Is ultrafast charging the future for electric vehicles in the Netherlands? A discrete choice experiment on user preferences for slow, fast and ultrafast charging

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Abstract

Ultrafast charging, with speeds of 350 kW and more, is developing and will soon be available to electric vehicles (EV). Charging at such speeds implies being able to load a range of 100 kilometres in a couple of minutes. This research focuses on the user preferences of the approximately 45,000 current Dutch full electric drivers for slow charging, fast charging and ultrafast charging (RVO, 2018). The research goal is to investigate the feasibility of ultrafast charging of EV in the Netherlands, based on a user perspective. A stated choice experiment with 171 respondents has been carried out, after which multinomial logit and mixed logit models have been estimated based on random utility maximisation theory. In total, 57 variables including charging point- and user characteristics have been tested in the models. Charging point characteristics including price, proximity to shopping facilities or the absence of facilities, certainty of availability, and (not) having to make a detour are influential factors for EV drivers in deciding which charging type to choose. Elasticity calculations do also show that price changes and (not) having to make a detour substantially affect user choices for the charging types. An interesting result from the model estimations is that when one finds comfort important, this increases one's likelihood of choosing ultrafast charging. Contrary to expectations, no significant results were found for, amongst others, urban density, age, technology awareness and importance of sustainability. Mixed logit models reveal that preference heterogeneity is found for ultrafast charging, but not for slow and fast alternatives. Additional semi-structured interviews with stakeholders emphasize the possible difference between expected and modelled users' preferences. Stakeholders acknowledge that the user perspective is important for their goals and strategies. The research results show that there is a possible future for ultrafast charging for EV in the Netherlands: people are willing to pay slightly more to charge ultrafast than to slow charge, but all else equal, they will also still opt for slow and regular fast charging.

Keywords: electric vehicles; charging behaviour; ultrafast charging; stated preference; discrete choice modelling.

1. Introduction

Electric vehicles (EVs) provide a promising sustainable possibility with regard to environmental problems, including rising CO_2 emissions, particulates and other pollution. As is inherent to new developments, challenges do and will occur due to the rapid growth of EV in the past five years (RVO, 2018). One of the main challenges is the provision of a solid network of charging infrastructure, for which many aspects are crucial to consider, including the type of charging

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points. Developments in the type of charging affect consumers as well as policy decisions about refuelling EVs. One of the most recent and possibly most impactful developments in this field is ultrafast charging (>350kW). Such speeds imply recharging 100 kilometres of range in approximately three minutes or less, compared to hours of slow charging.

Currently the charging system comprises of standard charging points (<22kW), used for destination charging – another term for slow charging – and an increasing amount of fast charging points (22-50kW). These fast charging points will likely become ultrafast charging points (350-450kW) in the near future. In the Netherlands, the first ultrafast charging points have been installed in July 2018 (Allego, 2018), even though currently, vehicles cannot yet charge at such high speeds. It is unclear how the EV drivers will make use of such infrastructure when their vehicles are ready for this technology in the near future. This charging behaviour is a key parameter in a well-functioning charging system. Ultrafast charging (>350 kW) has so far not been at the centre of attention of scientific studies, most likely because it is such a recent development (Hardman et al., 2018; Gnann et al., 2018; Neaimeh et al., 2017). This research therefore aims at finding which factors determine the user choice for certain types of charging, understanding charging behaviour, and collecting opinions and visions on the balance between destination charging, fast charging and ultrafast charging. This may help to develop strategies for promoting more efficient use of the charging infrastructure, as well as policies concerning the installation of different types of charging points (Ecofys, 2016).

Developing a basis for such charging infrastructure policies as mentioned above is the core research motive for this study. The development of charging infrastructure in the Netherlands is on the move from demand-driven to strategic data-driven methods. This implies that public charging infrastructure will be installed based on charging data instead of on the current charging-point-follows-car principle, where an EV driver requests a charging point to be placed near his or her home. The challenge is what the plan for the next five years should look like: is destination charging still necessary or can an ultrafast alternative serve the same purpose with less pressure on public space? Which alternative will EV drivers use the most? This research could inform municipalities and other stakeholders alike about user preferences on different charging types. Furthermore, concerning theoretical motives, this research would contribute to the existing body of research on EV charging infrastructure, and add new insights on user choices for destination charging, fast charging and ultrafast charging. To the best of the author's knowledge, no previous research on ultrafast charging has been conducted, emphasizing why this study will be a valuable addition to the field.

This research aims to facilitate the understanding of EV driver behaviour and to evaluate the potential of ultrafast charging in a constantly developing world of sustainable mobility. The following research goal provides the basis on which the research questions have been formulated. The goal of this study is to *investigate the feasibility of ultrafast charging of EV in the Netherlands, based on a user perspective.*

From the research goals, the main research question follows: *What is the quantitative influence of various factors on the EV user choices for destination charging, fast charging or ultrafast charging in the Netherlands?*

To be able to examine the feasibility and importance of ultrafast charging, it has to be compared to current alternatives, being fast charging and destination (slow) charging. Corresponding subquestions to guide the research have been formulated, relating to current behaviour, researched factors, sensitivity analysis and stakeholder perspectives.

1. What does current charging behaviour of EV users in the Netherlands look like?

2. What are the factors that influence charging behaviour of EV users in the Netherlands?

3. What happens to the likelihood of EV users' choices for charging types subject to parameter changes?

4. What are EV stakeholders' perspectives regarding user preferences for different charging types?

Important to note is the focus of this research on the user perspective in EV-charging. It is likely that differences will occur between government, business and user perspectives concerning choices for the ideal charging infrastructure (Bakker et al., 2014). Whereas a user might prefer ultrafast charging, for government this might be too expensive, there might be too little public space, or this could mean too much pressure on the grid during peak times. The other way around is also possible. For companies, it is relevant to develop a proper business model that should eventually align with user preferences as well as with government regulations. With the answer to the main research question, it is possible to derive recommendations for (local) governments and businesses on the installation and the ideal mix of public charging infrastructure, based on the user perspective.

The remainder of this thesis is structured as follows. First, theory and literature have been studied (section 2), after which primary factors to research were identified. The data collection took place through an online survey with stated choice experiment among EV drivers in the Netherlands (sections 3 and 4). After finishing the data collection and preparation, the data analysis has been completed. By evaluating descriptive statistics, estimating multinomial logit and mixed logit models, calculating elasticities and analysing stakeholder interviews, the answers to the research questions were found (section 5). The paper concludes with a discussion (section 6) and conclusion (section 7).

2. Background and literature

Due to the substantial contribution of the transport sector to current environmental problems, electromobility is seen by many as the future of mobility. A paradigm shift is required, meaning that the current dominant vehicle type, the Internal Combustion Engine Vehicle (ICEV), needs to be replaced by electric vehicles (EVs) powered with renewable energy (Gnann et al., 2018). In the Netherlands, the first plug-in EVs were sold in 2011 and their sales increased sharply afterwards. The term plug-in hybrid EV (PHEV) is internationally used for plug-in hybrid electric vehicles, like the Mitsubishi Outlander. A full electric vehicle is a battery electric vehicle (BEV), like the Nissan Leaf or Tesla models. The number of registered electric vehicles in the Netherlands increased from 87,552 in December 2015 to 134,062 in October 2018 (RVO, 2018). Next to PHEV or BEV, an electric vehicle can be a Fuel Cell EV (FCEV) which uses a fuel cell instead of a battery to power its electric motor. The number of FCEV is only marginal (21 in 2015 and 53 in 2018) meaning that the rise of PHEVs and especially BEVs account for the increase and put more pressure on the charging infrastructure. The focus of this study is on BEVs since market developments are primarily aimed at this type of EV. Besides, ultrafast charging is only suitable for BEVs; PHEVs do not have the required technology built in.

