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Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips

Ir. Menno D. Yap [a,b], Dr.Ir. Gonçalo Correia [a,*], Prof.Dr.Ir. Bart van Arem [a]

[a] Delft University of Technology, Department Transport & Planning, Delft, The Netherlands
[b] Goudappel Coffeng, Deventer, The Netherlands

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ABSTRACT

In the recent years many developments took place regarding automated vehicles (AVs) technology. It is however unknown to which extent the share of the existing transport modes will change as result of AVs introduction as another public transport option. This study is the first where detailed traveller preferences for AVs are explored and compared to existing modes. Its main objective is to position AVs in the transportation market and understand the sensitivity of travellers towards some of their attributes, focusing particularly on the use of these vehicles as egress mode of train trips. Because fully-automated vehicles are not yet a reality and they entail a potentially high disruptive way on how we use automobiles today, we apply a stated preference experiment where the role of attitudes in perceiving the utility of AVs is particularly explored in addition to the classical instrumental variables and several socio-economic variables. The estimated discrete choice model shows that first class train travellers on average prefer the use of AVs as egress mode, compared to the use of bicycle or bus/tram/metro as egress. We therefore conclude that AVs as last mile transport between the train station and the final destination have most potential for first class train travellers. Results show that in-vehicle time in AVs is experienced more negatively than in-vehicle time in manually driven cars. This suggests that travellers do not perceive the theoretical advantage of being able to perform other tasks during the trip in an automated vehicle, at least not yet. Results also show that travellers' attitudes regarding trust and sustainability of AVs are playing an important role in AVs attractiveness, which leads to uncertainty on how people will react when AVs are introduced in practice. We therefore state the importance of paying sufficient attention to these psychological factors, next to classic instrumental attributes like travel time and costs, before and during the implementation process of AVs as a public transport alternative. We recommend the extension of this research to revealed preference studies, thereby using the results of field studies.

1. Introduction

In the last years many developments took place regarding automated vehicles (AVs) technology. In fact automated vehicles are expected to become available on the market in the next 10–20 years (Shladover, 2015). Most studies on automated vehicles focus on the vehicle technology in relation to the effect on traffic flow characteristics, road capacity and traffic

* Corresponding author.
E-mail addresses: MYap@Goudappel.nl (M.D. Yap), G.Correia@TUDelft.nl (G. Correia), B.vanArem@TUDelft.nl (B. van Arem).

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safety. The relation between different penetration rates of automated and cooperative transport systems and road capacity has been for example studied by Van Arem et al. (2006), Tampère et al. (2009), Arnaout and Bowling (2011), Shladover et al. (2012), Hoogendoorn et al. (2014) and Schakel and Van Arem (2014). Kesting et al. (2005) also consider the effect of AVs on the capacity drop after congestion. The impact of AVs on traffic stability has, amongst others, been studied by Schakel et al. (2010). VanMiddlesworth et al. (2008) studied AVs in intersections management, whereas Van Driel and Van Arem (2010) considered the effect of AVs on both traffic flow efficiency and traffic safety.

It is however unknown to which extent the share of the existing transport modes will change as result of using AVs as a transit system (Correia et al., 2016). To the best of our knowledge this study is the first where traveller preferences for AVs are explored and compared to existing modes. Thereby its main objective is to position AVs in the transportation market and understand the sensitivity of travellers towards some of their travel attributes. Because there are no fully automated vehicles currently on the market we apply a stated preference (SP) experiment where the role of classic instrumental variables such as travel time and cost are explored. Moreover, due to the fact that these vehicles entail moving on the road network without a driver and entrusting that task to a computer, we expect that psychological factors translated through positive and negative attitudes play an important role in the choice to use automated vehicles. Therefore, in our SP experiment the role of attitudes in perceiving the utility of AVs is particularly explored in addition to these classical instrumental attributes.

Five different levels of automation are defined by Gasser and Westhoff (2012) and SAE International (2014). These 5 levels are driver support (level 1), partial automation (level 2), conditional automation (level 3), high automation (level 4) and full automation (level 5). A higher level of automation entails a less important role for the human driver in the driving task. Our study focuses on AVs which are able to operate according to level 5 automation, meaning that there is a full time performance of an automated driving system for all driving tasks, without any human intervention. In our SP experiment, we also explicitly assume that these vehicles are fully electrically powered, thus representing a lower environmental impact at least at the local level.

The scope of this paper is on studying the potential of AVs for the last mile trips between a train station and the travellers' final destination. We realize that a modal shift from car to trains as main mode on medium-distance (20–40 km) trips is an important policy goal of the Dutch government (Ministry of Infrastructure and Environment, 2015). A higher train usage entails a higher level of sustainability in transportation and can also reduce congestion levels, with its related economic and environmental impacts. Currently, in the Netherlands there is a relatively high share of multimodal trips for medium-distance trips between urban areas. Between the most developed urban areas in the Netherlands, up to 17% of the trips are currently considered as being multimodal (a trip in which a traveller uses at least two different modes) (Van Nes et al., 2014). In multimodal train trips, a relatively high disutility is especially caused by the access and egress trip stage (Hoogendoorn-Lanser, 2005), hence it is hypothesized that providing AVs as egress mode may have the potential to improve the attractiveness of multimodal train trips and to realize a modal shift to the train + AV combination. AVs are thus considered as potential means to increase the attractiveness of the total door-to-door trip, by providing a last mile service which brings travellers from the train station to the front door of their final destination in a sustainable way.

The paper is structured as follows. Section 2 presents the applied methodology to investigate travellers' preferences for using AVs. In Section 3, the survey and sample are shortly discussed. Section 4 shows and discusses the results of the final estimated model. At last, conclusions and recommendations for further research are presented in Section 5.

2. Methodology

2.1. Alternatives and attributes

Public transport (PT) trips usually consist of three stages: access, main part and egress. We define a multimodal PT trip in this paper as a trip where more than one mode is used, with one or more public transport modes being used for the main part of the trip. For each stage different alternatives are available, such as walking, cycling, private car or bus, tram and metro (denoted as BTM) for access; train or BTM for the main stage; and walking, cycling, car-sharing or BTM for the egress part. For all these stages different attributes - like in-vehicle time, waiting time and travel costs - are relevant for multimodal mode choice. The high number of possible combinations of mode alternatives and attributes makes it complex to incorporate all those in one SP experiment in a manageable way. Capturing the attribute sensitivity for all these combinations would lead to a high number of choice sets provided to each respondent, leading to a too complex task for the respondent, or requiring a very large sample of respondents.

In order to reduce this complexity, in our study we focused only on multimodal PT trips where trains are used in the main trip stage. Besides, we only consider trips in the direction going from a home-end origin, to a destination at the activity-end of a trip. As Hoogendoorn-Lanser et al. (2006) indicate, there are differences in mode availability, knowledge and use of multimodal trip alternatives between the home-end and activity-end of a trip. Therefore it is important to explicitly distinguish between the home-end and the activity-end of a trip, since attribute sensitivities can be different on each side of the trip. Consequentially in this study we have only considered the AV as egress transport from the train station to the activity-end destination of the trip. Furthermore, we provided respondents with attributes and attribute levels for the access and main stage of the multimodal rip together, whereas attributes for the egress stage of the trip were disaggregated by mode and explicitly mentioned separately (Fig. 1). This clustering is in line with the scope of the study which is exploring the

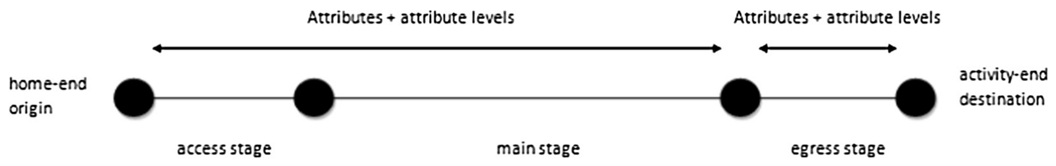


Fig. 1. Clustering of attributes for access and main trip stage; separate attributes for egress trip stage.

sensitivity of travellers to AV attributes on the egress stage of the trip only. This also means that different modes for the access stage of the trip were not explicitly mentioned in our study (Fig. 2). This decision allowed us to reduce the number of alternatives and attributes to be shown to the respondents in the SP experiment.

In this study we included access + train + AV as a multimodal trip alternative next to the two most common existing multimodal trip alternatives: access + train + PT (bus/tram/metro) and access + train + bicycle. We expect that AVs will not be used as substitute for walking on the egress stage, given the limited area around a train station which can reasonably be reached by walking. To get insight into the trade-offs between mode alternatives as well as sensitivity to AV attributes, walking is therefore not incorporated as egress mode in this study.

