A Stated Choice Experiment on Mode Choice in an Era of Free-Floating Carsharing and Shared Autonomous Vehicles

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ABSTRACT
New forms of shared mobility such as *Free-Floating Carsharing* services and *Shared Autonomous Vehicles* have the potential to change urban travel behaviour. In this paper a stated choice experiment on mode choice among a sample of the Dutch urban population is presented, in which the particular features of free-floating carsharing and shared autonomous vehicles in comparison to private vehicles and public transportation are examined. The most explanatory and robust mode choice models were obtained by estimating nested logit models with two categories capturing vehicle automation or vehicle ownership, and a nested logit model with three categories capturing who is performing the driving task (the commuter, a human driver or an autonomous vehicle). Interpreted as mode preference, the alternative-specific constants of the utility functions reveal a strong impact of vehicle automation on mode choice: while early adopters of mobility trends show a clear preference for shared autonomous vehicles over all other modes, normal and late adopters show a clear aversion towards this mode. In terms of vehicle sharing, no preference of sequentially shared modes over a simultaneously shared bus could be determined. Participants currently not having access to carsharing services show a stronger preference towards free-floating carsharing than the early adopters subscribed to carsharing.

Keywords: Free-Floating Carsharing, Shared Autonomous Vehicles, Stated Choice, Commuting Traffic, Mode Choice

1. INTRODUCTION

With progress in vehicle technology and communication technology, new types of vehicles and mobility services emerge. Two trending developments contributing to the diversification of mobility are vehicle automation and urban vehicle sharing *(1)*. With the development of vehicle automation progressing fast *(1, 2)* and the market for shared vehicles growing *(3, 4)*, the question rises how the broad implementation of both concepts will shape and transform traditional mobility patterns.

This study examines the role of vehicle ownership, vehicle sharing and the differences in the characteristics of in-vehicle time on mode choice. Public transport and privately owned vehicles are diametrically opposed to each other within these categories and define a field, in which modes with gradient degrees of vehicle sharing and varying levels of ownership can be positioned. We focus in this paper on two specific forms of shared mobility, *Free-Floating Carsharing* (FFCS) and *Shared Autonomous Vehicles* (SAV). FFCS falls into the categories "one-way" carsharing and "open destination" carsharing *(5)*. There is thus no designated infrastructure linked to this form of mobility and users can freely choose their departure time as well as their destination service area. SAVs are a form of FFCS in which vehicles travel autonomously, i.e. without human intervention, transporting at least one passenger to its final destination *(6)*. In this paper SAV are regarded as sequentially shared driverless vehicles providing a demand-responsive door-to-door service. SAV are also referred to as *autonomous taxis* or *aTaxi (7)*, as they are similar to taxi services apart from the absence of a human driver. Passengers in SAV and taxis experience a task-free in-vehicle time, just as they also do in conventional public transport services. Users of private cars and FFCS on the other hand face task-bounded in-vehicle time as they need to perform the driving task. The latter of course does not hold for their passengers.

A distinction can be made between simultaneous and sequential carsharing *(8)*. For FFCS and SAV the act of vehicle sharing is a sequential one, as a ride is not shared with unknown passengers. These modes offer therefore the same level of privacy as the private car. Examples for simultaneous ride sharing, implying the sharing of a vehicle with strangers, which is a downside for many users *(9)*, are *carpooling* or traditional public transport services. The impact of sequential carsharing on travel behaviour has lately been subject to extensive research, in particular in terms of the motives for carsharing: these include cost efficiency, environmentally conscious choices and convenience *(5, 10–12)*.

However, the knowledge on mode choice behaviour in case shared mobility becomes widely available is limited. Carsharing is still confined to a niche market, and any predication on usage rates for a potential closely meshed free floating carsharing network can only be estimated, not observed yet. The same holds of course for services based on SAV, as these are not market ready yet. This study is taking a first step into this field by investigating urban mode preferences in the event that FFCS and SAV are fully accessible to all users. For this purpose, a stated choice experiment has been devised and conducted, based on which mode choice models are estimated.

The remainder of this paper is structured as follows: in section 2, a review of the literature on stated choice experiments featuring taxi, FFCS or SAV is given. The methodological specifications for the stated choice experiment are given in section 3. In section 4, the mode choice model is described and the estimated results are presented and analysed. In section 5, the results are critically discussed and an outlook on further research requirements is given.

2. LITERATURE REVIEW

To be able to estimate the impact of the expansion of mobility services on mode choice, (potential) user behaviour must be observed and analysed. Since FFCS is still a new form of shared mobility and serves a niche market, while SAV are not operational yet, the primary sources of information on the user interaction with FFCS or SAV consists of stated preference experiments. To our knowledge, the only revealed data on mode choice preference for FFCS has been collected via travel diaries and booking data for FFCS in Germany *(5, 10, 13)*. In the following, findings on shared mobility, in particular FFCS and SAV, as well as on taxi services in the urban context are presented. The latter are discussed because taxi services are also included in the experiment presented in this paper to be able to directly see the influence of vehicle automation on mode preference.