Concerning policy, interesting to note is that European Union member states are required to design national action plans on charging point infrastructure. They have to install an appropriate number of electric recharging points accessible to the public by the end of 2020 (EU, 2014).

The following sections expand on the types of charging, charging infrastructure, charging behaviour and the research gap that this study aims to fill.

2.1. Types of charging: standard, fast and ultrafast

In Table 1, the three different types of charging regarded in this research are shown. Several characteristics, advantages and disadvantages are provided.

Table 1: Different types of charging and their characteristics, advantages and disadvantages (Hardman et al., 2018; Neaimeh et al., 2017).

	Slow charging	**Fast charging**	**Ultrafast charging**
Speed in kW (type)	< 22 kW (AC)	43 kW (AC) or 50 kW (DC)	> 350 kW (DC)
Time to charge 100 km	1-6 hours or more	20 minutes or less	3 minutes or less
Typical location	Shopping areas, office buildings, parking garages and on private property	Corridors and increasingly at standard charging spots	Corridors
Advantages	Possible with regular household grid connection Close to destination	Help to overcome perceived and actual range barriers	Similar to ICEV refuelling (almost no behavioural change required) No parking problems Lower occupancy rate
Disadvantages	Charging point congestion Unnecessary occupancy	Unnecessary occupancy Longer travel times to locations	Extreme electricity peak demands High installation costs Longer travel times to locations
Remarks	Also called destination charging Suitable for smart charging Complicated relationship with parking behaviour		Vehicle battery capacity and condition are important

In the future, a possible ideal charging infrastructure mix could be made up by only slow and ultrafast charging, by all three, or without ultrafast charging at all. The results of this study will provide some first guidance on expected future charging behaviour based on user preferences for slow, fast and ultrafast charging.

2.2. Charging infrastructure in the Netherlands

The charging infrastructure in the Netherlands is said to be the densest charging system in the world (InsideEVs, 2019). According to recent data of the Dutch government, as of October 2018 there are 134,062 electric passenger cars and 36,987 public and semi-public charging points (of which 19,812 public, the rest is semi-public). This means that there are on average 6.8 electric passenger cars per public charging point, and only 3.6 electric passenger cars per public or semi-public charging point, assuming interoperability. Note that these calculations include both BEV and PHEV. Only looking at the number of BEV (35,965 in October 2018) the ratio is almost 1 (0.97) BEV per public or semi-public charging point. The number of BEV has doubled during 2018, while the number of PHEV decreased by 3% and this trend will likely continue (CBS, 2019). In addition, there are 967 public and semi-public fast charging points registered; however, these are divided among just 206 geographical locations, meaning that the distribution is not too extended. Furthermore, it is estimated that there are about 93,000 private charging points in the Netherlands (RVO, 2018). In Figure 1, the growth and distribution of (semi)public charging points in the Netherlands is shown.

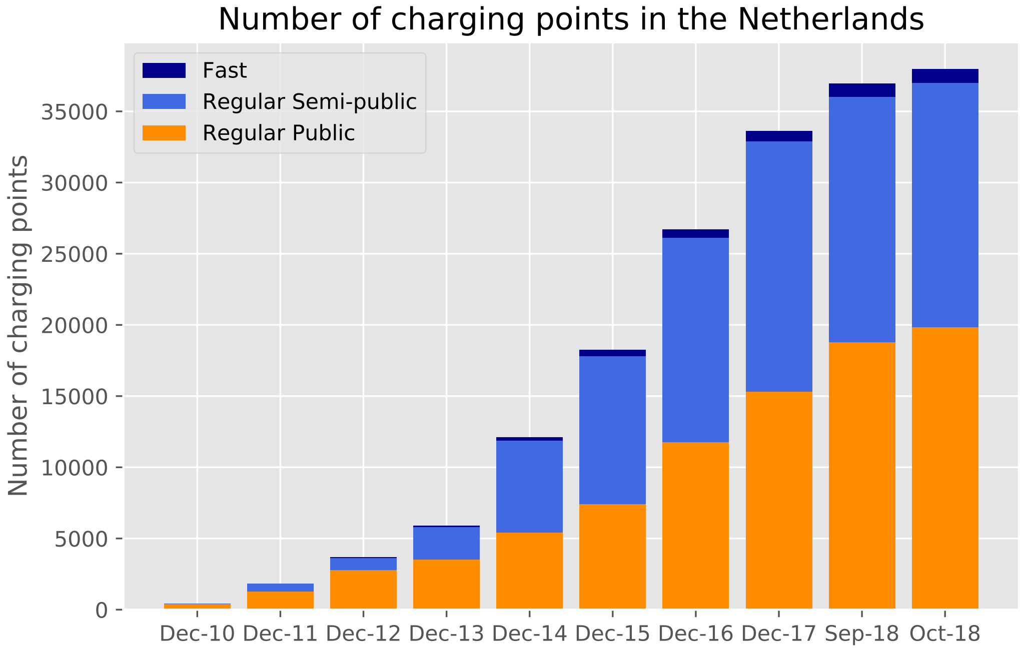


Figure 1: Development in the number of charging points in the Netherlands (RVO, 2018).

The distinction between public, semi-public and private charging points is often made. Figure 1 is based on data by ElaadNL, Nuon, EVBox, The New Motion and Essent and information provided by Eco-movement and oplaadpalen.nl (RVO, 2018). Semi-public charging points are interoperable and have been reported as accessible by their owners. These charging points can for example be found in shopping areas, office buildings, parking garages and at private property of persons who have made their charging point accessible to others (RVO, 2018). Private charging points are also referred to as home chargers, meaning they are privately owned, usually on someones private driveway or parking spot, and not accessible by others than the (land) owner.

2.2.1. Searching for an optimal charging infrastructure

Several studies have been conducted to determine the optimal density of charging infrastructure. The ratio of one fast charging point of approximately 150 kW per 1,000 vehicles is repeatedly mentioned (Funke and Plotz, 2017; Gnann et al., 2018), however uncertainties about battery development and vehicle ranges dominate these conclusions. Interesting to note is that this ratio is close to the current ratio of conventional refuelling stations (which is about 0.3 stations per 1,000 vehicles for Germany and 1.8 for Sweden (Gnann et al., 2018)). Previous studies assume that a fast charging network could be a good complement to slower (home) charging points (Gnann et al., 2018; Morrisey et al., 2016). The influence of private charging points to this fast charging network was not part of any of this research.

Hardman et al. (2018) note that wide conclusions on the number of required charging stations cannot be drawn from the above-mentioned studies alone, as more research is needed about different countries and with a larger number of electric vehicles. This implies that the number of required charging locations is currently unknown (Hardman et al., 2018).

2.2.2. Costs

Costs are an important aspect of EV charging, for governments and private parties as well as for the user. Usually the user either pays a start tariff per session or service costs in the form of a membership. An indication of the costs that the user pays per kWh for public charging in the Netherlands is provided in the table below. For reference, the average price per kWh at a homecharger is 0.23 euro per kWh excluding other costs like installation investments.