Two variants in which AVs are used as last mile transport are explicitly incorporated in the study. In one variant, a traveller has to drive the AV *himself* from the train station to the final destination. After reaching the destination, the AV can drive automatically without a human occupant to the next client or to the train station. We designate this mode as a car-sharing system, since when people are present the vehicle will be driven by a human. In the other variant, the AV will always drive automatically, regardless if a traveller is or is not present in the vehicle. This distinction allowed us to investigate whether differences in attitudes to, or valuations of, attributes of the AV exist in case the vehicle can be driven manual.

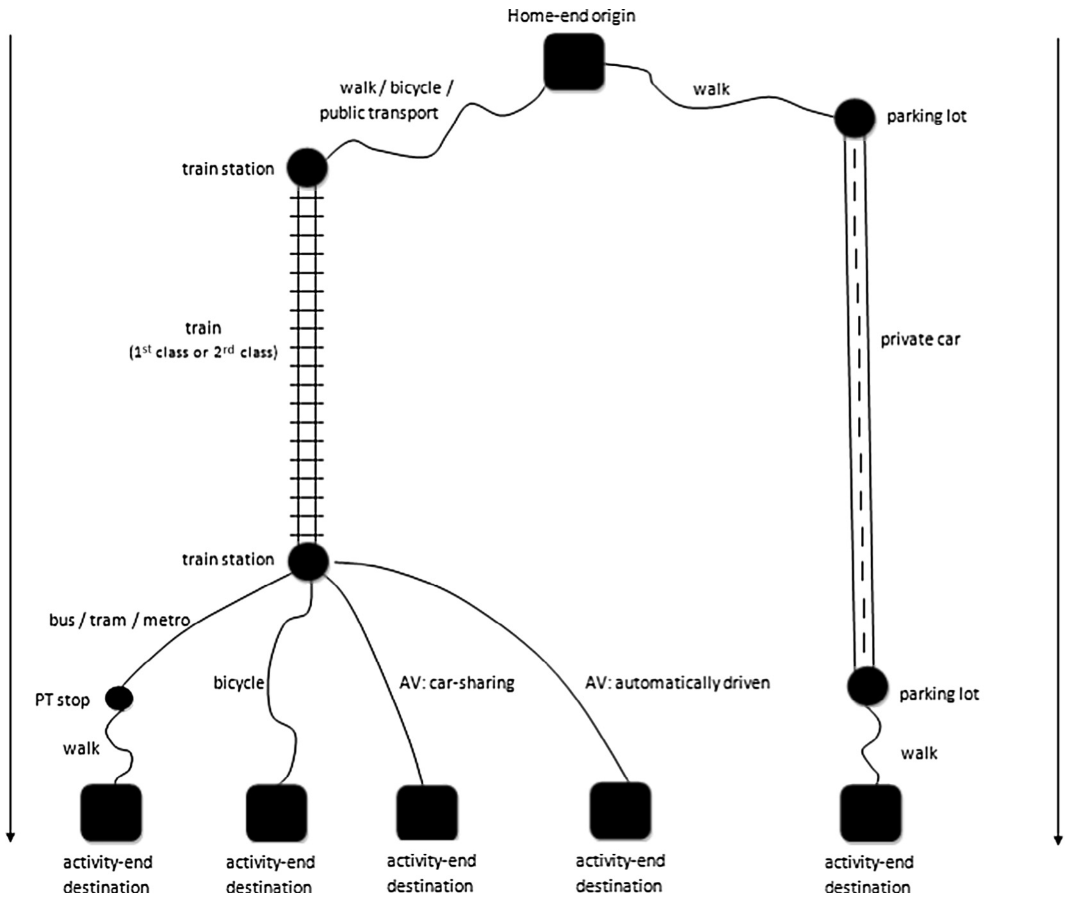


Fig. 2. Overview of trip alternatives incorporated in the SP experiment. Each multimodal trip alternative can be done using 1st class or 2nd class train carriages.

For the four multimodal alternatives we also distinguished whether a traveller uses the 1st class or 2nd class train carriages in the main part of the trip. This is meant to test the sensitivity of travellers toward AV attributes in relation to the use of 1st class train carriages, which can be of relevance for certain traveller segments like business travellers. This means that in total 8 multimodal trip alternatives are considered, of which 4 alternatives entail the use of an AV as egress (1st or 2nd class and driving or not driving the vehicle). Next to these multimodal alternatives, also a unimodal trip between home-end origin and activity-end destination by private car is incorporated. Hence in total 9 different mode alternatives were provided to respondents in our experiment, as it can be seen in Fig. 2.

Table 1 gives an overview of all attributes used in our SP experiment, with their corresponding attribute levels. In the experiment we used instrumental attributes related to travel time and travel costs of the different trip components, of which the attribute levels are based on values which hold for average medium-distance (20–40 km), regional trips in the Netherlands (CBS, 2013). Therefore, these attribute levels can easily be imagined by respondents in the country where the survey took place.

We assumed no waiting time for a bicycle as the egress. Besides we assumed that for using a bicycle or an AV as last mile transport, no walking time is needed from the place where a passenger stores his bicycle or disembarks the AV to the final destination. This is in line with the door-to-door service foreseen to be provided by AVs in this study. In the survey, walking time for these egress modes is indicated as '0 min' in each choice set. In line with European averages, attribute levels for fares for 1st class carriages in trains equals 150% of the fares charged for 2nd class. There are also costs included for using the bicycle as an egress mode since we are studying the activity-end of a trip where personal bicycle availability is usually limited. These costs reflect the possible costs for renting or parking a bicycle at the train station and are based on prices at Dutch stations. For the travel costs for AVs, a distinction is made between the AV fares if a passenger has travelled in the 2nd or 1st class in the train. In the experiment, we mentioned that a discount on the AV fare is provided to travellers who used the 1st class train carriages during the main stage of the trip. This allows us to investigate whether improving the attractiveness of the last mile transport between the train station and activity-end destination can specifically attract more passengers to the 1st class train carriages. This is relevant, since occupation rates in 2nd class train carriages in the Netherlands, especially during peak hours, are high. If the AV can attract more passengers to the 1st class train carriages (with lower occupation rates), available train capacity can be used in a more efficient and more sustainable way without increasing train length or frequencies. Moreover, for AVs we have incorporated the discrete variable 'sharing' as attribute, indicating whether a passenger has to share the AV with other passengers or not. In the survey we explicitly clarified to respondents that sharing the AV does not lead to a probability of making a detour to drop-off another passenger first, only passengers having the same destination would be allowed to share the AV.

2.2. Choice sets

Given the 9 mode alternatives and attributes mentioned in Fig. 1 and Table 1, we used a fractional factorial experimental design to provide choice sets to the respondents. We constructed efficient designs using the software package NGENE

Table 1
Overview of attributes and attribute levels used in the SP experiment.

Attribute	Attribute levels		
Travel time private car (walking time to car + driving time + search time parking space)	25 min	35 min	45 min
Travel time train (travel time access mode + train)	20 min	30 min	40 min
Waiting time BTM egress	5 min	10 min	15 min
Waiting time AV (car-sharing) egress	0 min	3 min	6 min
Waiting time AV (automatic) egress	0 min	3 min	6 min
Travel time bicycle egress	6 min	12 min	18 min
Travel time BTM egress	5 min	10 min	15 min
Travel time AV (car-sharing) egress	5 min	10 min	15 min
Travel time AV (automatic) egress	5 min	10 min	15 min
Walking time private car egress	2 min	6 min	10 min
Walking time BTM egress	2 min	6 min	10 min
Fuel costs + parking costs private car	€5	€10	€15
Travel costs train (ticket access + train) 2nd class	€5	€7.50	€10
Travel costs train (ticket access + train) 1st class	€7.50	€11.25	€15
Travel costs bicycle egress	€0	€1.50	€3
Travel costs BTM egress	€1	€2	€3
Travel costs AV (car-sharing) egress 2nd class	€2	€3	€4
Travel costs AV (car-sharing) egress 1st class	€0	€1	€2
Travel costs AV (automatic) egress 2nd class	€2	€3.50	€5
Travel costs AV (automatic) egress 1st class	€0	€1.50	€3
Sharing AV (car-sharing) egress	No sharing	Sharing with few passengers	
Sharing AV (automatic) egress	No sharing	Sharing with few passengers	

(ChoiceMetrics, 2012). Efficient choice experiment designs aim to minimize the standard errors of the estimates given known prior estimates. This means that for a given number of respondents the reliability of the parameter estimates increases. Our aim was to minimize the D-error, which takes the determinant of the asymptotic variance-covariance (AVC) matrix (Ω), in order to generate a D-efficient design (Bliemer and Rose, 2006, 2008; Rose et al., 2008).