2.1 Stated Choice Experiments Featuring 'Taxi Services'

Taxi services are featured in only a few stated choice experiments on mode preference. A study for the British market on different operational modes of taxi services revealed a strong preference for hailing taxis over waiting for one, but that waiting for a taxi is still preferred over walking to a pick-up point *(14)*. Also the vehicle type, driver quality and punctuality have an impact on users' choice behaviour, while the type of fare deduction (metered or unmetered) and vehicle quality in terms of cleanliness or the age of the vehicle have not. A stated choice experiment presenting taxi as one of various alternatives of egress transport modes provided at train stations has been conducted for the Dutch market *(15)*. The results show that, within the hypothetical situation specified in the study, taxi is the second-preferred mode, following low-frequency public transport services. Within the context of this study, the active modes walking and cycling were less preferred.

2.2. Stated Choice Experiments Featuring 'Carsharing'

Stated choice experiments on mode choice featuring station-based carsharing have been performed for various countries. However, no choice experiment featuring FFCS has been conducted so far to our knowledge. For this reason the scope for the literature review has been extend to station-based one-way carsharing. An elaborate experiment featuring station-based carsharing has been performed for the British market *(16)* by gaming simulations and choice experiments. The latter focused on avatar choices for both, mode choice as well as portfolio choices including for example car ownership costs and the selection of a neighbourhood. Further experiments for station-based carsharing have been undertaken for the Swiss market *(12)*, with carsharing characterized by the attributes travel costs, travel time and access time. For the Italian market stated-choice experiments were conducted for one-way station-based carsharing for urban trips, characterizing the carsharing services by the attributes travel costs, parking costs, the access time, the travel time and the parking time *(17)*, transportation between Park & Ride facilities and the city centre *(17)* and for inter-urban carsharing allowing access to restricted traffic areas *(18)*.

2.3 Stated Choice Experiments Featuring 'Shared Autonomous Mobility'

Though autonomous vehicles are to most users an even more abstract mobility concept then FFCS, more attention has been given to determine the user acceptance of (shared) autonomous vehicles *(19–21)*. In a stated choice experiment conducted among an Australian online panel, participants were asked to make mode choices for a reference trip similar to a previously performed one *(22)*. The alternatives in this experiment include shared and non-shared automated vehicles, as well as the originally chosen mode used in the reference trip. The alternatives were specified by the attributes travel cost, travel time and waiting time. Shared and non-shared automated mobility showed to be perceived as two distinctive modes by the participants.

Sequentially and simultaneously SAV have also been introduced in a stated choice experiment as an access and egress mode for last mile trips to a train station in the

Netherlands, next to public transport modes and bicycles *(23)*. The alternatives are described by the attributes waiting time, travel time, travel costs and the level of sharing. The findings suggest there is no significant difference between sequentially and simultaneously shared autonomous vehicles and that autonomous vehicles do not outperform manually steered vehicles.

3. STATED CHOICE EXPERIMENT

To determine the impact of an increasing level of vehicle sharing and vehicle automation on mode choice, a stated choice experiment has been performed. The online survey was conducted using the *Collector* software, an online survey software which allows to specify a variety of different question types and to store the collected answers on a server owned by the Delft University of Technology. In this section the layout of questionnaire (Section 3.1) and the design of the stated choice experiment (Section 3.2) are described.

3.1 Questionnaire and Survey Design

3.1.1 Survey Structure

The stated choice experiment was conducted as part of a survey consisting of 22 questions per participant, nine of which constituted the choice experiment. Respondents were asked to state the following: postal code, age, working status, highest education level, driver license availability, the usually used mode for commuting, distance to their workplace and if they had heard of, or had made use of, the ride-sourcing transport service Uber. The latter was asked for categorizing the participants in terms of their receptiveness to new mobility trends. In a second part, the choice experiment was presented to the participants. Finally, the following information on the household of the participants was gathered: household composition, number of cars available to the household, household income and if one or more household members are subscribed to carsharing services.

3.1.2 Layout of Stated Choice Experiment

Participants were confronted with nine scenarios in which they had to choose a mode for a commuting trip to a fictitious work place or educational institution in their home town, approximately 8 kilometres (5 miles) away from their home. The choice experiment is conducted for the trip purpose of commuting, as it is believed that the willingness to opt for shared mobility, automated or not, is lower for commuting than for example recreational purposes. However, commuting is one of the main trip purposes in the Netherlands, especially when focusing on mid-and long-distance trips *(24)*. Gaining shares from commuting traffic will have a major impact on the success of shared mobility services and the success of spatially inclusive and comprehensive vehicle sharing systems, especially if the overall aim of introducing such systems is to reduce motorized traffic or the total number of vehicles.

Respondents were familiarised with the concepts of FFCS and SAV by the descriptions shown in TABLE 1. They were free to choose any mode option irrespective of their current situation in terms of car ownership and driving license possession. The participants were informed that travel times as presented in the choice experiments were not subject to uncertainties such as delays or the unavailability of parking spots. This is justified given that this experiment aims to catch overall mode preferences in the era of free-floating car sharing and potentially shared autonomous vehicles rather than the perception of risk or of the reliability associated to the presented modes.

TABLE 1 Description of FFCS and SAV Services as Presented to the Participants (Translated from Dutch).