Table 2: Costs per kWh that user currently pays for public charging points in the Netherlands (Flowcharging, 2019)

	Destination charging	**Fast charging**	**Ultrafast charging**
Price in euro/kWh (incl VAT)	0.22-0.35	approx. 0.59	> 0.69

The installation (one-time costs) and exploitation (periodical costs) of a charging point are crucial for EV infrastructure but are not cheap. These costs, generally borne by (local) governments and private companies, add up to a price of approximately 3,000 euro per charging point installation plus 600 euro periodical costs per year and additional costs dependent on the number of kWh sold (taxes and energy prices) (NKL, 2018). For ultrafast charging the costs are higher, especially due to a more expensive grid connection and extra requirements for e.g. liquid cooling cables.

2.3. Charging behaviour

Several studies on charging behaviour have been conducted recently. It is repeatedly found that the majority of EV charging takes place at home chargers (Franke and Krems, 2013; Funke and Plotz, 2017; Hardman et al., 2018), but it is argued that, despite this current trend, away-from-home charging is needed to grow BEV markets (Caperello et al., 2015; Neaimeh et al., 2017). Such public infrastructure may include fast chargers (50 kW) or in the near future, ultrafast chargers ($>$ 350 kW).

Neaimeh et al. (2017) explored the impact of fast chargers (50 kW) on driving behaviour in the US and UK, in order to demonstrate the importance of fast chargers. They found that both fast charging and slow charging have a statistically significant and positive effect on daily distance, where the impact of fast charging is more influential than slow (Neaimeh et al., 2017). Since better coverage of charging infrastructure increases the possibility to drive longer distances (and recharge halfway), it is said that increased coverage of a fast charging network will increase EV adoption (Axsen and Kurani, 2013), which is favourable for national and international policy goals. Vice versa, creating uncertainty about the availability of charging stations reduces the purchase intention for full EVs (Wolbertus et al., 2018c).

Hoekstra and Refa (2017) surveyed Dutch EV drivers to find out about their characteristics. Their conclusions include that Dutch EV drivers are found to be middle aged males, highly educated, with high incomes, who purchased the car because tax incentives made it cost effective and because they like to try new technology. This latter characteristic hints at the idea that the current EV drivers are still early adopters in the technology diffusion model as proposed by Rogers (1983). In addition, the EV drivers surveyed by Hoekstra and Refa find themselves environmentally friendly. Lastly, they are generally unsatisfied about their vehicles range, however, instead of a very large vehicle range, they would rather like good fast charging infrastructure. All respondents strongly disagree with the idea that fast chargers can replace standard chargers (Hoekstra and Refa, 2017). Note that this study considered fast chargers of 50 kW, and that ultrafast charging ($>$ 350 kW) was not considered. It is possible that users would regard ultrafast charging as a plausible alternative. Robinson et al. (2013) emphasize the potential of public charging infrastructure, as different user types appear to have different charging patterns. This would ensure optimal usage of public charging infrastructure (Robinson et al., 2013). This finding stresses the importance of considering user type factors in research on different charging types.

In his research, Spoelstra (2014) found that as the average charging frequency increases, the average energy transfer decreases, implying that frequent users commonly charge with a less depleted battery (Franke and Krems, 2013). In addition, it was found that if the power supply of a charging point increases (up to 50 kW only), the amount of energy transfer per transaction increases only marginally. This implies that the battery level and/or battery capacity might not have an effect on the EV drivers' choice for a certain charging point type. This is surprising because the required charging duration may increase drastically when charging a large capacity vehicle with a low power output charging point (Spoelstra, 2014). When the differences between power supply increase (current difference is between 11 and 50 kW, while ultrafast power of $>$ 350 kW will become a reality), it is expected that this will affect the user's choice.

Future scenarios for EV have been developed by research institutes Ecofys and CE Delft in 2016 and 2017 respectively. Ecofys emphasizes the need for a covering fast charging network to gain the EV drivers' trust in the possibility of driving long distances with electric cars. In addition, only about 25% of Dutch households has access to a private parking space (Hoekstra and Refa, 2017), stressing the importance of public charging infrastructure. It is suggested that fast chargers might change roles with slow (destination) chargers (Ecofys, 2016). CEDelft (2017) concludes that access to private parking, the number of EV, trip distance and charging speed all influence individual choices for a certain type of charging point.

2.4. Research gap and contributions

This research is initiated due to the lack of knowledge on user behaviour considering the potential of ultrafast charging. In 3-5 years, ultrafast charging will most likely be technically possible for cars, however in current climate policies this ultrafast charging is not considered as a possibly dominant EV-charging option (Klimaatakkoord, 2018). Ultrafast charging could solve the parking and charging issues that are steadily developing due to waiting times for charging points, increasing number of EV, attractive pricing policies for parking at charging spots and more (Wolbertus et al., 2018b,c). To the best of the researcher's knowledge, the potential of ultrafast charging from a consumer perspective has not yet been studied. It has been suggested in recent literature to pursue this line of research, in order to possibly influence charging infrastructure decisions in a way that less charging points can meet growing demands and therefore put less pressure on the availability of public space (Wolbertus et al., 2018b). Therefore, it is valuable to look into the factors that influence EV charging behaviour with a focus on ultrafast charging. Recent literature also suggested to explore potential effects of e.g. one's residential situation (rural versus urban) and charging possibilities at work and at home to get a more complete picture of user needs and desires for (fast) charging (Philipsen et al., 2016). This research will make it possible to subsequently analyse what the findings might mean for the decision making on future infrastructure. Consequently, this ensures both the scientific and societal relevance of this line of research.

This study attempts to fill the research gap that exists on factors that possibly influence the consumers choice between standard charging (up to 22 kW), fast charging (around 50 kW) and ultrafast charging ($>$ 350 kW). In this pursuit, a stated choice experiment is performed to explore such influential factors. In addition, elasticity calculations as well as stakeholder interviews help to place the findings in perspective. This research contributes to understanding how ultrafast infrastructure would and could be used by consumers in the near future (approximately in the year 2025). Estimation results from both MNL and ML models point out factors that are important to EV drivers' choices for slow, fast and ultrafast charging points.

3. Data collection, preparation and description

In this section, first the data collection and preparation will be described, followed by some descriptive statistics of the sample.

3.1. Data collection

A stated choice experiment was distributed as part of a survey among EV drivers in the Netherlands. Such stated preference methods, in which the respondent is asked for a discrete choice, offer the possibility of examining user choices for future options that not yet exist - so cannot be measured by revealed preference methods. The focus of the survey was on regular EV passenger cars, excluding taxi transport and public transport. EV users themselves are found most capable of comparing different charging type alternatives and picking their best one, since they know what charging an EV is like. For research purposes, it is assumed that current EV mobility patterns (like trip purpose and regular trip length) are similar to future EV patterns. An attempt is made to include as many different EV users as possible, including lease drivers, EV owners and users of shared EVs. This research looks at the Netherlands and Dutch EV users only.