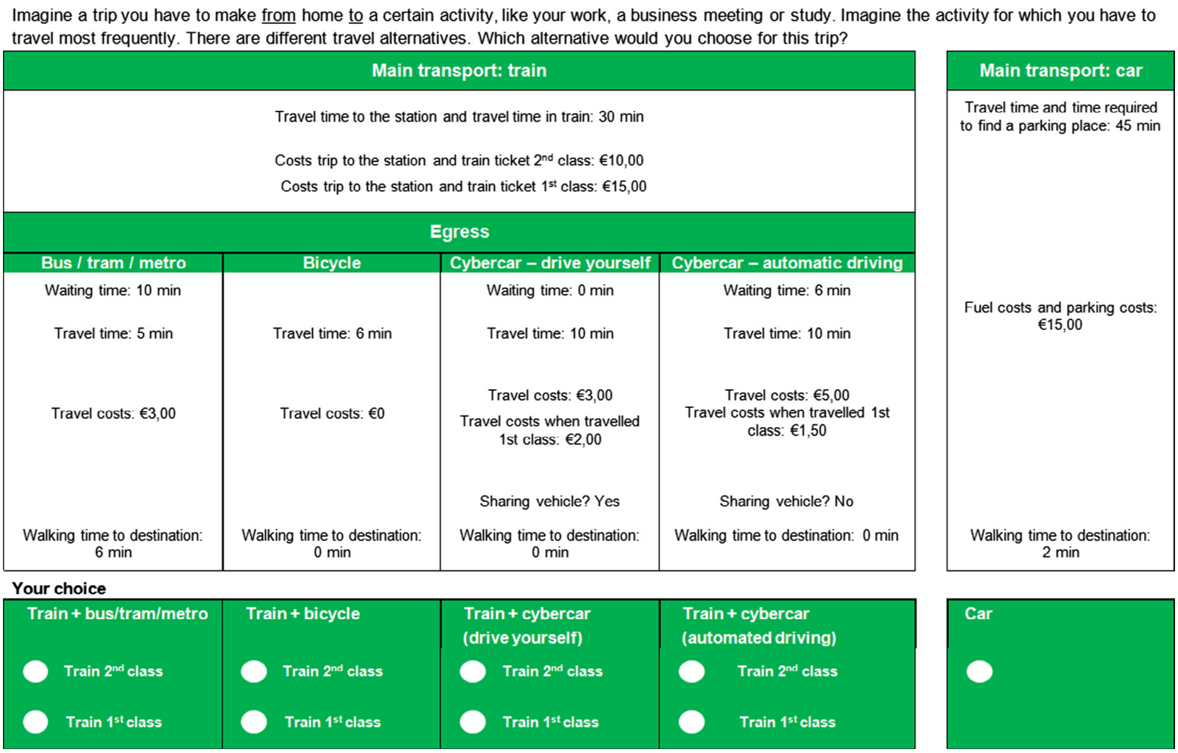
Arentze and Molin (2013) investigated traveller preferences in multimodal networks in the Netherlands. We used their estimated coefficients for the egress trip stage and main trip stage as prior to the coefficients in our study related to these trip stages. In Arentze and Molin (2013), no estimates were however available for in-vehicle time coefficients in the AV, since to the best of our knowledge our study is the first which explores these values. Thus as prior estimates we assumed that in-vehicle time coefficients for automated vehicles equal the in-vehicle time coefficients estimated for private car driving. Since the binary attribute 'sharing the automated vehicle' was not included in that study as well, for this attribute we used the estimated coefficient from Van Zuylen et al. (2010) – a Dutch study focusing on PRT systems – as prior and scaled this value to the coefficients estimated by Arentze and Molin (2013). We must note however that in Arentze and Molin (2013), respondents having work or study as trip purpose were not included in the sample. Moreover, as referred, sensitivity to attributes of AVs was not known beforehand. Because of this uncertainty around these prior parameter estimates, we generated a Bayesian efficient design which aims to minimize the expected D-error (Eq. (1)), in order to get a more stable experimental design which is robust to this uncertainty (Bliemer et al., 2008).

$$\overline{D\text{-}error} = \int_{\tilde{\beta}}^{1} \det\left(\Omega_1(X,\tilde{\beta})\right)^{\left(\frac{1}{K}\right)} f(\tilde{\beta}|\omega)\,d\tilde{\beta} \tag{1}$$

In Eq. (1), K indicates the total number of parameters to be estimated. Estimates of the priors $\tilde{\beta}$ were drawn from a uniform distribution by quasi random Monte Carlo draws using Halton sequences to approximate Bayesian efficiency (Halton, 1960). Lower and upper bounds of the distribution for each parameter are determined by applying −10% and +10% margins around the parameter estimate found in Van Zuylen et al. (2010) and Arentze and Molin (2013).

In total 12 different choice sets were generated, which were divided in two blocks of 6 choice sets. This means that every respondent had to answer 6 choice sets. By providing each respondent only a limited number of choice sets, we aimed at reducing the time needed to answer the survey, thereby increasing the rate of response and representativeness of the sample. Besides, we aimed at preventing a reduced performance of the respondents when making their choices, since we know that distraction increases with the experiment complexity and size.

Fig. 3 shows an example of one of these choice sets, as it was presented to respondents in the survey. As can be seen from Fig. 3, we used a design in which the combinations of attribute levels over all alternatives were constrained in order to


Imagine a trip you have to make from home to a certain activity, like your work, a business meeting or study. Imagine the activity for which you have to travel most frequently. There are different travel alternatives. Which alternative would you choose for this trip?

Main transport: train

Travel time to the station and travel time in train: 30 min

Costs trip to the station and train ticket 2nd class: €10,00

Costs trip to the station and train ticket 1st class: €15,00

Egress

Bus / tram / metro	Bicycle	Cybercar – drive yourself	Cybercar – automatic driving
Waiting time: 10 min		Waiting time: 0 min	Waiting time: 6 min
Travel time: 5 min	Travel time: 6 min	Travel time: 10 min	Travel time: 10 min
Travel costs: €3,00	Travel costs: €0	Travel costs: €3,00 Travel costs when travelled 1st class: €2,00	Travel costs: €5,00 Travel costs when travelled 1st class: €1,50
		Sharing vehicle? Yes	Sharing vehicle? No
Walking time to destination: 6 min	Walking time to destination: 0 min	Walking time to destination: 0 min	Walking time to destination: 0 min

Main transport: car

Travel time and time required to find a parking place: 45 min

Fuel costs and parking costs: €15,00

Walking time to destination: 2 min

Your choice

Train + bus/tram/metro	Train + bicycle	Train + cybercar (drive yourself)	Train + cybercar (automated driving)	Car
Train 2nd class	Train 2nd class	Train 2nd class	Train 2nd class	
Train 1st class	Train 1st class	Train 1st class	Train 1st class	

Fig. 3. Example of choice set as provided to respondents in survey.

reduce task complexity for the respondents. For each multimodal trip alternative with a specific egress mode, the attribute levels for the variants using the 1st and 2nd class train carriages were constrained to be equal in the choice set (see the left column in Fig. 3). Moreover, the attribute levels for travel time and travel costs of the main part of the trip were constrained to be equal for all alternatives which use train as main travel mode. In this way respondents were able to make clear trade-offs between attributes, while not being provided with too many variations simultaneously. As can be seen in Fig. 3, we have designated AVs as 'cybercars' in our SP experiment. In the general introduction of the SP experiment in the survey, Fig. 2 was shown to the respondents. By designing the choice sets as shown in Fig. 3 with a similar presentation of the alternatives and attributes, we intended to provide as much clarity as possible in a type of experiment that is prone to mistakes. Rose and Hensher (2006), Hensher and Rose (2007) and Hensher et al. (2011) have shown with their studies that respondents are able to understand and answer relatively complex choice sets, as long as these choice sets are meaningful and can be easily imagined. In every choice set it was clearly stated to the respondents that they had to imagine a trip *from* home *to* a certain activity, in order to safeguard that the attributes for the egress trip stage were related to the activity-end of the trip.

2.3. Model specification and estimation

In order to explore preferences of travellers for using automated vehicles, a discrete choice model consisting of three different components was estimated. We used a utility maximization framework in the specified model, where we assumed that each individual chooses a certain alternative m if the utility $U_m > U_{n \neq m}$. For each of the 9 alternatives m included in the choice sets, the utility can be calculated using Eq. (2).

$$U_m = \beta'_x x_m + \beta'_\kappa \kappa_m + \beta'_\eta \eta_m + \vartheta_m + \varepsilon \tag{2}$$

The first component of the structural utility component of the estimated model consists of all the instrumental attributes as mentioned in Table 1. This means that this component is based on the attributes which were provided in the SP experiment only. In this equation β'_x is a $[Kx1]$ vector which represents the importance of all instrumental variables x included in the alternative specific utility function U_m. $\beta'_x x_m$ is specified to be linear-in-parameters. Separate coefficients are estimated for different travel time components, and for in-vehicle time in different modes, in different trip stages and in different train classes. Also, separate coefficients are estimated for travel costs for different modes and different train classes.