FFCS: ***"Auto-to-go"*** 	SAV: ***"Self-riding vehicle"*** 
• *You can hire these vehicles if you have a driving license.* • *You can reserve a vehicle (max. 15 minutes in advance) or you can use a vehicle without reservation.* • *You can see online (computer or smartphone) where the closest vehicle is located and the average walking distance –and time towards this vehicle.* • *When entering the vehicle, you check if the vehicle is in a good state. On a touchscreen in the vehicle you can indicate if everything is in order, for example if the vehicle is clean enough.* • *You drive the vehicle yourself.* • *You can travel in a group of maximal 5 people in the vehicle. The number of people does not influence the price. You share the vehicle only with the group of people you are travelling with and never with other people outside of this group.* • *Once arrived at your destination, you have to park the vehicle. This can be done on any ordinary parking spot, including payed parking spots. You do not have to pay parking fees.* • *The costs for your travel in the vehicle are metered per minute and are automatically withdrawn from your bank account.*	• *You call or reserve the vehicle upfront for a desired time.* • *The vehicle is coming to you.* • *You have access to up-to-date information on the location of the vehicle and the expected arrival time.* • *The vehicle is driving automatically, you do not have to steer the vehicle or pay attention to traffic.* • *You can travel in a small group within the same vehicle. The number of people has no impact on the price. You never share the vehicle with people who are not in the group you are travelling with.* • *The costs for your travel in the vehicle are metered per minute and are automatically withdrawn from your bank account.* • *Once arrived at your destination, you exit the vehicle. You do not have to search for a parking spot nor do you have to pay for parking costs.*

A pilot survey including 37 participants, consisting of students of the Delft University of Technology and their relatives, was performed in order to increase the clarity of the survey based on participants' feedback. The outcome of the pilot study was not used for developing an efficient design of the survey, therefore bias in the experimental design due to the selection of the respondent group for the pilot study is not possible. Following the pilot, the total number of questions in the final survey was reduced from 29 to 22 questions and more emphasis was put on the exemplary nature of trip and trip purpose. Also attribute levels for SAVs and taxis were adapted to increase the realism of the choice situations to avoid that, by presenting attribute levels contradicting the experiences of the respondents, the perceived realism of the experiment is decreased *(25)* and the number of questions in which one alternative clearly outperforms the others has been reduced. Attributes related to costs were highlighted in a different colour than attributes related to time and time-related attributes were visualised with bars for an easier understanding. To reduce confusion, the order of the presented modes was fixed per block. An example of the final layout of the choice experiment is shown in FIGURE 1.

In order to diminish bias, the order of the modes was randomised per block, as was the order if the set of cost –or time related parameters was shown first. The order among the time and cost parameters was not altered, as it follows the logical order of all elements forming one complete trip.

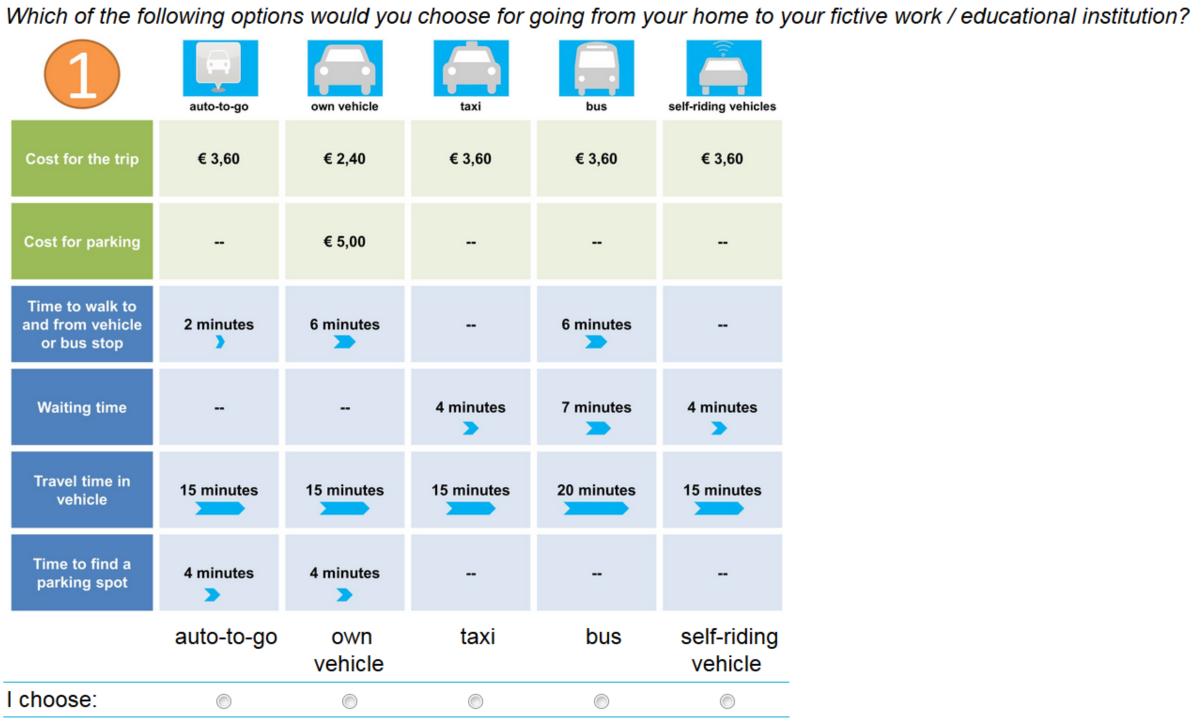

FIGURE 1 An Illustration of a Choice Experiment as Presented in the Survey (Translated from Dutch).

