribution around the mean value of the estimated coefficients. In squared brackets we reported also the confidence interval for each of them. The results in Table 9 show that high LV values lead to a reduction in the VTTS. Moreover, we note that having the highest value on the LVs in the sample lead to higher number of negative VTTS. In this case, for the PAV, 9.4% of the values are negative and for the SAV 13.13%.

Table 9: VTTS computed using the values of the trust and travel experiences in the different percentiles of the distributions of the LVs

AV concept	Percentiles of the LVs				
	10%	**25%**	**50%**	**75%**	**90%**
PAV	8.14 [0.30,15.98]	7.79 [-0.08,15.65]	7.35 [-0.29,14.99]	6.85 [-1.14,14.84]	6.41 [-1.69,14.45]]
SAV	7.11 [0.51,13.70]	6.70 [0.08;13.32]	6.23 [-1.04,13.32]	5.82 [-1.00,12.64]	5.40 [-1.60;12.40]

A comparison between the mean VTTS among people holding relatively negative attitude (10th percentile of the LVs distributions) and those holding relatively positive attitude (90th percentile of the LVs distributions) shows that the VTTS of the first group are about 24% higher than the values of the second one. However, these are not significantly different. Simultaneously, as shown in section 5.1, there are indeed statistically significant differences in the VTTS between user groups which are defined by both their socio-economic characteristics and their attitudes. Attitudes are defined in the model by certain socio-economic characteristics and a random term. The fact that significant differences are found between certain user groups but not when simulating the VTTS according to the random distribution of the LV suggests that these differences are explained by the characteristics that define the user groups. These findings underline the impact of the considered LVs on VTTS and the importance of considering individual characteristics, such as attitudes when analysing the effect of new mobility concepts on VTTS.

A comparison of the results from the group-specific analyses of the LV values with the group-specific VTTS reveals in fact the following insights: the groups with highest Travel Experiences and Trust values have low VTTS, and some groups also show negative VTTS for AVs, an exception is the group of men with university or higher education level (groups 16 and 22). This result suggests that high trust and travel experiences compensate for the disutility due to travel time. These two groups are statistically significantly different than the following user groups: (i) women over 50 years old with educational level lower than university and with experiences with ADAS, (ii) men under 30 with educational level lower than university and with experience with ADAS, and (iii) women and men over 30 years old with experience with ADAS and at least university education level.

The low and partly negative VTTS for the AVs result potentially from the positive utility of travel time spent in an AV perceived by the part of the sample with strongly positive attitudes toward the technology. In other words, the results suggest that people who expect riding in an AV to be a positive experience and trust the technology might not perceive time spent in the car as “lost time” which they seek to minimize, but as potentially beneficial.

6. Conclusions

This study discusses and provides empirical evidence on the impact of *Trust* on technology and *Travel Experiences* (besides individual preference for activities conducted during travelling) in travel time preferences for AVs. Understanding the sources of variation in travel time preferences for AVs is crucial for developing more realistic and differentiated scenarios about the impact of autonomous driving on mode choices and travel demand.

An online survey with a stated choice experiment and psychometric scales was conducted. Besides currently available transport modes, also a privately-owned AV (PAV) and a shared AV (SAV) were included in the choice sets. The data was analysed using a hybrid choice model, including (i) direct effect of several socio-economic (SE) characteristics, (ii) interaction effect between SE and travel time and (iii) interaction between the two psychological constructs and travel time. Different VTTS depending on user groups defined by their socio-economic characteristics were calculated. T-test and confidence intervals of the estimated VTTS are computed to assess if the VTTS are statistically significant and statistically different among user groups.