The survey starts with a screening question ('How often do you drive an EV?') and furthermore consists of the following parts: (A) questions on current mobility pattern, charging behaviour and user satisfaction, (B) attitude statements, (C) the discrete choice experiment, and (D) sociodemographic and personal characteristics. In the design of the stated choice experiment, the first step is to specify alternatives (the choice options) and their attributes and levels. The selection of factors to be included is based on literature (e.g. Axsen and Kurani (2013); Björnsson and Karlsson (2015); Dong et al. (2014); Figenbaum (2017); Nicholas and Tal (2014)). After selecting the alternatives, attributes and levels, the choice sets are chosen, creating the experimental design and finally constructing the survey. JMP14 (SAS, 2019) and Excel were used for this purpose. Different designs were compared and an orthogonal design with the highest D-efficiency was chosen. An orthogonal design is desired since it is produced so as to have zero correlations between the attributes in the experiment, making it excellent for estimating linear models (Ortúzar and Willumsen, 2011). The D-efficiency measures the goodness of a design relative to hypothetical orthogonal designs. When the D-efficiency is 0, one or more parameters cannot be estimated. When it is 100, the design is perfectly balanced and orthogonal. Values in between mean that all of the parameters can be estimated, but with less than optimal precision (Kuhfeld, 2010). The D-efficiency of the design used in this research is 99.6. This design has 16 choice sets with four alternatives each. Pilot testing in small groups of 8 and 10 respondents improved earlier versions of the questionnaire. The main changes that were incorporated after the pilots include a reduction of the amount of choice sets per survey and improvements in the formulation of the attitude statements. An example of a choice set used in the survey is shown in Figure 2. Using a blocking variable, four blocks of four choice sets were generated. Each respondent randomly received one of the four blocks. The entire choice experiment design can be found in the appendix.

Choice (1/4)

You are driving in your electric car and you are going to charge your car. Take the following into account:

- You will charge […] kilometres of range.
- You pay for all costs yourself.

The duration and location of the charging session are fixed. The other variables vary per choice.

	Ultrafast charging	**Fast charging**	**Destination charging**
Duration of charging session	3 min for 100 km	20 min for 100 km	4 hours for 100 km
Location of charging session	Along the route	Along the route	Close to your destination
Price	€5.00 for 100 km	€15.25 for 100 km	€8.49 for 100 km
Certainty of availability	Uncertain (waiting time unknown)	Uncertain (waiting time unknown)	Certain (<5 min waiting time)
Having to make a detour (5 min extra walk/drive)	Yes	Yes	No
Facilities nearby	Covered waiting room	Small shop/café	None

Which type of charging do you choose?

	Ultrafast charging	**Fast charging**	**Destination charging**	No preference
I prefer to choose…	O	O	O	O

Figure 2: Example of a choice set as used in the stated choice experiment. The input for 'You will charge [...] kilometres of range' is taken from the previous question on the respondent's most recent charging session.

The survey is web-based and was distributed digitally, using the university's Qualtrics environment. The survey was drawn up in Dutch to accommodate Dutch respondents who are the target group. Several organisations and car sharing initiatives were asked to help spread the survey. Social media platforms have also been used. A flyer has been designed and distributed at several fast charging locations in the west of the Netherlands. This flyer has also been emailed to several lease companies in the Netherlands that lease out electric cars. Since the survey was distributed using a so-called anonymous link, it cannot be said which of those distribution methods have been the most effective. The survey was open for responses from the 1st to 28th of April 2019. The original version and an English translation of the survey can be found in the appendix.

3.2. Data preparation

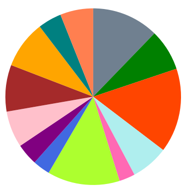
The total number of respondents that participated in the survey is 311. From this, 265 indicated to drive a BEV, the rest drives in a plug-in hybrid vehicle and were excluded from the sample for this reason. 37 BEV drivers were excluded because they had not completed the choice questions. A further 57 respondents were excluded because they opted for the same choice in all four scenarios, which indicates that the choice context was not properly defined for these respondents. This leaves 171 respondents to be analysed. Since each respondent received four choices, a total of 684 observations can be regarded in the choice modelling procedure. Four respondents only made one out of four choices, which means 12 observations were excluded as these did not include a choice (3 open choices*4 respondents=12 observations). A final number of 672 observations is used in the remainder of this paper for analysis.

All binary and categorical variables were dummy-coded for usage with Biogeme software (Bierlaire, 2003). Concerning the attitude statements, the 'don't know' option was only picked by one user per statement, so it is decided to add these to the 'neutral' category.

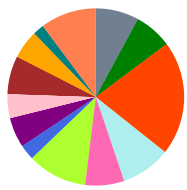
3.3. Descriptive statistics

After data collection and preparation, a descriptive analysis of the sample was carried out. The distribution of vehicle types within the sample was compared to publicly available data on all electric vehicles in the Netherlands (RDW, 2019). This indicates a rather good fit of the sample with respect to the vehicle types, as can be seen in Figures 3a and 3b.

Figure 3: Distribution of vehicle types in the sample (l) and in the Netherlands (r).

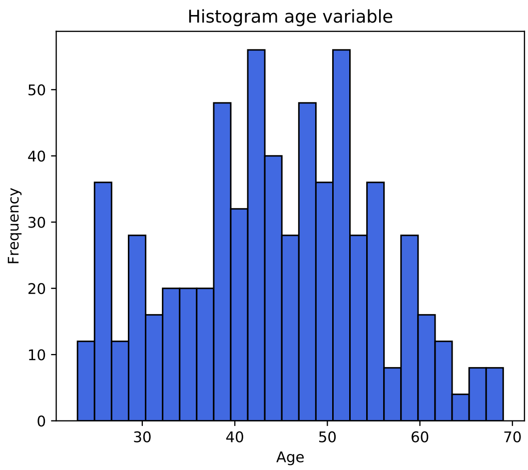


(a) Distribution of BEV types in the sample used in this research

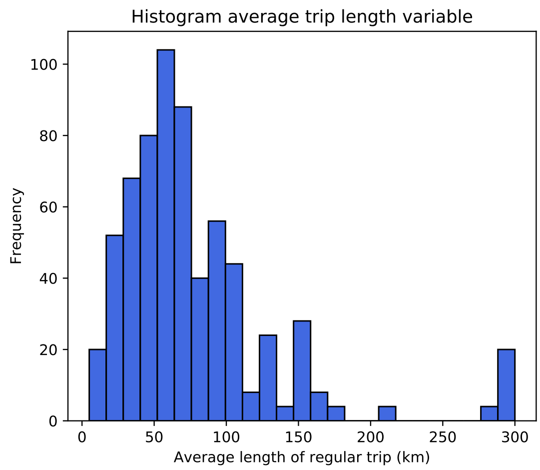


(b) Distribution of BEV types in the Netherlands (RDW, 2019)

A comparison is made with available data of a large group of Dutch drivers who are interested in driving EV (n=694) (ANWB, 2019). This has been one of the few studies on the characteristics of (future) Dutch EV drivers. The sample of 171 respondents in this research includes considerably more highly educated people (80% compared to 38% in the Netherlands), males (90% compared to 60%), and people who live in strongly or extremely urbanised areas (43% compared to 25%) than the sampled population by ANWB (2019). 43% of the sample is younger than 45, while 64% of Dutch EV-enthusiasts is this age. This should be taken into account when analysing the results of this study. This *age* variable is rather well distributed, with 19% aged between 25-35, 30% aged between 35-45, 31% aged between 45-55, and 15% aged 55-65. This distribution as well as the frequencies of *average length of regular trip in km* are shown in Figure 4. It can be seen that most of the EV users have regular trip lengths between 5 and 100 kilometres, with some outliers in the direction of 300 kilometres.



(a) Age in years



(b) Average length of regular trip (km)

Figure 4: Histograms for age and average trip length in km. The youngest respondent is 23 years old, the oldest is 69. The average trip length in km ranges from 0 to 300 km; the last category captures respondents who answered 300 km or more.