In the second component of the estimated model, we extended the utility functions of the four alternatives where automated vehicles are used as egress transport with socio-economic variables. For both the variant where the AV is driven by a human, and the variant where the AV drives fully automatically (both for the 1st and 2nd class train travelling alternatives in the main trip stage), these additional variables are added to explore which factors add explanatory power to the preferences for using automated vehicles as last mile transport for multimodal train trips. In Eq. (2), β_κ is the vector which reflects the importance of different socio-economic variables κ. Table 2 shows all socio-economic variables which were included in the study. By adding the variable 'current most frequently used main transport mode' we incorporated the possible reluctance of respondents to change from the current mode choice. Separate coefficients β_κ were estimated for the variables κ_m for the two alternatives in which the AV is driven to the destination by the traveller (who used either 1st or 2nd class train carriages in the main trip) on the one hand, and the two alternatives where the AV always drives fully automatically (with the traveller either using 1st or 2nd class train carriages in the main trip stage) on the other hand.

When exploring travellers' preferences for using automated vehicles, it is important not just to consider instrumental attributes. Especially regarding this topic, it is hypothesized that attitudes for or against machine automation in general,

Table 2
Overview of socio-economic variables and their categories as added to the estimated model.

Socio-economic variable	Categories			
Age	<26	26–65	>65	
Car ownership (owner/lease)	Yes	No		
Usual train travelling class	1st class	Alternately 1st and 2nd class	2nd class	No usual train travelling
Driving license	Yes	No		
Education level	Low	Medium	High	
Trip frequency (average # trips/week) (a two-directional journey is considered as 1 trip)	<1	1–3	>3	
Gender	Female	Male		
Nett income (€/month)	<€1000	€1000–€3000	>€3000	
Mobility allowance by work/government	Yes	No		
Current most frequently used main transport mode	Train	Bus/tram/metro	Bicycle	Car
Public transport pass	Yes	No		
Most frequent trip purpose	Business	Commuting	Study	Leisure
Current average door-to-door travel time (average # minutes/single trip)	<30	30–60	>60	
Daily business	Work	Study	No work or study	

and for or against automated vehicles specifically, play an important role. Regardless of the performance of AVs as last mile transport compared to other multimodal trip alternatives in terms of instrumental attributes such as travel time and costs, attitudes of travellers regarding safety, reliability and functionality. of AVs may be of relevance when choosing to use AVs as a last mile transport. This means that considering attitudes is important when exploring travellers' preferences for or against AVs. Therefore, we incorporated this aspect explicitly in our modelling, allowing investigating their explanatory power in the mode choice.

Since attitudes against using AVs are often implicit and cannot be measured directly, we performed an exploratory factor analysis to investigate the underlying, latent attitudinal factors related to automated vehicles. Casley et al. (2013), Merritt et al. (2013) and Payre et al. (2014) defined several manifest indicators which are relevant when measuring attitudes towards automation and automated transport. Based on these studies we made a selection of 23 indicators which were relevant for exploring attitudes regarding the use of AVs as last mile transport. Some indicators where slightly adjusted to fit better the objective of the study. We asked respondents to indicate to which extent they agreed with the provided 23 statements, using a 7-point Likert scale ranging from *totally disagree* to *totally agree*. The first 8 indicators S1-S8 are related to the service provided by AVs as last mile transport, whereas the next 15 indicators A1-A15 focus on the automation aspect of this last mile transport mode. Some indicators were reversely formulated. Table 3 shows all 23 indicators used in the study.

Eq. (3) shows for all 23 attitudinal indicators the measurement equations as specified in the exploratory factor analysis, indicating the estimated latent variable model. Based on the eigenvalue criterion it is determined how many latent factors are underlying these indicators, and which indicators load on which latent factors. In Eq. (3) this is reflected by Υ, which is a matrix containing factor loads of all manifest indicator variables y_m which are related to a specific latent construct η_m, for all latent constructs M, and ε_m being the measurement error (Temme et al., 2008).

$$y_m = \Upsilon \eta_m + \varepsilon_m \tag{3}$$

The factor scores of the resulting latent constructs η_m are then incorporated as composite factors in the third component of the utility function of the discrete choice model as shown in Eq. (2). In this way, psychological factors relevant for AV preferences are captured in the discrete choice model. The latent variable model used in the exploratory factor analysis, and the discrete choice model, are estimated in a sequential way. This means that first the latent variable part of the model is estimated, resulting in factor scores for each latent attitudinal construct η_m. The computed factor scores are then used as replacement of the latent constructs η in the discrete choice model. This procedure assumes that the factor scores representing the latent constructs are error-free. Moreover, with this method more complex behavioural relations between socio-economic, latent attitudinal constructs and instrumental attributes cannot be investigated (Walker and Ben-Akiva, 2002). Simultaneous estimation of the latent variable model and discrete choice model overcomes these shortages and can correct for these measurement errors and test more complex relations. However, simultaneous estimation requires a substantial increase of calculation times and more advanced estimation software, since multidimensional integrals are involved in the procedure. A sequential estimation method is deemed sufficient for this exploratory study: more detailed and complex estimations are left for follow-up studies.

Table 3
Indicators used in exploratory factor analysis (Casley et al., 2013; Merritt et al., 2013; Payre et al., 2014).

S1	I am afraid that there will be no car available at the station (reversed)
S2	I am worried that the car is not clean after its previous use (reversed)
S3	I dislike it that I might have to share the car with unknown passengers (reversed)
S4	I like it that I'm going to use a 100% electric vehicle from the train station to the final destination
S5	I am afraid that the electric car will run out of battery during the trip from the train station to the final destination (reversed)
S6	I like it that the car does not produce pollutant emissions
S7	I am afraid that the car will not arrive on time at my destination (reversed)
S8	I am afraid that there will be no car available for the return trip to the train station (reversed)
A1	I like it that I can be more productive on other tasks if I'm riding in an automated vehicle
A2	I am afraid that the automated vehicle will malfunction (reversed)
A3	I enjoy driving a car myself
A4	I trust that a computer can drive the cybercar with no assistance from me
A5	I like it that I can delegate the driving to the automated driving system in case I'm tired
A6	I would be comfortable entrusting the safety of a close family member to an autonomous car
A7	I dislike the idea of automated driving[a] (reversed)
A8	I believe a computer-operated car would drive better than the average human driver on populated streets.
A9	I am afraid that the automated vehicle will not be fully aware of what is happening around him (reversed)
A10	I like it that it is required by law that the car stops if the system fails
A11	I dislike it that I don't have control of how the car drives[a] (reversed)
A12	I like it that I can delegate the driving to the automated driving system if I'm over the legal alcohol limit
A13	I think that the automated driving system provides me more safety compared to manual driving
A14	I wish that automated vehicles are not around in the future[a] (reversed)
A15	I like it if I can recover control from the automated pilot if I do not like the way it is driving

[a] Indicators are slightly adjusted to fit better the objective of the study.

In Eq. (2), β'_η is a vector which represents the importance of all composite factors η_m representing travellers' attitudes in the alternative specific utility function U_m. Composite factors which represent service related attitudinal indicators are included in the utility functions of all four alternatives with automated vehicles: both the alternatives where the AV is driven by the traveller, and the alternatives where the AV drives fully automatically. Composite factors representing a attitudinal construct which is purely related to automation, are only incorporated in the utility functions of the two alternatives where the AV always drives fully automatically (with 1st and 2nd class train travelling alternatives). Generic coefficients β'_η are estimated for these attitudinal constructs.