The results of the study show firstly that the two selected psychological factors have a significant effect on the VTTS for the two concepts of automated vehicles, a PAV and an SAV, and consequentially on mode choices for such vehicles. Positive evaluation of travel experiences when riding autonomously and trust in the AVs, i.e. in the system and its safety, influence the valuation of travel time in an AV positively. Secondly, various socio-demographic factors affect personal attitudes. Experience with ADAS, gender (male) and age (being under 30 years old) influence trust in the technology of automated vehicles positively. The same age group is also the one that is more likely to evaluate potential travel experiences in an AV as a positive one. Thirdly, VTTS vary between different user groups defined by their socio-economic characteristics and considering the direct as well as the indirect (through their influence on the attitudes) effect of the socio-economic factors. Younger people (under 30) tend to have lower VTTS compared to older persons. Also, higher education level is associated with higher VTTS and experience with ADAS with lower VTTS. These findings underline not only the importance of considering individual attitudes when analysing user preferences for AVs, but also looking specifically at different user groups.

On the methodological side, our results confirm the importance of (i) measuring these impacts quantitatively, (2) disentangling the role of SE through the latent attitudes from the direct role in the VTTS and (3) using statistical tests the significance of the VTTS. For example, in line with previous funding our results show that the average VTTS for SAV is between 18% and 28% lower than for PAV. However, our results show also that in both cases, the difference is actually not statistically significant. In addition, in line with almost all the qualitative literature, our results show that men trust the technology more than women and they also to have potentially higher technology affinity. However, our results show also that they perceive higher marginal disutility for travel time. These two effects have opposite direction and overall the VTTS for PAV is not statistically different between male and female. Nevertheless, having estimated both effects is critical to be able to address policies correctly.

Our results also show that not considering attitudinal effects might lead to false conclusions about the impact of ADAS. In fact, we found that having experience with ADAS has a positive effect on the preference for SAV. However, when we included in the model also the impact of ADAS indirectly through the trust on the technology, the direct effect in SAV became insignificant. This is correct, because in the SAV drivers cannot take control of the vehicle, hence having experience with ADAS has also an indirect impact on the use of SAV as increases the trust on the technology.

Lastly, we like to mention that the descriptive analyses of the effect of different activities which people would perform in an AV shows that relaxing or performing rather passive activities affect decreases the disutility of travel time spent in car. Simultaneously, working is among the least preferable activities in an AV. These results support focusing more on benefits of AVs related to individual well-being instead of only potential productivity gains, discussed in early theoretical works in the context of autonomous driving.

Several implications for policy and deployment strategies for AVs can be derived from the results. First, the empirical insights from the study underline the importance for developing communication strategies for autonomous driving targeting different user groups considering also attitudes of potential users. Second, the results support the importance of the role of experience with the technology (or in this case with ADAS) to increase the trust and positive evaluation regarding automated driving. One strategy can be enabling gaining experience with automated systems, for instance on test fields or under real-world conditions (if feasible). Such tests are already part of government funded research activities (e.g. in Germany, BMVI, 2017). Third, the findings underline the need to target different groups of the population, including for instance elderly people, in order to reach also people currently less in favour of the new technology and increase acceptance of AVs. Furthermore, the expectation of people that autonomous driving would improve the experience of their commuting trip suggest that future tests can focus on analysing whether these expectation holds under real-world conditions and which implication they have on vehicle design and mobility services in the context of AVs. Last but not least, even though the results of this study suggest that people would prefer rather relaxing or passive activities in an AV, previous studies found also a positive effect of office interior on the travel time perception in an AV (Correia et al., 2019). Thus, the implications for future interior concepts of AVs are ambiguous, but the results suggest in general that comfort level as well as infotainment features might be important elements of such concepts.

All in one, the results of the analyses reveal an important mechanism behind user preferences on AVs. Specifically, individual characteristics, such as attitudes, influence travel time sensitivity in an AV and therefore also mode choices for AVs. While it is plausible to assume that attitudes towards the technology influence mode choices also directly, the insights on their impact on the travel time sensitivity are important for several reasons: first, VTTS is an important element in transportation cost-benefit analysis and looking for sources of preference heterogeneity with regard to travel time allows analysing more differentiated and accurate scenarios in the context of AVs. For instance, previous studies that discuss or empirically analyse the positive utility of travel (e.g. Mokhtarian and Salomon, 2001, Singleton, 2017) stress the importance of considering the determinants of travel time sensitivity when developing policies based on VTTS analyses. Our results show the importance of this especially in the context of AVs where a potential change in the value of time is assumed to be among the most important reasons behind potential behaviour changes due to AVs.