The current sample has also been compared to a similar research that was conducted two years ago by Hoekstra and Refa (2017). Some frequencies of specific characteristics of the sample are shown in Table 3. It can be seen that the majority of the sample (84.5%) drives an EV four or more days a week, indicating a substantial charging need. The majority, 90.5%, of the respondents were male (compared to 92% in Hoekstra and Refa's research), whereas only 9.5% were female EV drivers. The variables income and education also have a very unequal distribution: many respondents have a high income (40% income of 77,500 euros or more) and are well-educated (42% WO Bachelor and 34% WO Master). In Hoekstra and Refa (2017), 68% of the respondents earns more than 50,000 on a yearly basis, and 73.7% has followed high education, which is very similar to the sample in this study. It is decided not to use weights in this research due to the lack of data about the total population of Dutch EV drivers. Note that therefore, all results are specific to the studied sample.

Table 3: Frequencies of EV driving, type of EV driver and gender of the sample (n=171)

Frequency of EV driving (%)		**Type of EV driver (%)**		**Gender (%)**	
<1 day per year	0.6	Ownership	33.8	Male	90.5
1-5 days per year	0.6	Private lease	0.6	Female	9.5
6-11 days per year	0.6	Business lease	54.3		
1-3 days per month	3.0	Private car sharing	0.6		
1-3 days per week	10.7	Business car sharing	6.5		
4 or more days per week	84.5	Other	6.7		

The first research question about what is the current charging behaviour of Dutch EV users, can be answered on the basis of descriptive analysis. In Figure 5, one can see what percentage of respondents chooses to use a certain type of charging how often. It can be seen that destination charging at work, on-street slow charging, and fast charging are used more than once a week by 25-55% of the respondents. In contrast, charging at sportsclubs is the least popular, as about 75% of the respondents indicates to use this type of charging less than one day per year. Interesting is that almost 40% of the respondents uses fast charging 11 days or less per year, which means that a very large part of the EV drivers is not a regular fast charger. To the question why people do not make use of fast charging at all (if they indicated they do not, n = 10), answers include that fast charging is not necessary (n = 3), it is too expensive (n = 1) and that one's car does not have the technology to fast charge (n = 6).

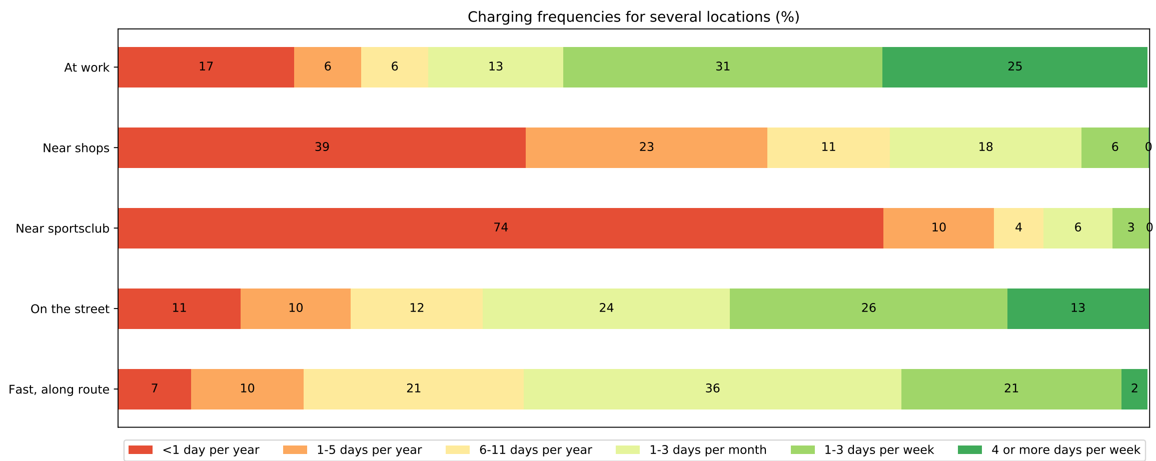


Figure 5: Charging frequencies for several locations (%).

Without executing any model analysis yet, the respondents' choices show that there is a slight preference for ultrafast charging (34%) compared to slow (31%) and fast (32%) charging. The no preference alternative was chosen in 3% of the choice scenarios. In Table 4, different sample segments are presented along with their choices. These variables are significantly related to *choice* as can be seen in the most right column of the table. Also *importance of travel costs* is significantly related. However, since another cost variable (*price*) is explored in the choice models later, this is left out. Insignificant variables are not shown.

The Cramer's V test is executed for the categorical variables, checking whether there is a relationship between the selected variables. When the Cramer's V statistic is significant, this means that the null hypothesis stating that there is no relationship, can be rejected, implying that there is a relationship. For the continuous variables, the ANOVA test procedure is used, using the F statistic in the same way as Cramer's V, testing the independence between a continuous variable and a categorical variable (in this case *choice*) (IBM, 2019). Note that this analysis of correlations is purely exploratory, meaning that relationships between variables are not taken into account. In statistics, when the null hypothesis cannot be rejected, it does not necessarily mean that there is no relationship. However, no final conclusion can be derived about the relationship between these variables.

It can be seen that the largest age group (41-50 years old) together with the youngest age group (23-30 years old) are the only groups of which the largest share opted for ultrafast charging. An interesting finding is that the respondents who value driving comfort the most ('very important'), choose for ultrafast charging in the most scenarios. The degree of urban density does not seem to encourage the choice for ultrafast charging. On the contrary, the 'extremely urbanised' group favours slow charging most of the time, while the 'not urbanised' group has a preference for ultrafast charging. These findings could be used to guide the model estimation process in a later stage.

Table 4: Choices made per sample segments by age, importance of driving comfort and degree of urban density. These variables are significantly related to the *choice* variable.

Variable	**Segment**	Sample composition **Freq (%)**	Choice **Slow**	**Fast**	**Ultra**	**No**	p-value for variable
Age	23-30 years	13.1	39.8	15.9	40.9	3.4	0.001 (F=5.215; df=3)
	31-40 years	19.0	37.5	28.1	32.8	1.6	
	41-50 years	35.1	27.5	33.9	34.3	4.2	
	51-60 years	23.8	25.0	37.5	35.0	2.5	
	61-70 years	6.5	29.5	40.9	25.0	4.5	
	Unknown	2.4	31.3	31.3	31.3	6.3	
Importance of driving comfort	Neutral	6.0	37.5	40.0	12.5	10.0	0.014 (Cramer's V=0.109)
	Important	44.5	29.4	33.1	33.8	3.7	
	Very important	49.6	30.9	29.4	37.5	2.1	
Degree of urban density	Extremely urbanised	16.7	43.8	23.2	30.4	2.7	0.002 (Cramer's V=0.133)
	Strongly urbanised	26.8	26.1	42.2	30.6	1.1	
	Moderately urbanised	14.9	26.0	27.0	44.0	3.0	
	Hardly urbanised	20.8	34.3	24.3	35.7	5.7	
	Not urbanised	14.9	22.0	36.0	38.0	4.0	
	Unknown	6.0	35.0	35.0	25.0	5.0	

4. Methodology

In this section, the theoretical conceptual framework and the technical analytical framework are explained.

4.1. Conceptual framework

A conceptual framework was set up to show the expected relationships of the variables that, after careful selection on the basis of literature, were included in the survey. The Technology Acceptance Model (TAM), originally developed by Davis in 1986 to forecast the use of information systems (Davis, 1989), serves as the basis for the conceptual framework of this research. The model depicts how external factors influence core factors *perceived usefulness* and *perceived ease of use* directly. It shows the relationship of these factors to attitude towards using a new technology and behavioural intention. Extending this model, by adding the factors *social influence*, *facilitating conditions*, *performance expectancy* and *effort expectancy*, the model is said to explain the usage of new technology (Samaradiwakara and Gunawardena, 2014). The resulting model is called the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT is most suitable to serve as theoretical framework because it deals with the impact of a concrete technological development. The factors that are expected to influence the behavioural intention of the respondents (the choice in the choice experiment), are shown in Figure 6. A list of all variables that are examined can be found in the appendix.