3.2 Design of Stated Choice Experiment

The choice experiment has been formulated as a fractional factorial design with non-random blocking, which is an effective way of achieving an efficient experimental design *(25)*. The D-error, a common measure for the statistical efficiency of the design of stated-choice experiments, has a value of 0.013, which is not optimal but still low. Five mode alternatives were presented to the participants in the choice experiment: privately own vehicles *(car)*, free-floating carsharing *(FFCS)*, taxis *(taxi)*, a direct bus line *(bus)* and shared autonomous vehicles *(SAV)*. The mode alternatives are characterized by the following six attributes on three levels (the exchange rate from Euro to US dollar was 1.14 as of the 1st of April 2016):

- Travel costs [€]: TC^{car} [1.2; 2.4; 3.6], TC^{FFCS} [1.2; 2.4; 3.6], TC^{bus} [1.2; 2.4; 3.6], TC^{FFCS} [1.2; 2.4; 3.6], TC^{taxi} [3.6; 4.2; 4.8], TC^{SAV} [2.4; 3.6; 4.8]
- Parking costs [€]: PC^{car} [0; 2.5; 5]
- Access and egress time while walking to the vehicle or the bus stop [min]: AT^{car} [2; 4; 6], AT^{FFCS} [6; 10; 14], AT^{bus} [2; 6; 10]
- Waiting time [min]: WT^{bus} [1; 4; 7], WT^{taxi} [1; 4; 7], WT^{SAV} [1; 4; 7]
- In-vehicle time (without time searching for parking spot) [min]: IVT^{car} [15; 20; 25], IVT^{FFCS} [15, 20, 25], IVT^{bus} [20; 25; 30], IVT^{taxi} [15; 20; 25], IVT^{SAV} [15; 20; 25]
- Time searching for a parking location [min]: ST^{car} [1; 4; 7], ST^{FFCS} [1; 4; 7]

By presenting five alternatives with six attributes (FIGURE 1), the respondents were confronted with a complex choice experiment. The distinction of the various components of travel cost and travel time in the choice experiment allowed characterizing the modes in detail, in particular the attributes specific to shared mobility. It has been shown that respondents cope well with complex scenarios and that a higher relevance of the choice alternatives can increase response quality *(25, 26)*.

4. RESULTS

4.1 Respondent Panel and Sample Composition

The stated choice experiment has been conducted in April 2016 among 840 members of an online panel. The participants were older than 18 years old and originated from the four largest cities of the Netherlands (Amsterdam, The Hague, Rotterdam and Utrecht). In order to capture the actively commuting population, only respondents studying or working more than 12 hours per week (employed, self-employed or as volunteers) were included.

By excluding inconsistent answers while obtaining an orthogonal answer set, the final data set has been reduced to 732 responses (87% of total sample). The main characteristics of the respondents in this data set are presented in TABLE 2. While the distribution of gender, income and the access to at least one vehicle per household correspond with the Dutch national average *(27, 28)*, the sample shows an overrepresentation of highly educated respondents, driving license holders, carsharing users and high income households compared to the national average *(29–31)*. This can be explained by the geographical constraint put on the sample: the selected cities lie in the metropolitan Randstad region, which is more prosperous and has a higher level of education than the rest of the country *(32)*. No information on the national average of users of the ride-sourcing company Uber is available, but it is expected that, similar to carsharing usage, the share of users of Uber is higher in the sample than the national average. The group of over 60-year-old participants is substantially lower than the national average *(28)*. The reason for this is that not enough active commuters could be reached in this age group, as the formal retirement age in the Netherlands lies at 65 years.

TABLE 2: Main Socio-Demographic Characteristics of Respondents

Characteristic	total number (percent) [class]
Respondents	732
Mean Age (standard deviation)	42.33 (14.2)
Age classes (in percent) [class]	180 (24.59%) [18-29]; 152 (20.77%) [30-39]; 139 (18.99%) [40-49]; 152 (20.77%) [50-59]; 109 (14.89%) [60-80]
Gender: male; female (in percent)	369 (50.41%); 363 (49.59%)
Driving license holder (in percent)	623 (85.11%)
Household has access to at least one vehicle (in percent)	549 (75.00%)
Highest level of education (in percent) [class]	103 (14.07%) [Primary school and lower education]; 290 (39.62%) [High school or mid-level education]; 338 (46.17%) [higher education]
Yearly household income (in percent) [class]	171 (23.36%) [0 – 30,000 Euro]; 292 (39.89%) [30,000 Euro – 60,000 Euro]; 140 (19.13%) 130 (17.76%) [more than 60,000 Euro]
Households with at least one household member subscribed to a carsharing service in general and to a free-floating carsharing service in particular (in percent)	67 (9.15%) [Carsharing in general]; 18 (2.46%) [free-floating carsharing]
Uber user and/or chauffeur (in percent)	84 (11.48%)

4.2 Model Estimation

4.2.1 Model Structures

Four types of choice models have been estimated based on the stated choice experiment. Next to a multinomial logit model (*MNL*) under the assumption of random utility maximisation, various nested structures have been estimated to capture the perception of shared mobility as an interlink between privately owned vehicles and conventional public transport services. By introducing nested logit (NL) models, unobserved correlations between the mode alternatives were included in the model estimation. The following NL models with two or three categories were found to improve estimation results:

- *NL,ownership*: privately owned (*car*) or shared (*FFCS, SAV, taxi, bus*)
- *NL,automation*: manually driven (*car, FFCS, taxi, bus*) or vehicle automation (*SAV*)
- *NL,driver*: driving the vehicle (*car, FFCS*), being driven by a human driver (*bus, taxi*) or an autonomous vehicle (*SAV*)

No significant or robust model could be estimated for nested logit models with two categories capturing the privacy in the vehicle, with full privacy (*car, FFCS, SAV*) and limited privacy (*taxi, bus*) or distinguishing between task-bounded and task-free in-vehicle time (*car and FFCS* versus *SAV, taxi and bus*). Also no significant model could be estimated for the nested logit models with three categories capturing carsharing, nesting privately owned (*car*), sequentially shared (*FFCS, SAV, taxi*) or simultaneously shared (*bus*) vehicles, or investigating the directness of the transportation, with transportation by a door-to-door service (*SAV, taxi*), travelling from parking-to-parking (*car, FFCS*) or from bus stop-to-bus stop (*bus*). Also no significant and robust cross-nested logit (*CNL*) models for the above mentioned categories could be estimated.

4.2.2 Model Formulation

All coefficients for parameters related to travel time and travel cost, as well as the socio-economic parameters, were first estimated as mode-specific parameters and only carefully grouped if no significant differences between the mode-specific parameters were obtained. Not in all cases significant and robust coefficients could be estimated by applying the approach to specify from mode-specific parameters towards more generic parameters, as only parameters yielding significant results and statistically significant improvement of the model fit were included in the final model structure. Estimation results for the most robust model suggest that the travel cost coefficient is not mode specific, which is an expected result when assuming that decision makers regard monetary costs rationally. Parameters for travel time components on the other hand are alternative specific, or specific among a group of similar alternatives. Remarkable in this context is that the in-vehicle time in modes requiring driving tasks (*car*, *FFCS*) were found to have an insignificant effect on their choice probabilities and were thus not included in the model. The in-vehicle time for bus is modelled mode specific, as is the in-vehicle time for taxis, automated or manually driven. The access and egress time spent while walking to the vehicle or station is modelled generically. Waiting time is mode specific for the bus and the taxi. The waiting time for SAV proved insignificant in the model estimation process and is thus not included in the formulation of the utility function.

In terms of the socio-economic parameters, interactions with alternative specific attributes were found insignificant, while the impact of the following generic variables proved significant for the utilities of the modes: gender (β_{gender}), possessing a drivers' license ($\beta_{license}$), having a lower education ($\beta_{education}$), the household having currently access to at least one private vehicle ($\beta_{private\_vehicle}$) and at least one household member being currently subscribed to at least one carsharing service ($\beta_{carsharing}$).

The successfully estimated model structures (*MNL*, *NL,ownership*, *NL,automation*, *NL,driver*) show the best model fit with the most robust results for the following specification of the utility functions per mode, excluding the nested parameters (formula (1) to (5)):

$$V^{car} = \beta_{cost} * (TC^{car} + PC^{car}) + \beta_{walk} * AT^{car} + \beta_{private\_vehicle} * PV + \beta_{license} * LH + \beta_{gender} * MA + \beta_{education} * LE + \beta_{carsharing} * CS \quad (1)$$

$$V^{FFCS} = ASC_{FFCS} + \beta_{\cos t} * TC^{FFCS} + \beta_{walk} * AT_s^{FFCS} + \beta_{license} * LH \quad (2)$$

$$V^{bus} = ASC_{bus} + \beta_{\cos t} * TC^{Bus} + \beta_{IVT,bus} * IVT^{bus} + \beta_{walk} * AT^{bus} + \beta_{WT,bus} * WT^{bus} + \beta_{license} * LH \quad (3)$$

$$V^{taxi} = ASC_{taxi} + \beta_{\cos t} * TC^{taxi} + \beta_{IVT\_(a)taxi} * IVT^{taxi} + \beta_{WT,taxi} * WT^{taxi} \quad (4)$$

$$V^{SAV} = ASC_{SAV} + \beta_{\cos t} * TC^{SAV} + \beta_{IVT\_(a)taxi} * IVT^{SAV} \quad (5)$$

With:
U^m: Utility of mode alternative *m*
ASC^m*:* Alternative-specific constant of mode alternative *m*
β_{cost}: coefficient for travel cost
β_{walk}: coefficient access and egress time for walking to vehicle/bus stop
$\beta_{WT,bus}$: coefficient for waiting time for bus
$\beta_{WT,taxi}$: coefficient for waiting time for taxi and SAV
$\beta_{IVT,bus}$: coefficient for in-vehicle time for bus
$\beta_{IVT,(a)taxi}$: coefficient for in-vehicle time for taxi and SAV
MA: dummy for male gender
LE: dummy for lower education level
LH: dummy for license holder
PV: dummy for access to a private vehicle (household level)
CS: dummy for access to a carsharing service (household level)

An exception to the presented model structure are the nested logit models with two groups (*NL,owning* and *NL,automation*), for which the waiting time for the mode bus (WT^{bus}) was found insignificant and was therefore not included in the utility function.