Different model types (multinomial logit and mixed logit models) were tested, of which the mixed logit model as explained below resulted in the best fit. Because unobserved correlations are expected between different multimodal alternatives in the SP experiment, we estimated a mixed logit model with error component structure. In total, six different nests are incorporated in the estimated model. For each of the egress modes (BTM, bicycle, AV-manual and AV-automatic), there is an alternative using the 2nd class train carriages during the main trip stage, and an alternative using the 1st class train carriages. It is expected that there will be unobserved communalities between each of these two alternatives due to similarities in egress mode. Therefore, in total four nests $\vartheta_{BTM}, \vartheta_{bicycle}, \vartheta_{AV\text{-}manual}, \vartheta_{AV\text{-}automatic}$ are added which capture the communalities between the two multimodal alternatives having the same egress mode. Besides, unobserved correlations are expected between the four multimodal alternatives using the 2nd class train carriages in the main trip stage, and between the four alternatives using 1st class train carriages. Especially characteristics related to comfort, crowding and chance on a free seat might be relevant and are not incorporated in the structural part of the utility function. Therefore, two nests $\vartheta_{1st\ class}, \vartheta_{2nd\ class}$ are also added. This means that each multimodal alternative consists of two nests ϑ_m, next to the i.i.d. error component ε of the utility function. The nesting structure for the estimated mixed logit model can be seen from Fig. 4. Because each respondent answered 6 choice sets, the mixed logit model is estimated using a panel structure capturing serial correlations between answers given by the same respondent. The panel data structure is addressed by using individual-specific error terms, in which the product of choice probabilities by an individual is integrated over the error terms. The latent variable model is estimated using the statistical package SPSS, whereas Biogeme is used as maximum-likelihood estimation software for estimating the error component mixed logit model with panel structure (Bierlaire, 2003). Eq. (4) shows the formulation of the choice probabilities for the two multimodal alternatives using fully automated AVs as egress mode.

$$P_{train1+AV} = \int_{\vartheta_{1st}} \int_{\vartheta_{AV}} \left(\prod_{t=1}^{6} (P^t_{train1+AV} | \vartheta_{1st}, \vartheta_{AV}) * f(\vartheta_{1st}, \vartheta_{AV}) \right) d\vartheta_{1st} d\vartheta_{AV}$$

$$P_{train2+AV} = \int_{\vartheta_{2nd}} \int_{\vartheta_{AV}} \left(\prod_{t=1}^{6} (P^t_{train2+AV} | \vartheta_{2nd}, \vartheta_{AV}) * f(\vartheta_{2nd}, \vartheta_{AV}) \right) d\vartheta_{2nd} d\vartheta_{AV} \tag{4}$$

3. Survey and sample

We designed an online survey which was divided in several parts. At the start, automated vehicles and their role as last mile transport for PT trips were introduced in a brief and objective way. In the survey (which is in Dutch), AVs were introduced by using the italic text below which is translated from Dutch language, including two pictures of AVs and a schematic overview of the door-to-door trip with the relevant unimodal and multimodal alternatives:

"Over the last years, many developments took place regarding vehicles which are able to drive partially, or even fully automated. A vehicle which is able to drive fully automated, without driver intervention, is called a cybercar. One of the possible applications of such a cybercar is to increase the attractiveness of the door-to-door journey for which train is used as main mode of transportation. The cybercar would then be used for egress between the train station where a traveller leaves the train and the final destination of the journey. When a passenger leaves the train, the cybercar is waiting near the station for the transport to the

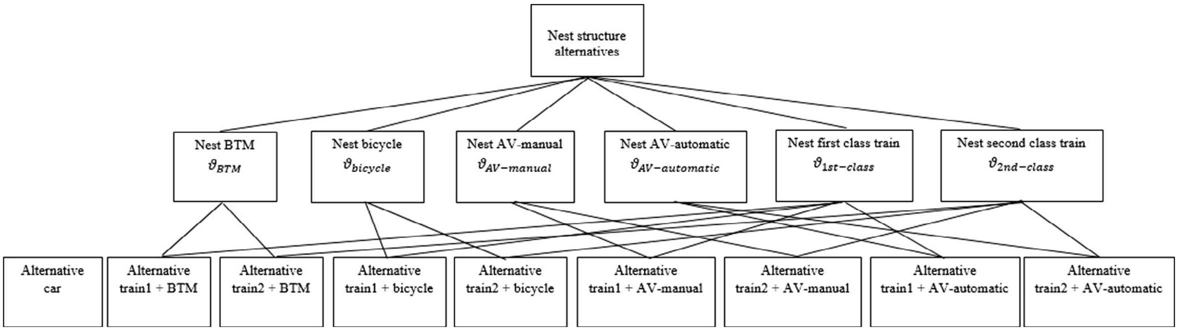


Fig. 4. Nesting structure of estimated mixed logit model.

final destination. This 100% electric vehicle always supplies a direct, non-stop connection to the final destination and always stops direct in front of the destination. The cybercar can also be used to travel back from an appointment to the train station. During a trip the cybercar can be accessible only for you as traveller (with a possible travel partner), or the cybercar has to be shared with a few unknown fellow travellers having the same destination".

After the introduction, the questionnaire consisted of four main parts. In the first part, some general characteristics about the regular trips made by the respondents were questioned in order to introduce respondents to the topic and to determine some socio-economic explanatory variables included in the discrete choice model. The second part of the survey consisted of the SP experiment which started by first explaining the experiment and the attributes by showing a figure similar to Fig. 2 and then, presenting 6 choice sets to each respondent. Each choice set was presented to the respondents in a manner similar to what is depicted in Fig. 3. Each respondent was assigned randomly to one of the two sets of 6 choice sets, so that in total all 12 choice sets of the experiment were answered by an equal number of respondents. The third part of the survey measured the attitudes of respondents towards the AVs as last mile transport, where the 23 attitudinal indicators on a 7-point Likert scale were shown to the respondents. The fourth and last part of the survey contained questions about the socio-economic profile of the sampled travellers.

A large national online panel in the Netherlands was used for gathering respondents for the designed online survey. Only respondents older than 18 years were allowed to answer the survey. Besides, only respondents who travelled at least twice a month on average could answer the survey. By this selection we made sure that respondents had sufficient experience with travelling in general to understand the different attributes in the SP experiment. The sample was meant to be as much as possible representative for the Dutch population of travellers regarding different socio-economic variables. Some respondent segments were slightly oversampled when distributing the online survey, based on the historic statistics of non-response per segment. For example, since historic data in the online panel showed that non-response of male respondents is higher than non-response of female respondents, males were slightly oversampled. An interlocked stratification procedure was applied for the segments gender and age aiming at obtaining a distribution of respondents regarding gender and age in the sample which is as much representative for the Dutch population as possible.

In total, 1149 respondents started the survey, of which 1053 (91.6%) completed all questions. The average duration to complete the survey was 880 s (14 min and 40 s). In order to estimate our models based on reliable input, we excluded respondents based on two criteria:

- If the time to complete the survey was shorter than 7 min, we assumed that respondents did not provide reliable answers;
- If a respondent gave exactly the same answer on all 23 attitudinal indicators (for example: all 23 indicators were answered as 'neutral' on the 7-point Likert scale), the respondent was excluded as well, since we assumed there was no serious answering to the questions.

We applied a relatively strict selection procedure in this step in order to improve the reliability and representativeness of the sample, thus producing valid results. In total, these criteria led to the exclusion of 292 respondents (28%), leading to a remaining sample size of N = 761 respondents. For the SP experiment, this meant that $6 * 761 = 4566$ choices were observed in total.

Table 4
Comparison between sample and Dutch population for different socio-economic variables.

Socio-economic variable	Category	Share sample	Share population
Gender	Female	51.7%	50.5%
	Male	48.3%	49.5%
Age	20 to <40	32.4%	31.7%
	40 to <65	53.1%	45.8%
	65 to <79	14.1%	17.0%
	⩾80	0.4%	5.5%
Education level	Primary school	0.7%	9.9%
	Lower vocational/secondary education	19.3%	21.0%
	Higher/intermediate/pre-university education	48.5%	41.0%
	Higher vocational education	23.1%	17.9%
	University	8.4%	10.1%
Employment	Full-time job	40.6%	35.5%
	Part-time job	20.4%	26.9%
	Jobless	11.9%	5.8%
	Student	7.0%	5.7%
	Retired	14.3%	26.0%
	Other	5.7%	–
Average net income (€/month)		€2.020	€1.829

Table 4 shows a comparison between the shares of categories for different socio-economic variables in the sample and in the Dutch population. Regarding age it can be concluded that the percentage of females and males in the sample is representative of the population (CBS, 2014b). Since the survey was only allowed for respondents older than 18 years old, we compared age categories starting at 20 years and higher. In general we may conclude that the sample is representative of the population regarding age (CBS, 2014b). In the sample there is a slight overrepresentation of respondents with age 40 to <65 years, at the cost of a slight underrepresentation of respondents having an age ⩾80. This can be explained by the fact that in general elderly people travel less frequently than adults. Therefore, it is possible that more people with age ⩾80 are excluded from the survey based on the required minimum average travel frequency. It is also possible that the online survey was less accessible for elderly people, given their less frequent use of Internet.

The sample is also representative for the population regarding education level (CBS, 2014b), although there is a slight overrepresentation of respondents having completed a higher education level at the cost of the number of respondents having completed primary school only. This can be explained by the fact that only respondents older than 18 years were allowed to participate in the survey. Our sample is also representative of the population regarding employment (CBS, 2012, 2014a, 2014b, 2014c; DUO, 2013). The higher percentage of jobless people in our survey can mainly be explained by differences in definitions applied in the categorization. In the population data, people who cannot work anymore (for example due to physical limitations) are not categorized as 'jobless', whereas in the survey they are considered as 'jobless'. The average nett income of the sampled respondents is comparable to the income in the population. Although the average income in the survey is slightly higher than in the population, this can be explained because our sample has slightly more working people between 40 and 65 years old, who in general have higher incomes compared to the population average. We therefore conclude that the sample is sufficiently representative for the population. The slight oversampling of adult, working people is not considered to be a problem, since this is a relatively important target group for the AV application as last mile transport.