Several hypotheses were drawn up, amongst which are the following. More hypotheses can be found in the appendix.

- Price is expected to have the largest influence (negative relationship, the higher the price, the less it is chosen).
- Ultrafast charging is generally favoured over slower charging types.
- A high valuation of travel time makes that people prefer ultrafast charging over other alternatives.
- Drivers that make longer trips prefer faster charging.
- Drivers with access to a homecharger prefer slow charging in the choice scenarios.

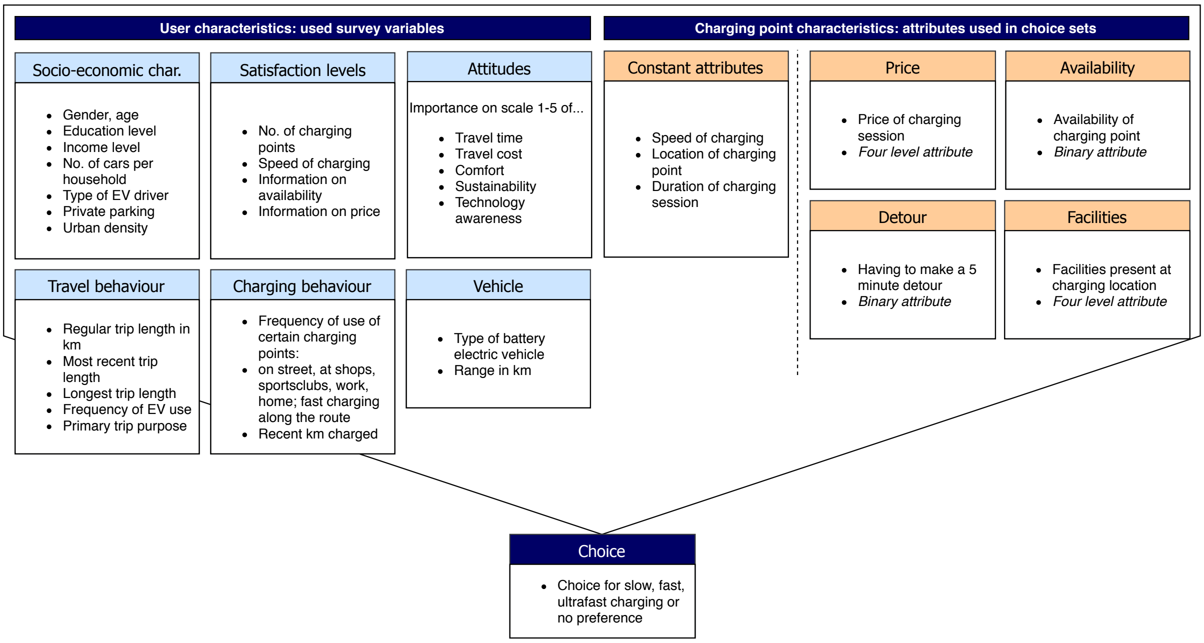


Figure 6: Conceptual framework based on the UTAUT model to derive the quantitative influence of user and product characteristics on the choice for slow, fast or ultrafast charging. Each box contains variables that may or may not influence the final choice (bottom box). The light blue headings indicate that these variables are related to the user, while the orange headings indicate a relation with the product (the charging point). Both user and product characteristics influence the final (utility of each) choice.

4.2. Analytical framework

To investigate the influence that the variables mentioned in Figure 6 have on the preferences of EV users and their use of different charging types, discrete choice modelling is used. Such modelling procedures are widely used in transport behaviour studies to model the decision makers choice between alternative services, often transport modes. Since the goal of this research is to explore which factors influence a users choice for certain charging types – which are alternative services – discrete choice modelling is found applicable. The estimated models can determine which variables are most important in influencing the user's choice, on the basis of many different observations. This approach is based on the idea that every individual subject to a choice, chooses the option (called *alternative*) that maximises their net personal utility. The utility of an alternative is derived from its characteristics and the individual. The vast majority of travel demand models are based on this concept of utility maximisation (Ortúzar and Willumsen, 2011; Louviere et al., 2000). This rational way of choosing the option with the highest utility matches with the UTAUT model, of which the basic assumption is that the decision maker is rational (Yoo et al., 2017). The UTAUT model indicates that a relationship exists between the perceived utility and the decision makers intention to use a new technology. Utility maximisation theory follows this idea and theorises that the higher the utility, the higher the adoption or use rates. Both theories are central to this research.

For each alternative, the utility can be expressed as a function of the weighted sum of attributes of the alternative. The utility of selecting a certain charging type by individual q is function $U_q(a_1, a_2, ..., a_{|A|})$ where $j \in \{a_1, a_2, ..., a_{|A|}\}$ is a possibly chosen alternative and $A = \{a_1, a_2, ..., a_{|A|}\}$ the set of all possible alternatives. Note that the decision maker q can only choose one alternative. That is, if $j = 1$, then $j' = 0, \forall j' \in \{A\} \setminus \{j\}$, and j will be chosen if its utility is higher than the utility of selecting any other alternative.

Lancaster (1966) defined the utility function of selecting an alternative $j \in A$ by individual q as $U_{jq} = U(x_{jq})$ where $x_{jq} = x_{jq1}, ..., x_{jqn}, ..., x_{jqk}$ is the vector of the attribute values for every alternative j by a decision maker q. The utility U_{jq} has two components. The first is a measurable, systematic or representative part V_{jq} which is a function of the measured attributes x (expressed as $V_{jq} = \sum_{n=1}^{k}(\beta_{jn}x_{jqn})$ where $n \in \{1, 2, \ldots, k\}$ and with β constant for all individuals but possibly varying across alternatives). The second is a random part ε_{jq} which reflects particular preferences of each individual, together with any measurement or observational errors made by the modeller. That is to say, this component includes the importance of factors that are not included in V_{jq} because they are not known to the researcher or cannot be observed (Louviere et al., 2000; Ortúzar and Willumsen, 2011; Train, 2002). This is expressed by the following equation.

$$U_{jq} = V_{jq} + \varepsilon_{jq} \tag{1}$$

By including the random component, two situations can be explained. The first is that two individuals with the same characteristics and facing the same choice set might choose differently. The second is that some individuals may not always select what appear to be the best alternative (considered by the researchers) (Ortúzar and Willumsen, 2011). That is, alternative $j \in A$ might be selected by individual q even if $\exists j' \in A$ such that $V_{j'q} > V_{jq}$. The random component ensures that these situations can be explained by the utility maximisation model. Per alternative j, the utility function can be expressed as:

$$U_{jq} = \beta_{j1}x_{jq1} + \beta_{j2}x_{jq2} + \ldots + \beta_{jk}x_{jqk} + \varepsilon_{jq} \tag{2}$$

where U_{jq} is the net utility function for charging type j of individual q. $\beta_{j1}, \beta_{j2}, \ldots, \beta_{jk}$ are k numbers of coefficients (that indicate the relative importance of the attribute). The sign of the βs in the model estimation results shows whether the attribute contributes positively or negatively to the utility of the alternative. $x_{jq1}, x_{jq2}, \ldots, x_{jqk}$ are the attributes for charging type j of individual q. Attributes used in this study include price, whether a detour has to be made, certainty of availability and the presence of facilities. ε_{jq} is the random component. Based on the maximising-utility-reasoning, the individual q selects the alternative j if and only if:

$$U_{jq} \geq \max_{i \in A} U_{iq} \tag{3}$$

where j is the chosen alternative from the set of alternatives A.