4.2.3 Estimated Model Coefficients and Model Fit

The model coefficients have been estimated with the software Biogeme *(33)* under use of the optimization algorithms BIO and DONLP2 intrinsic to the software. In TABLE 3 the estimated utility and nest coefficients are presented with the robust t-statistics for the models *MNL*, *NL,ownership*, *NL,automation* and *NL,drive.*

The nested-logit models show a significantly better model fit than the MNL, with the nested structure capturing vehicle automation (*NL,automation*) and the three-nested NL capturing who is performing the driving task (*NL,driver*) showing a slightly higher adjusted rho-square value than the nested logit model capturing vehicle ownership (*NL,ownership*).

TABLE 3 Estimated Coefficients and Indicators of Model Fit for the Models *MNL*, *NL,ownership*, *NL,automation* and *NL,driver*.

	MNL	***NL,ownership***	***NL,automation***	***NL,driver***
Utility Coefficients: estimated value [robust t-statistics]; Significant values are marked by * (robust p-value < 0.05) and ** (robust p-value < 0.01) na: not applicable				
ASC_{ffcs}	-0.67** [-3.69]	-6.41** [-3.30]	-1.55** [-3.28]	-1.36** [-3.08]
ASC_{sav}	1.68** [7.29]	0.26 [0.37]	4.39** [5.83]	2.19** [7.27]
ASC_{taxi}	1.03** [4.62]	-1.72 [-1.63]	2.00** [4.29]	-0.41 [-0.66]
ASC_{bus}	-0.03 [-0.11]	-3.66** [-3.39]	-0.30 [-0.61]	-2.23** [-3.21]
β_{cost}	-0.06** [-6.45]	-0.13** [-8.81]	-0.03* [-1.97]	-0.06** [-6.27]
β_{walk}	0.04** [6.51]	0.08** [6.61]	0.09** [5.42]	0.06** [7.21]
$\beta_{WT,taxi}$	0.05** [5.16]	0.15** [4.76]	0.08** [4.07]	0.09** [5.26]
$\beta_{WT,bus}$	0.03* [2.35]	na	na	0.05** [3.20]
$\beta_{IVT,bus}$	0.02** [3.85]	0.04** [3.37]	0.06** [3.94]	0.04** [4.68]
$\beta_{IVT,(a)taxi}$	0.02** [4.26]	0.02* [2.05]	0.03** [5.10]	0.03** [4.51]
β_{gender}	0.32* [2.70]	0.30* [2.53]	0.66** [3.00]	0.32* [2.53]
$\beta_{license}$	0.91** [5.90]	1.53** [5.40]	1.21** [4.90]	1.33** [5.66]
$\beta_{education}$	0.65** [3.40]	0.70** [3.52]	0.87* [2.57]	0.71** [3.42]
$\beta_{private\_vehicle}$	1.30** [7.85]	1.22** [7.23]	2.62** [5.85]	1.38** [6.80]
$\beta_{carsharing}$	-0.56** [-3.02]	-0.59** [-3.16]	-0.86*[-2.59]	-0.61** [-3.02]
Nest Coefficients	na	n1: shared (FFCS,SAV, taxi, bus); n2: owned (car)	n1: automation (SAV); n2: no automation (car, FFCS, taxi, bus)	n1: driving (car, FFCS); n2: driver (bus, taxi); n3: automation (SAV)
n1	na	0.32** [4.25]	1.00 [0.00]	0.70* [5.31]
n2	na	1.00 [0.00]	0.44** [6.43]	0.28** [4.29]
n3	na	na	na	1.00 [0.00]
Model Fit				
Initial log-likelihood	-10602.98	-10602.98	-10602.98	-10602.98
Final log-likelihood	-9435.44	-9404.67	-9386.34	-9390.74
Adjusted ρ^2	0.109	0.112	0.113	0.113

By simply excluding early adopters from the dataset, a better model fit was attained. The adjusted ρ^2 – value for *NL,automation* for example is 0.125 for the reduced data set, which is a significant increase for the one of 0.113 obtained for the complete data set. The model fit also improves when excluding the early adopter from the MNL (adjusted ρ^2 – value: 0.121), the model *NL,ownership* (0.124) and the model *NL,driver* (0.124). However, no significant and robust model could be obtained for the dataset consisting only of early adopters, therefore models with interaction parameters for early adopters and normal/late adopters were estimated. The model structure remained the same as presented before (formulas (1) to (5)), with the exception that access to carsharing was not included as a socio-economic parameter. Also certain parameters have proven to be insignificant for the models of early adopters and were thus not included, as indicated in TABLE 4.

The models were also estimated for specific groups among the respondents, both for reduced data sets and by estimating models that include interaction parameters. In particular, the group of so-called "early adopters" has been defined in contrast to normal or late adopters in order to examine the potential influence of the receptiveness towards new mobility. Users of the ride-sourcing company Uber or participants living in a household in which at least one member is subscribed to at least one carsharing company are considered "early adopters", amounting to 131 survey participants (17.90% of the sample). The attribute "early adopter" proved to be not significantly correlated with gender or income levels, but shows a strong correlation to the group of under 40 years old ($\chi^2(1,N=732) = 19.14$, $p = 0.00$).

TABLE 4: Estimated coefficients and indicators of model fit for the models *MNL*, *NL,ownership*, *NL,automation* and *NL,driver* estimated with interaction parameters for "early adopters" and "normal /late adopters".