4. Results

4.1. Results of the latent variable model

In Table 5 we show the results of the estimated latent variable model to determine the latent attitudinal factors relevant for the choice of AVs as last mile transport. After checking communalities between indicators and first checking whether a simple structure could be reached when performing a skewed rotation, a simple structure could be obtained by performing an orthogonal, varimax rotation. Indicators with a communality <0.25 or with all factor loads <0.50 were excluded from the exploratory factor analysis. In Table 5, two indicators have factor loads <0.30 on two factors. For these indicators, the factor load on one factor is high, whereas the factor load on the other factor is just above 0.30. Therefore this is not considered to be a problem, since a simple structure is maintained.

We may conclude that 16 out of the 23 indicators are part of the final 3-factor solution. The latent attitudinal factor 1 can best be described as 'trust in automated vehicles', representing the extent to which travellers trust the safety of a trip using an automated vehicle. Factor 2 reflects the attitude of travellers respecting to service reliability of an automated vehicle as last mile transport on the activity-end of a multimodal trip. This factor reflects the attitude regarding AVs on-time departure

Table 5
Estimation results of latent variable model (factor loads < 0.30 are not shown).

		Factor 1	Factor 2	Factor 3
A6	I would be comfortable entrusting the safety of a close family member to an autonomous car	0.757		
A13	I think the automated driving system provides me more safety compared to manual driving	0.727		
A4	I trust that a computer can drive the cybercar with no assistance from me	0.720		
A5	I like it that I can delegate the driving to the automated driving system if I was tired	0.701		
A8	I believe a computer-operated car would drive better than the average human driver on populated streets	0.687		
A7	I dislike the idea of automated driving (reversed)	0.594		
A14	I wish that automated vehicles are not around in the future (reversed)	0.583		
A12	I like it that I can delegate the driving to the automated driving system if I was over the drink driving limit	0.517		
S8	I am afraid that there will be no car available for the return trip to the train station (reversed)		0.759	
S7	I am afraid that the car will not arrive in time at my destination (reversed)		0.701	
S1	I am afraid that there will be no car available at the station (reversed)		0.628	
A2	I am afraid that the automated vehicle will malfunction (reversed)	0.352	0.616	
S5	I am afraid that the electric car will run out of battery during the trip from the train station to the final destination (reversed)		0.612	
S2	I am worried that the car is not clean after its previous use (reversed)		0.566	
S4	I like it that I'm going to use a 100% electric vehicle from the train station to the final destination	0.385		0.759
S6	I like it that the car does not produce pollutant emissions			0.502
A1	I like it that I can be more productive on other tasks if I am riding in an automated vehicle	No communalities with other factors		
A3	I enjoy driving a car myself	No communalities with other factors		

from the train station and on-time arrival at the destination. Latent factor 3 is representing the attitude of travellers regarding the sustainability of the AV, considering the indicators which focus on electric and clean driving.

From the 7 indicators which were excluded from the exploratory factor analysis, there are 2 indicators which clearly measure two different attitudes relevant for this study in addition to the three identified latent factors. These two indicators are shown at the bottom of Table 5. Apparently, the communality of these two indicators with the other indicators in the study was not sufficient to be put under one of the three underlying attitudinal factors. However, since both clearly measure an attitude relevant for this study, for each indicator a separate underlying factor is defined. For the indicator *'I like it that I can be more productive on other tasks if I'm riding in an automated vehicle'*, the underlying factor 'productivity during automated driving' is defined. The indicator *'I enjoy driving a car myself'* reflects the factor 'enjoy car driving'. This means that in total 5 attitudinal factors are identified in our study of which the factor scores are incorporated as composite factor in the estimated discrete choice model.

4.2. Results of the discrete choice model

Table 6 shows the statistics of the estimated discrete choice model. In total, 68 parameters were estimated. 2000 two-dimensional Halton draws were used in order to get stable parameter estimates. The adjusted Rho-square of this model – incorporating instrumental attributes, socio-economic variables and attitudinal composite factors – equals 0.429. After this model was estimated for our sample, a final model was estimated where only the remaining significant coefficients were included. Re-estimation of this model is necessary, since we applied efficient designs in which correlations between the attributes occur. Excluding non-significant coefficients can therefore slightly change the estimation results of the significant coefficients. The adjusted Rho-Square of the final model, containing 42 parameter estimates, equals 0.430. The estimated discrete choice model correctly predicted 36% of the observed mode choices, using an all-or-nothing criterion which assumes that each individual chooses the mode alternative with the lowest disutility. Since this criterion just selects the alternative with the lowest disutility, and does not consider the relative differences in disutility between the alternatives and does not consider taste heterogeneity between respondents, the correctly predicted value of 36% can be considered as slight underestimation. When considering this, we can conclude that the model has an average prediction accuracy. It should however be mentioned that the estimated model is not used for prediction purposes in this study, but for exploring and explaining traveller preferences only.

In our estimations we applied effect coding for all attribute levels, for which the constant of each alternative reflects the average utility over all choice sets. The estimated marginal values for each attribute level represent the contribution of each attribute level to the total utility, expressed as the deviation from the average utility. The unimodal car alternative is used as reference alternative, to which the estimated values of the other alternatives are expressed. All continuous instrumental attributes are incorporated with three attribute levels, so that linearity can be tested. This means that for each of these attributes two indicator variables are used where the highest attribute level is effect coded $\{1\,0\}$, the middle attribute level $\{0\,1\}$ and the lowest attribute level $\{-1\,-1\}$. For socio-economic attributes, and for the nominal instrumental attribute 'sharing', we used the highest effect coding for the attribute level we expected to have the most positive preferences, in order to make it easier to interpret the coefficients. For each nominal variable having I attribute levels, $I-1$ indicator variables are estimated. Table 7 shows the applied effect coding for the attribute levels of the significant nominal attributes. The factor scores of the latent attitudinal factors are scaled between the same range $\{-1\,1\}$ which is used for the effect coding.

In Table 8 we show the estimation results of the final discrete choice model. Only coefficients having a p-value <0.10 are incorporated in the final model. Since it is an exploratory study, we used a relatively high threshold for the p-values because it is also important to identify the direction of the relation between the explanatory variables and the choice for the AV. In Table 8, for each attribute consisting of I attribute levels, the corresponding indicator variables are numbered from I to $I-1$, the last Roman number of the parameter name representing the number of the indicator variable.

Looking at the alternative specific constants, we conclude that all multimodal trip alternatives are valued more negatively when compared to the unimodal car alternative, of which the utility is fixed to zero. This can logically be explained because multimodal alternatives require at least two transfers, often longer travel times and less comfort and privacy compared to a private car alternative. We note that for multimodal trips using first class train carriages in the main trip stage, using automatically driven AVs as last mile transport is valued most positively (manual: −5.90; automatic: −6.17) compared to the existing modes bicycle (−7.23) and BTM (−8.32), ceteris paribus. The average preference for a multimodal, first class train trip, using AVs as last mile transport, either manual or automatically driven, is more positive than a multimodal first class

Table 6
Statistics discrete choice model estimation.

	Final model
Number of observations	4566
Number of estimated parameters	42
Null log-likelihood	−10,033
Final log-likelihood	−5677
Adjusted Rho-Square	0.430

Table 7
Effect coding used for attribute levels of nominal variables.

Socio-economic variable	Category	Indicator variable I	Indicator variable II	Indicator variable III
Sharing the AV	Yes	−1		
	No	1		
Gender	Female	−1		
	Male	1		
Age	<26	−1	−1	
	26–65	0	1	
	>65	1	0	
Average nett income (€/month)	<€1000	−1	−1	
	€1000–3000	0	1	
	>€3000	1	0	
Most frequent trip purpose	Leisure	−1	−1	−1
	Study/school	0	0	1
	Commuting	0	1	0
	Business	1	0	0

train trip with the other egress modes BTM and bicycle. Therefore, we can conclude that for first class train travellers, introducing AVs as new means of transportation between the train station and the final destination has potential. The average unexplained part of utility for multimodal trips using first class train carriages is however substantially more negative compared to multimodal trips using second class train carriages in the main trip stage. This was expectable given the profile of the first class passengers who usually give a special preference to faster and more direct connections. This is a preference that many times cannot be expressed just on the travel time coefficient or in the number of transfers which are typically included in the utility function. Apparently for this type of traveller having an automated vehicle in the least worst of all his options. For second class multimodal trips, AVs as egress are valued somewhat more negatively (manual: −1.81; automatic: −1.84) than trips made by bicycle (−1.33) and bus/tram/metro (−1.51) as egress. Manual and automatically driven AVs are on average almost similarly valued by second class train travellers. This shows that AVs as last mile transport have mainly potential for first class train travellers. Besides, Table 8 shows that the estimated parameters for the 6 specified nests ϑ_m (indicated as 'sigma_' in Table 8) are all significant.