The probability of choosing alternative j is given by:

$$P_{jq} = \Pr(V_{jq} + \varepsilon_{jq} \geq \max_{i \in A}(V_{iq} + \varepsilon_{iq})) \tag{4}$$

As ε_{iq} is a random variable, $\max_{i \in A}(V_{iq} + \varepsilon_{iq})$ will be also a random variable. The same holds true for $V_{jq} + \varepsilon_{jq}$. The distribution of the above terms is derived from the underlying distribution of the disturbances (errors).

This study focuses on the systematic component, since the random component of the utility function cannot be observed. This systematic component can be determined on the basis of the outcomes of the choice experiment that has been executed. Both multinomial logit and mixed logit models will be used to estimate the unknown values of this component, or in other words: the betas of the factors that are chosen to be incorporated in the choice experiment will be estimated. Maximum likelihood estimators (MLE) are used to estimate the parameters $\beta_{j1}, \beta_{j2}, ..., \beta_{jk}$ from a (random) sample of observations. This way, the level of influence of these factors on the utility of certain charging types can be determined. The beta values indicate the size and sign of possible relationships. This will be further elaborated in the next sections.

4.3. Multinomial logit

If the disturbances follow a Gumbel distribution and are independent and identically distributed (IID assumption) (Gkiotsalitis and Stathopoulos, 2015; Louviere et al., 2000), then the probability of selecting alternative j is given by the multinomial logit (MNL) model:

$$P_{jq} = \frac{e^{V_{jq}}}{\sum_{i \in A} e^{V_{iq}}} \tag{5}$$

In Eq.5 the utility of alternative $j, (U_{jq})$, is compared with the total utility of all available alternatives ($\sum_{i \in A} U_{iq}$). The assumption that errors follow a Gumbel distribution and they are independent and identically distributed is used since only rankings of alternatives are observed, and not actual utilities, and thus the scale of the utility function has to be normalised. This is done by normalising the variance of the unobserved effects (ε), which for logit models, is assumed to be the same for all alternatives. That the errors are "independent" implies that there are zero covariances or correlations between these unobserved effects (ε), while "identical" implies that the distributions of the unobserved effects are all the same (Hensher et al., 2015).

4.4. Mixed logit

Mixed logit (ML) is highly flexible and can approximate any random utility model (McFadden and Train, 2000). In contrast to the MNL model that has several limitations due to its various assumptions, ML allows for random taste variation, unrestricted patterns and correlation in unobserved factors over time. For instance, ML takes into account unobserved factors that persist over time for a given decision maker.

In ML, β_j is not the same across all decision makers, but is treated as a random variable β_{jq} that follows a probability distribution $f(\beta|\theta)$ where θ are the parameters of the distribution of β_{jq} over the population (i.e., mean and variance).

Using mixed logit, the unconditional probability of decision maker q choosing alternative $i \in A$ is the integral of the logit formula over the density of β_{jq}:

$$P_{iq} = \int L_{iq}(\beta) f(\beta|\theta) d\beta \tag{6}$$

where $L_{iq}(\beta)$ is the logit probability evaluated at parameters β_{jq}, and $f(\beta|\theta)$ is a density function. When utility is linear with β, the portion of the utility that depends on parameter β_{jq}, $V_{iq}(\beta_{iq}) = \beta'_{iq} x_{iq}$. In this case, the mixed logit probability becomes:

$$P_{iq} = \int \frac{e^{\beta' x_{iq}}}{\sum_{j \in A} e^{\beta' x_{jq}}} f(\beta|\theta) d\beta \tag{7}$$

To account for panel effects, error components can be added to the utility functions. These components vary between respondents, but not between observations for the same respondent. They indicate the loyalty of a respondent to a specific alternative. A positive value for this error component indicated that respondents opted for the same alternative in different situations; a negative value means the opposite. Simulation is required to estimate the parameters for the ML model, as there is no closed form function for the integral in Eq. 6. How this simulation works is illustrated in Algorithm 1. 250 draws are used to estimate the model in this study. Up to 1000 draws were tested, but this made no substantial difference with respect to the results.

Step 1: Take a draw from probability density function $f(\beta|\theta)$. Label the draw β^r for $r = 1$ representing the first draw;

Step 2: Calculate conditional probability $L_q(\beta^r)$;

Step 3: Repeat at least 250 times, for $r = 2, ..., R$. R is the total number of draws taken from the distribution, r is one draw;

Step 4: Average the results. Calculate a value for the probability of alternative j for individual q using:

$$\tilde{P}_{jq} = \frac{\sum_r L_{jq}(\beta^r)}{R} \tag{8}$$

Algorithm 1: Simulation of the choice probability value used in ML.

4.5. Model specification

The goal of estimating choice probabilities is to specify the (linear) utility function per alternative. This is called parameter estimation. It will be done by maximum likelihood estimation using the open source software Biogeme (Bierlaire, 2003). To decide which variables $x_k \in x$ enter the utility function, a search process is executed. Variations are tested at each step to check whether they add explanatory power to the model. If they do, they are kept; if not, they are left out. One of the values of x is defined equal to one, for all individuals that have a given alternative available. This is interpreted as the alternative specific constant (ASC). This ASC is taken as reference (fixing it to 0 without loss of generality) so the remaining $(N - 1)$ values obtained in the estimation process can be interpreted as relative to that of the ASC. In this research, the no-preference-alternative is the reference alternative. Ortúzar and Willumsen (2011) mention that it is not always easy or clear to decide in which alternative utility or utilities the variable should appear, even for a small number of options and attributes. If we lack insight and there are no theoretical grounds for preferring one form over another, the only viable alternative is trial and error. The maximum likelihood estimator is the value of θ that maximises the function of $LL(\theta)$ expressed in Eq. 10.

4.6. Goodness of fit

To evaluate the models' goodness of fit, the likelihood ratio index is used, measuring how the model with the estimated values for the parameters performs compared to the null model (when all betas are equal to zero). This is expressed in Eq. 9. This equation is based on the log-likelihood, shown in Eq. 10.

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{9}$$

where $LL(\beta)$ is the log-likelihood function of the model with estimated values for the parameters (βs), and $LL(0)$ is the log-likelihood function of the model when all betas are equal to zero (null model). This log-likelihood function is expressed in Eq. 10.

$$LL(\theta) = \sum_{q=1}^{Q} \sum_{j=1}^{A} y_{qj} \ln P_{qj}(\beta|\theta) \tag{10}$$

where Q is the number of individuals that choose an alternative j from the set of choice alternatives A. y_{qj} is the observed choice (0 or 1) and P_{qj} is the probability that y_{qj} equals one.

If $\rho^2 = 1$, this indicates a perfect fit. However, Louviere et al. (2000) state that a value of ρ^2 between 0.2 and 0.4 is considered to indicate extremely good model fits (p.54). The likelihood ratio index can be improved by keeping in mind the degrees of freedom (Louviere et al., 2000). When doing this, one calculates this $\tilde{\rho}^2$ as in Eq. 11.

$$\tilde{\rho}^2 = 1 - \frac{LL(\beta) - K}{LL(0)} \tag{11}$$

where K is the number of estimated parameters (indicating the degrees of freedom).