Overall, this study provides empirical evidence for the important role of attitudes when analysing VTTS for new mobility options, such as AVs. It is therefore a valuable contribution to the research of potential impact of autonomous driving on user preferences as well as to the literature on determinants of VTTS and consideration of the effect of LVs on VTTS. A limitation of the study is the focus on selected LVs and their individual effect on VTTS and mode choices. The complex relationship between the single psychological factors was not in focus of the analyses although it is plausible to assume that anticipated travel experiences in an AV are related to trust in the technology.

Further studies have to continue looking into effect of attitudes on VTTS. Also, we show that considering various user groups depending on their socio-economic characteristics together with the effect of these characteristics on attitudes allows more differentiated analyses of the impact of AVs on user preferences than calculating only average values. Thus, future research as well as AV development works may look deeper into the requirements and concerns of different user groups as this can be a key factor to increase acceptance of the technology.

Author contribution statement

Viktoriya Kolarova: conceptualization of the study, methodology, formal analysis, investigation, data curation, writing – original draft; **Elisabetta Cherchi:** supervision of conceptualization of the study, methodology, data analyses and writing – original draft, review and editing.

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ANNEX 1: Presentation of the concept of automated vehicle in the study

The concepts of AV were presented using the following short sentence:

“The autonomous car is a road vehicle which can perform the driving task. This means that the vehicle can break, steer, accelerate and stop by itself. The driver don´t have to pay attention to the traffic and the driving task, so he or she can do something else while travelling (e.g. read, watching movies, use the internet, etc.).”

The text introduction was followed by two videos that showed how the use of an AV might looks like: one video refers to the case of a PAV, the other one to the case of individually used SAV, i.e. not shared with other passengers. In the second survey, three videos were presented.

Figure A1 shows the storyboard for a trip with a PAV. Mrs. Schmidt calls her vehicle using an app on her smartphone, the vehicle drives by itself out of the garage and pick her up. During the trip, she can decide whether she would like to drive manually or which of the automated function of the vehicle and ride she wishes to set in automated drive mode.

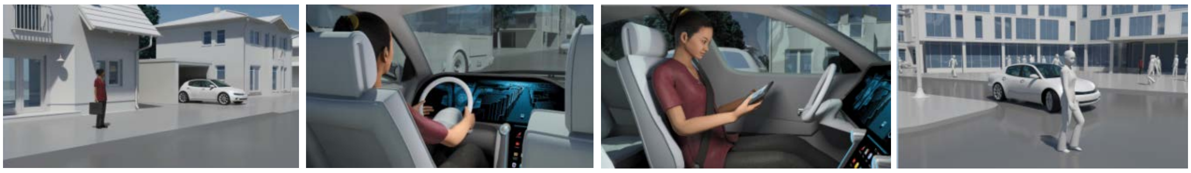

Figure A1: Storyboard of the animated video used to present a trip with a privately-owned automated vehicle (PAV)

Figure A2 presents the storyboard for a trip with an SAV, used individually (i.e. not used in a ride-sharing arrangement). Mrs. Schmidt calls a vehicle using an app on her smartphone, the vehicle picks her up and drives her fully autonomous to her predefined destination. In contrast to the PAV, the SAV is a vehicle without steering wheel or breaks, so it cannot be driven manually.

Figure A2: Storyboard of the animated video used to present a trip with a shared automated vehicle (SAV) - vehicle used individually

Figure A3 presents the storyboard of an SAV, used in a ride-sharing arrangement. The SAV, as presented in the video, shows Mrs. Schmidt calling a vehicle with her app and then sharing the ride with other user who uses similar routes with the benefit of having lower cost per person for the ride.

Figure A3: Storyboard of the animated video used to present a trip with a shared automated vehicle (SAV) - vehicle used in a ride-sharing arrangement