	MNL		***NL,ownership***		***NL,automation***		***NL,driver***	
Utility Coefficients: estimated value [robust t-statistics]; Significant values are marked by * (robust p-value < 0.05) and ** (robust p-value < 0.01) na: not applicable								
	Early Adopters	Normal/ Late Adopters	Early Adopters	Normal/ Late Adopters	Early Adopters	Normal/ Late Adopters	Early Adopters	Normal/ Late Adopters
ASC_{ffcs}	-0.65 [-1.79]	0.48* [2.41]	-2.85** [-3.62]	3.10** [4.08]	-1.56 [-1.78]	1.48* [2.41]	-0.95** [-3.20]	0.84* [1.96]
ASC_{sav}	1.43* [2.26]	-1.85** [-7.30]	-0.58 [-0.96]	-1.31** [-3.45]	4.80** [3.61]	-4.99** [-7.29]	2.11* [2.28]	-2.30** [-7.33]
ASC_{taxi}	1.01 [1.62]	-1.14** [-4.65]	-1.01 [-1.58]	0.09 [0.19]	2.35 [1.91]	-2.13** [-4.20]	-0.48 [-0.44]	0.78 [1.32]
ASC_{bus}	0.55 [1.57]	0.16 [0.63]	-0.53 [-1.01]	1.82** [3.50]	1.04 [1.23]	0.88 [1.36]	-1.66* [-2.42]	2.96** [4.18]
β_{cost}	na	0.06** [6.98]	na	0.12** [7.75]	na	na	na	0.07** [6.96]
β_{walk}	0.05** [3.17]	-0.05** [-7.44]	0.08** [3.26]	-0.07** [-6.80]	0.11** [3.73]	-0.12** [-6.48]	0.07** [3.48]	-0.08** [-8.02]
$\beta_{WT,taxi}$	0.05* [2.13]	-0.06** [-4.66]	na	-0.11** [-4.39]	0.09* [2.04]	-0.08** [-3.27]	na	-0.10** [-4.94]
$\beta_{WT,bus}$	na	-0.03* [-2.19]	na	na	0.11* [2.39]	-0.10** [-3.47]	0.07* [2.01]	-0.05* [-2.76]
$\beta_{IVT,bus}$	na	-0.02** [-3.66]	na	-0.03** [-3.13]	na	-0.07** [-4.16]	na	-0.05** [-4.41]
$\beta_{IVT,(a)taxi}$	0.04** [3.34]	-0.02** [-3.15]	0.04* [2.06]	-0.02* [-2.21]	0.06** [4.79]	-0.02** [-3.76]	0.05** [4.48]	-0.02** [-3.73]
β_{gender}	na	-0.35* [-2.68]	na	-0.34* [-2.60]	na	-0.78** [-3.10]	na	-0.34* [-2.49]
$\beta_{license}$	1.23* [2.30]	-0.86** [-5.27]	na	-1.26** [-5.00]	1.95* [2.16]	-1.06** [-3.93]	2.07* [2.47]	-1.24** [-5.15]
$\beta_{education}$	na	-0.59** [-2.88]	na	-0.63** [-2.98]	na	-0.80* [-2.11]	na	-0.63** [-2.92]
$\beta_{private\_vehicle}$	0.77* [2.10]	-1.41** [-7.62]	0.98* [2.56]	-1.36** [-7.21]	2.06* [2.40]	-2.92** [-6.41]	0.83* [2.49]	-1.44** [-6.30]
Nest Coefficients			n1: shared (FFCS,SAV, taxi, bus); n2: owned (car)		n1: automation (SAV); n2: no automation (car, FFCS, taxi, bus)		n1: driving (car, FFCS); n2: driver (bus, taxi); n3: automation (SAV)	
n1	na		0.51** [7.31]		1.00 [0.00]		0.80 [4.78]	
n2	na		1.00 [0.00]		0.40** [6.95]		0.24** [5.34]	
n3	na		na		na		1.00 [0.00]	
Model Fit								
Initial log-likelihood	-10602.98		-10602.98		-10602.98		-10602.98	
Final log-likelihood	-9413.86		-9404.59		-9356.07		-9367.89	
Adjusted ρ^2	0.110		0.111		0.115		0.114	

When reading the estimated ASC as a the captured mode preferences for the two groups, the following observation can be made: (in the significant cases) early adopters find modes requiring driving and parking (*car*, *FFCS*) the least attractive and prefer demand-responsive modes with a task-free in-vehicle time (*taxi*, *SAV*). In contrast, the normal and late adopters reject strongly automated vehicles (*SAV*), but prefer other shared forms of mobility (*taxi*, *bus*, *FFCS*) over the privately owned vehicle (*car*). The coefficients of the models estimated with interaction parameters differ considerably from the ones estimated for the complete data set. The interaction models reveal that participants categorized as normal or late adopters, in contrast to the early adopters, have an aversion to all included travel time components, which can be seen by the negative sign of the time components. In terms of travel costs, no significant coefficients could be estimated for the early adopters, however for the normal and late adopters the costs show an unexpected positive sign.

4.2.4 Findings on Mode Preference

Model estimation findings reveal insight into the mode choice preferences of the Dutch urban population and their attitude towards shared mobility for commuting purposes. However, the results must be discussed in the context of the experimental set-up and provide caveats on the interpretation of actual mode choice behaviour, now or in the future.