The marginal values of the continuous travel time and travel cost attributes are expressed in utils/min and utils/Euro, respectively. For in-vehicle time of different modes, only the first indicator variable showed to be significant. This shows that the part-worth utility decreases linearly with an increasing in-vehicle time. The marginal value for in-vehicle time for access + main trip stage, when travelling in first class train carriages, is lower (−0.041) than for the access + main trip stage when travelling in second class train carriages (−0.051). This indicates that in-vehicle travel time valuation when travelling first class in trains is about 20% lower compared to second class train travelling. An explanation for this might be the higher comfort level, lower crowding level and better working opportunities in first class train carriages. Table 8 also shows that the in-vehicle time coefficient for the unimodal car alternative is lower (−0.031) compared to the in-vehicle time coefficients for access + main trip stage in multimodal alternatives for both first (−0.041) and second class (−0.051) train carriages. When comparing sensitivities for in-vehicle time of different egress modes, the in-vehicle time coefficient for BTM and bicycle equals −0.040 and −0.080, respectively. This indicates that in-vehicle time by bicycle is perceived substantially more negative than by BTM. The marginal value for in-vehicle time in a manually operated AV (−0.054) as egress is considerably lower than for automatic AVs (−0.084). Thus our empirical results show that the in-vehicle time valuation in automatically driven AVs is higher than when these have to be driven by the traveller. This means that travellers associate a higher disutility for trips of equal duration by an AV being driven automatically, compared to a manually driven AV. Comparing the in-vehicle time valuation of different egress modes, results show that in-vehicle time in a manually driven AV is valued between the values for bus/tram/metro (−0.040) and bicycle (−0.080) In-vehicle time of a manually driven AV is thus perceived less negatively compared to bicycle use, but more negatively than BTM use. In-vehicle time valuation in an automatically driven AV (−0.084) is valued similarly to in-vehicle time valuation when using a bicycle as egress mode, but more negatively compared to using bus/tram/metro as egress mode.

Estimates for valuation of waiting time, walking time and travel costs for different modes also show significant results. Moreover for these attributes, only the first indicator variable was significant, indicating a linear relation between the marginal utility and these attribute levels. For egress, waiting time for bus/tram/metro is valued 1.6 times more negatively than in-vehicle time in bus/tram/metro. Walking time to the destination is valued 1.8 times more negatively as in-vehicle time in bus/tram/metro as egress mode. Regarding waiting time, this is slightly lower than Dutch values found by Bovy and Hoogendoorn-Lanser (2005), where waiting time was valued 2.2 times more negatively than in-vehicle time. Regarding walking time, this valuation is comparable to the ratio of 1.6 between one minute walking time and one minute in-vehicle time found by Bovy and Hoogendoorn-Lanser (2005). The ratio between the marginal value for egress waiting time on the one hand and egress in-vehicle time on the other hand found in our study is however resembling the ratio found by Arentze and Molin (2013). They found a ratio of 1.6 for waiting time compared to in-vehicle time, very similar to the ratio

Table 8
Estimation results of discrete choice model.

Parameter	Value	T-value	P-value	Robust std.error
constant_car	0.00	–	–	–
constant_first_class_train + btm	−8.32	−18.2	0.00	0.480
constant_first_class_train + bicycle	−7.23	−17.4	0.00	0.436
constant_first_class_train + AV-manual	−5.90	−14.9	0.00	0.410
constant_first_class_train + AV-automatic	−6.17	−15.2	0.00	0.249
constant_second_class_train + btm	−1.51	−7.36	0.00	0.236
constant_second_class_train + bicycle	−1.33	−5.52	0.00	0.258
constant_second_class_train + AV-manual	−1.81	−7.98	0.00	0.252
constant_second_class_train + AV-automatic	−1.84	−7.58	0.00	0.251
in-vehicle-time_carI	−0031	−4.51	0.00	0.071
in-vehicle-time_access + first_class_trainI	−0041	−3.97	0.00	0.107
in-vehicle-time_access + second_class_trainI	−0051	−7.22	0.00	0.070
in-vehicle-time_egress_btmI	−0040	−2.88	0.00	0.063
in-vehicle-time_egress_bicycleI	−0080	−7.11	0.00	0.067
in-vehicle-time_egress_AV-manualI	−0054	−3.96	0.00	0.065
in-vehicle-time_egress_AV-automaticI	−0084	−5.65	0.00	0.076
waiting_timeI	−0062	−8.38	0.00	0.039
walking_timeI	−0073	−5.75	0.00	0.050
sharing	0.080	2.22	0.03	0.039
travel_costs_carI	−0.20	−13.1	0.00	0.082
travel_costs_first_class_trainI	−0.22	−7.12	0.00	0.105
travel_costs_second_class_trainI	−0.19	−6.03	0.00	0.079
travel_costs_btmI	−0.57	−8.16	0.00	0.071
travel_costs_bicycleI	−0.46	−10.1	0.00	0.071
travel_costs_AV-manual_first_classI	−0.54	−4.15	0.00	0.131
travel_costs_AV-manual_second_classI	−0.67	−8.39	0.00	0.078
travel_costs_AV-automatic_first_classI	−0.29	−3.46	0.00	0.124
travel_costs_AV-automatic_second_classI	−0.41	−8.81	0.00	0.070
purpose_AV-manualI	0.40	2.46	0.01	0.175
age_AV-manualI	0.68	3.50	0.00	0.192
nett-income_AV-automaticII	0.34	2.66	0.01	0.103
gender_AV-automatic	−0.20	−2.35	0.02	0.09
trust_AV-automatic	1.53	5.15	0.00	0.303
service-reliability_AV	0.65	2.43	0.02	0.271
sustainability_AV	1.69	5.73	0.00	0.340
productivity_in_AV-automatic	0.39	1.94	0.05	0.197
enjoy-car-driving_AV-automatic	−0.33	−2.12	0.03	0.155
sigma_btm	2.26	13.7	0.00	−0.189
sigma_bicycle	2.60	15.0	0.00	0.184
sigma_AV-manual	0.99	7.25	0.00	0.132
sigma_AV-automatic	1.08	7.49	0.00	0.159
sigma_first_class	4.32	11.7	0.00	0.384
sigma_second_class	4.41	17.3	0.00	0.285

Travel time measured in minutes.
Travel costs measured in Euros.

found in our study. Mode-specific travel cost coefficients are also presented in Table 8. We can conclude that travel costs made by car (−0.20) are perceived similarly to travel costs when using train in first class (−0.22) or second class (−0.19) as main mode. The marginal travel costs of all egress modes are valued more negatively compared to travel costs for the main mode. Travel costs in a manually operated AV (−0.67) are valued more negatively compared to an automatically driven AV (−0.41). Table 8 also demonstrates the effect of providing a discount to the AV fare for first class train travellers to the travel cost sensitivities. Providing this discount leads to a substantially less negative valuation of AV travel costs (−0.54 and −0.29 for a manual and automatic AV respectively), compared to the marginal values for AV travel costs when using second class train carriages with no discount provided (−0.67 and −0.41 for a manual and automatic AV respectively).

Table 9 shows the calculated willingness-to-pay (WTP) in Euros for different modes for a 10 min reduction of in-vehicle time. The WTP is determined by dividing the marginal travel time valuation by the marginal travel cost valuation. For example, the marginal travel time for a fully automatically driven AV equals −0.084 utils/min (see Table 8). The marginal travel costs (when no fare discount is provided) equals −0.41 utils/Euro. This results in a WTP of −0.084/−0.41 = 0.206 Euro/min. A reduction of egress travel time by 10 min then leads to a WTP of €2.06 (shown in a bandwidth between €2.00 and €2.10 in Table 9). In line with the marginal in-vehicle time valuation for different modes, results show that for the automatically driven AV (when no fare discount is provided) the WTP per 10 min travel time savings is relatively high (€2.00–€2.10) and

Table 9
Willingness-to-pay in Euros for different modes per 10 min.

Part of trip	Egress mode	Willingness-to-pay (€) per 10 min
Main	Private car	€1.55–€1.65
Egress	Bus/tram/metro	€0.65–€0.75
Egress	Bicycle	€1.70–€1.80
Egress	Automated vehicle: manually driven (no fare discount provided)	€0.75–€0.85
Egress	Automated vehicle: automatically driven (no fare discount provided)	€2.00–€2.10

somewhat higher than WTP values for private car (€1.55–€1.65). The WTP value for travel time savings found for automatically driven AVs is in line with the WTP values for 10 min travel time reduction for private car for short trips of 5 km (€2.07) found by Arentze and Molin (2013). WTP for manually driven AVs (€0.75–€0.85) is considerably lower than for automatically driven AVs and private cars.