First, the impact of vehicle automation on mode choice behaviour is discussed in more detail. The stated choice experiment included two modes which are not (widely) available yet: FFCS services and SAV services. While stated choice experiments are an opportunity to capture preferences about novel alternatives, they bear the risk that uncertainty, expectations and current risk perception are influencing the choices made. The outcome has to be interpreted more as a snapshot on the current perception of the new modes rather than as an outlook on mode preference once the presented modes will become broadly available. This snapshot in terms of autonomous vehicles shows the following: vehicle automation has a strong impact on mode preference, and while normal and late adopters show a strong aversion towards SAV, early adopters select autonomous vehicles over all other presented modes. This outcome is not confirmed by, but in line with, previous findings *(22)*.

The importance of the vehicle automation for the choice behaviour also shows in the comparison of model fit for the estimated models: the best result could be achieved for the model with the nested structure capturing vehicle automation (*NL,automation*). This demonstrates the importance of vehicle automation in mode perception, which is also seen by the direct comparison of *SAV* and *taxi*: In the experimental setting both modes are described as demand-responsive door-to-door transportation with a task-free in-vehicle time and both showed the same attribute levels. However, the preference for or the aversion to *SAV* expressed by the early adopters or normal/late adopters respectively, is much more pronounced than the one for the taxi service.

Secondly, the contribution of the various parameters to the total utility of a mode is evaluated by computing the product of the coefficients and the mean attribute values. Only the main and consistent trends are discussed. It is remarkable that the magnitude of the alternative specific constant in most cases is higher than the parameters of travel costs and travel time. Travel costs play a smaller role than travel time. Among the travel time components, the in-vehicle time has the strongest impact, followed by the access/egress time. This has to do with the applied attribute levels, if comparing the perception of each travel time component per minute, it shows that one minute of waiting time or access/egress time influence the utility more than one minute of in-vehicle time. It is also remarkable that the waiting time for the modes SAV and taxi, differing to the mode bus, showed to have no significant impact on the utility of the respective modes. This can be interpreted as a difference in the perception of waiting time at a pick-up location as opposed to waiting time at a bus stop, presumably because waiting time in case of a door-to-door service is less idle than at a stop of a scheduled public transport service.

The interpretation of the signs shows that the travel time components decrease the utilities for the normal and late adopters, while they increase the utility for the early adopters. The cost parameters lead to utility increase for the normal and late adopters, but proved insignificant for the early adopters (showing a negative sign though). An explanation for the unexpected increase of utility related to travel time and costs lies in the complex experimental set-up: five alternatives with six attributes, of which only the element of parking costs showed a strong variance in attribute levels and among the modes while the other presented parameters were, for the sake of an increased realism, not differing strongly. The positive signs of the coefficients are interpreted in the way that within this complex choice-set certain aspects had less influence on participants than others, which led to a non-observance of these aspects for these parameters. For the group of late and normal adopters the less important parameters are the ones related to cost, for the early adopters these are the ones related to time.

Thirdly, the mode preferences are discussed in the light of vehicle sharing and vehicle ownership. Previous experiences with carsharing play a role in the choice experiment. Estimation results suggest that the early adopters, consisting of participants experienced with carsharing, have no preference towards FFCS, while the normal and late adopters currently not having access to carsharing services show a clear preference for FFCS over a privately owned vehicle. This shift in trend can be interpreted as a validation of the assumption that normal and late adopters of mobility trends follow the early adopters of mobility trends. A preference of sequentially shared modes over the simultaneously shared bus could not be observed.

5. DISCUSSION AND CONCLUSION

New forms of mobility services are entering the market, which are amplified by new communication and vehicle technology. Once vehicle automation is operational, the step from the currently trending free-floating carsharing services towards shared autonomous vehicles, or *aTaxis*, can be made. Shared autonomous vehicles have the advantage over current shared mobility services in that they can provide demand-responsive door-to-door service with a task-free in-vehicle time for the passenger. Currently the labour-cost intensive, and therefore heavily subsided, demand-responsive transport services are provided mainly to the elderly, passengers with special needs or in rural areas. With the introduction of SAV, demand responsive transport could be offered on a larger scale, targeting also demand for urban transport, active travellers and commuters. In this study, the acceptance of such a transport service among these new potential target groups is investigated.

The findings reported in this paper, based on a stated choice experiment on mode choice conducted among the Dutch urban population, reveal that SAV were perceived more favourably among early adopters of mobility trends than FFCS. Normal and late adopters however rejected autonomous vehicles, but showed a preference for FFCS. This does not reflect actual mode choice behaviour, but the current perception of the modes, as the experimental setting was a hypothetical commuting trip. Moreover, it is uncertain whether the same enthusiasm for vehicle automation would be observed in a similar experiment if it would have been conducted shortly after the first deadly traffic accident linked to failure of driverless vehicle technology *(34)*.

Further research is required in order to assess the prospects and impacts of vehicle sharing and vehicle automation, two potentially disruptive technological and organizational trends, on urban mode choice behaviour. The scope of the choice experiment performed in this study could be expanded by including more trip purposes and differing trip durations. Another important aspect is the perception of reliability, as the shared modes add a new dimension in this respect the uncertainty of vehicle availability. Additionally, new mobility services can potentially contribute to a long-term shift in car-ownership. This is not unlikely if the trend towards a more positive perception of shared autonomous vehicles, as presented in this paper, is continued.

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