Regarding the attribute trip purpose, only the 1st indicator variable is significant for manually driven AVs. This means that travellers with a business trip purpose value multimodal alternatives with a manually driven AV as egress mode marginally more positively (0.40 for manual AV driving). The marginal value for travellers with commuting and study/school trip purposes equals 0.00 for manual AV driving, whereas this marginal value equals −0.40 for leisure trip purposes. For automatically driven AVs, the marginal value for all trip purposes is not significant and therefore equals 0.00 for all purposes. For manually driven AVs, the marginal value of using a manually driven AV for people older than 65 years equals 0.00, 0.68 for people 26–65, and −0.68 for people <26 years. This shows the preference of using car as egress mode for people with age 26–65, often associated with working people. Results also show that people with medium incomes value automatically driven AVs as last mile transport more positively than people with lower or higher incomes. Females give more utility to automatically driven AVs than males (marginal values of 0.20 and −0.20 respectively), whereas no significant difference in preferences could be shown between males and females for manually driven AVs.

Results from Table 8 show the importance of the latent attitudinal factors in the utility of a multimodal trip alternative with AV as egress mode. The attitude regarding AV sustainability is the most important attitudinal factor influencing the total utility for using AVs (marginal value equals 1.69). A better (perception of) AV sustainability decreases the disutility for AVs as egress mode. The attitudinal factor 'trust in an automated vehicle' (only relevant for automatically driven AVs) has the second-largest contribution of all attributes in the model to the total utility, having a marginal value of 1.53. This means that this is a very important attitudinal factor influencing the use of AVs as last mile transport. The strongly positive sign indicates that a higher trust perception of travellers regarding AVs leads to lower disutility for AVs and possibly to a higher willingness to use AVs. A positive attitude regarding service reliability of AVs (marginal value equals 0.65) and work productivity during the trip (marginal value equals 0.39) also contribute in a positive way to the total utility. This result shows that travellers' perception that AVs provide a reliable service where you can be productive during the trip contributes positively to the use of AVs. Positive attitudes regarding the joy to drive a car yourself have a slightly negative contribution (marginal value equals −0.33) to the total utility of automatically driven AVs. This shows that travellers who enjoy driving a car associate a slightly higher disutility to using AVs, and are therefore less willing to use AVs.

The correlations between coefficients of the structural part of the utility function in the model are low. The highest correlations can be found between coefficients which relate to factors other than the observed attributes, for example between the alternative specific constant of an alternative m and a nest ϑ_M incorporated in the utility function of that same alternative to capture unobserved correlations with another alternative $n \neq m$. When considering correlations between coefficients of observed attributes, there is only 1 significant correlation having a correlation coefficient larger than 0.35. This is a correlation of 0.47 between the travel cost coefficient for first class and second class train travelling, in Table 8 indicated as 'travel_cost_first_classI' and 'travel_cost_second_classI'. No significant correlation is found between the coefficients estimated for age and trip purpose - which could be correlated in practice – for a manually operated AV, in Table 8 indicated as 'age_AV-manualI' and 'purpose_AV-manualI'. All other correlation coefficients are smaller than 0.35. We can therefore conclude that correlations between coefficients of observed attributes are low in this model, and therefore hardly influence the model results and interpretation.

5. Conclusions and discussion

The aim of this study was to position automated vehicles in the public transport market and to understand the sensitivity of travellers towards instrumental travel attributes – like different travel time components and travel costs – socio-economic variables and attitudinal factors. Because there are no fully-automated vehicles currently on the market, we applied a SP experiment. Based on the results of this experiment, we can formulate several main conclusions. First, by travellers using first class train carriages in the main stage of their multimodal trip, using automated vehicles as last mile transport is on average valued more positively than using BTM or bicycle. This means that for a first class train trip, there is an average preference for using AVs as last mile transport, compared to the use of other egress modes BTM and bicycle. Moreover for multimodal second class train trips, the average preference for a trip with AVs as egress is more negatively valued compared to other egress modes. Results indicate that second class train travellers on average prefer the use of a bicycle or bus/tram/

metro as egress mode. Therefore, we can conclude that especially for first class train travellers, introducing AVs as new mode of transportation between the train station and the final destination has potential.

Once the choice for first or second class train travelling in the main trip stage has been made, it can be concluded that the average preference for using a manually driven AV is more or less similar compared to an automatically driven AV. This suggests it can be worthwhile to provide an AV in which travellers can choose whether to drive automatically, or drive the vehicle themselves. This could be even more relevant for a transition stage where people do not trust the technology yet, but when this is already available on the market.

We also conclude that travellers on average associate more disutility to the in-vehicle time in an automatically driven AV, compared to a manually driven AV. As a consequence, the willingness-to-pay for a certain travel time reduction in an automatically driven AV is considerably higher, compared to a manually driven AV. The willingness-to-pay for a certain travel time reduction in an automatically driven AV as egress is somewhat higher than the willingness-to-pay for that same travel time reduction when using a private car as unimodal trip alternative. From a theoretical perspective we had hypothesized in the beginning of this study that the travel time disutility in an AV would be lower compared to a manually driven car or even BTM, since passengers would be able to spend their travel time doing other things in a redesigned vehicle interior (like using their phone, mailing, working) instead of driving, which was explicitly mentioned in the beginning of the survey. Our results however suggest that passengers do not perceive this theoretical advantage, at least not yet. This can be explained by an uncomfortable feeling that travellers might be feeling when imagining riding in a driverless automobile. By its turn this might be (partly) explained because respondents did not have any real experience of travelling in an automated vehicle, maybe not even a semi-automated vehicle with ACC for example. Another explanation can be the fact that the egress trip stage is only a relatively short part of the total multimodal trip. It might be the case that travellers would see more advantages in using their time in the longest stage of the journey. At last, the perception of safety might be an important aspect here. As shown in Table 5, the two indicators A6 and A13 having the highest factor load on the latent factor 'trust in AVs' are both related to safety perception of AVs. Given the importance of this latent factor 'trust in AVs' in the discrete choice model (see Table 8), this study shows evidence that the current safety perception of travellers towards AVs contributes to a situation in which passengers do not fully perceive the theoretical advantages of AVs regarding travel time valuation.

Through our study we are also able to conclude that travellers' attitudes play an import role in the attractiveness of using AVs as last mile transport. Travellers' attitudes regarding 'sustainability of automated vehicles' is the most important attitudinal factor for using the AVs, confirming the ever increasing importance of environmental concerns in transport mode choice. The perception of trust in AVs has shown to be the second-most important factor influencing the stated use of automated vehicles. Measures which can improve travellers' trust and safety perception in AVs have therefore a great potential to contribute to a successful implementation of this technology as a public transport option. Contrary to what was expected at the outset of the study, attitudes regarding service reliability and work productivity play a less important role in the total utility associated to travelling by AV as egress transport. This indicates that the usually referred advantages of automobile automation may not be yet perceived as such by today's travellers.

The importance of attitudinal factors in the mode choice leads to uncertainty on how people will react when AVs are introduced in practice. It shows that psychological factors can play an important role in the choice of travellers to use automated vehicles as last mile transport. Since automated driving is a quite new and innovative way of mobility, the classic instrumental attributes like travel time and costs do not tell the whole story. We therefore state the importance of giving sufficient attention to these psychological factors before and during the implementation process of AVs, because these may have a great influence on how technology will be adopted in the future. Given our results, we can prioritize different measures aimed at improving travellers' perceptions and attitudes. Measures influencing the perception and attitude regarding trust and sustainability of AVs have more potential compared to measures influencing attitudes regarding service reliability and work productivity. Based on our results we can also conclude that the joy to drive a car contributes in a slightly negative way to the choice to use automated vehicles, which is something decision-makers should be aware of.

Three topics for further research are proposed. First, a simultaneous estimation of the latent variable model and the discrete choice model is recommended, in order to explore more complex relations between instrumental attributes, socio-economic variables and attitudinal indicators and to incorporate the error-term of the latent attitudinal constructs in the discrete choice model. Second, in our study we only explored preferences of travellers for using the automated vehicle as last mile transport at the activity-end of a multimodal trip. It is recommended to explore preferences of travellers for using AVs as mode for the main part of the trip, for example as replacement for unimodal trips currently made by manually driven privately owned cars. Since AVs then contribute to a larger part of the total door-to-door trip, compared to the egress trip stage only in our study, we expect that more differences between AVs and other modes of transportation can be found. Third, we recommend the extension of this research to revealed preference studies, thereby using the results of field studies which will be implemented in the Netherlands soon.

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