4.7. Model application: scenario analysis

In the last step, model application, we investigate the percentage change in the choice probability of an alternative with respect to a marginal change in the explanatory variable. The size of such changes in probabilities indicate direct elasticities of the model. This is given by the following equation:

$$E_{P_{iq},x_{ikq}} = \beta_{ik} x_{ikq}(1 - P_{iq}) \tag{12}$$

where $E_{P_{iq},x_{ikq}}$ is the direct point elasticity, or the percentage change in the probability of choosing i with respect to a marginal change in a given attribute x_{ikq}.

The cross-point elasticity is given by:

$$E_{P_{iq},x_{jkq}} = -\beta_{jk} x_{jkq} P_{jq} \tag{13}$$

where $E_{P_{i}q,x_{jkq}}$ is the cross-point elasticity, or the percentage change in the probability of choosing i with respect to a marginal change in the value of the kth attribute of alternative j, for individual q.

It is important to note that this cross-point elasticity is independent from alternative i. This means that all cross-elasticities of any option i with respect to attributes x_{jkq} of alternative j are equal (Ortúzar and Willumsen, 2011).

5. Model estimation results

The model estimation results follow in the subsequent sections and are shown in Table 5. The first column of this table refers to the mathematical notation as used in Eq. 2. The columns of Table 5 titled 'Value' contain the estimated parameter values of the variables named on the left. The columns titled 'T-test' contain the value of the T-test, of which a value of $> |1.96|$ indicates a significant contribution to the model (McClave et al., 2011).

Several models were estimated using the attributes included in the choice experiment. Variables were added one by one to the model, per category as outlined in the UTAUT framework in Figure 6. When they are insignificant, they are removed from the model, otherwise they are kept. Three models are reported to show these steps that have been taken in the model estimation process. The MNL model in this research contains 18 significant variables, the reported ML models contain 17 and 18 significant variables respectively, and the final ML model contains 21 significant variables. In total, 57 variables have been tested as both alternative-specific and generic parameters. Using this approach, it can be tested whether the utility of an attribute depends on the alternative. For example, certainty of availability might be valued differently for the ultrafast alternative than for the slow charging alternative. It can be assumed that if an

Table 5: Model estimation results. This table only displays the significant factors, which is why not every attribute is mentioned for slow, fast and ultrafast. A positive variable value can be interpreted as having a positive relationship with the utility of the alternative (Slow, Fast or Ultrafast) mentioned, a negative value indicates a negative relationship.
** Used as reference level; ** Insignificant, but kept in the model*

		Multinomial logit		Mixed logit (1)		Mixed logit (2)		Mixed logit, final model	
	Variable	**Value**	**T-test**	**Value**	**T-test**	**Value**	**T-test**	**Value**	**T-test**
ε_{S1}	ASC (S)	2.43	6.01	3.78	7.43	3.49	6.94	2.19	5.82
ε_{F1}	ASC (F)	1.24	2.63	2.48	8.03	1.33	2.95	1.26	2.65
ε_{U1}	ASC (U)	2.6	3.21	3.6	3.24	1.94	1.33*	1.06	0.91**
ε_{no}	ASC (no preference)	0	Fixed*	0	Fixed*	0	Fixed*	0	Fixed*
β_1	Certainty of charging point availability (S)	0.729	3.59	0.863	4.16	0.878	4.47	0.797	3.86
β_2	Certainty of charging point availability (F)	1.36	6.62	1.05	5.4	1.03	5.25	1.42	6.27
β_3	Certainty of charging point availability (U)	-1.34	-6.73	-1.51	-6.62	-1.58	-6.81	-1.47	-6.43
β_4	Not having to make a detour (U)	-0.988	-5.08	-1.17	-5.65	-1.15	-5.5	-1.14	-5.56
β_5	Price (S, F and U)	-0.0511	-3.41	-0.0676	-4.61	-0.0651	-4.42	-0.0569	-3.83
β_6	Proximity to shopping area (S)	0.979	3.47	0.531	2.07	0.739	2.99	1.03	3.45
β_7	Proximity to small shop/caf (S)	-1.37	-2.76	-1.48	-2.99			-1.45	-2.83
β_8	No facilities nearby (S)	0.961	4.1					0.973	4.69
β_9	No facilities nearby (F)	1.2	4.3					1.27	4.25
β_{10}	No facilities nearby (S, F and U)			0.557	4.65	0.684	6.41		
β_{11}	Current frequency of using fast charging (F)	0.341	4.11			0.299	3.9	0.344	4.41
β_{12}	Income level (S)	-0.00013	-2.5					-0.000135	-2.44
β_{13}	Income level (F)	-0.00014	-2.79					-0.000138	-2.41
β_{14}	Income level (U)	-0.00015	-3.02					-0.000151	-2.48
β_{15}	Access to private parking (S)	-0.392	-2.01						
β_{16}	Importance of comfort (U)	0.458	3.07			0.495	2.61	0.52	2.74
β_{17}	Age (S, F and U)			-0.0359	-3.85				
β_{18}	Age (S)					-0.0351	-3.71		
β_{19}	Age (U)					-0.0252	-2.14		
β_{20}	Education level (U)			0.25	2.39	0.224	2.3	0.236	2.56
β_{21}	Importance of travel time (U)			0.235	2.06				
ε_{S2}	Sigma (S)			0.316	1.13**	-0.271	-0.95**	-0.472	-1.96**
ε_{F2}	Sigma (F)			-0.0869	-0.44**	0.0267	0.86**	0.0409	0.73**
ε_{U2}	Sigma (U)			0.648	4.13	0.559	2.82	0.548	2.74
	Model statistics								
	Null loglikelihood		-909.409		-909.409		-909.409		-909.409
	Final loglikelihood		-692.562		-704.891		-703.762		-689.898
	Rho-squared		0.238		0.225		0.226		0.241

ultrafast charging point is not available at the moment the driver arrives, it will be very soon, while for slow charging this is not the case.

All models are estimated using ASCs (alternative specific constants), attributes of the choice experiment, socio-economic variables and attitude statement variables. Important to note is that the ASCs capture the errors (ε as in Eq. 1) associated with each alternative. The 'no preference' alternative is used as the reference level in all models. For illustrative purposes, Eq. 14 shows the systematic component of the utility function for the slow charging alternative (S) in the estimated MNL model. The variable names used in this equation can be found in Table 5 (*cer* refers to certainty, *shoparea* to shopping area, *smallshop* to small shop or cafe, *nf* to no facilities, *inc* to income, and *park* to private parking).

$$V_S = 2.43 + 0.729x_{cer_S} - 0.0511x_{price} + 0.979x_{shoparea_S} - 1.37x_{smallshop_S} + 0.961x_{nf_S} - 0.00013x_{inc_S} - 0.392x_{park_S} \quad (14)$$

For example, the estimated parameter value of the x_{price} variable is -0.0511, meaning that if prices (of all three options, since this is a generic parameter) increase, the overall utility for the S (slow) alternative decreases, given all other attributes are held the same. When there is a shopping area near the slow charging point, this will increase the utility of the slow charging alternative, since the parameter for this variable is positive (0.979). Again, the interpretation is valid when all other parameters are held constant. All utility functions and their parameters work similarly for each alternative in each model. This way, using the information provided in Table 5, utility functions for all alternatives in all models can be constructed and interpreted. We continue with exploring the found parameter values of the MNL model, followed by the evaluation of the ML models.

5.1. MNL model

For the estimated MNL model, first the significant parameters related to the charging point (the attributes of the choice experiment) are discussed, after which the user- and vehicle-related parameters follow.

The *certainty of availability* parameter has a surprising outcome, since it is found to be negative for the ultrafast alternative, meaning that when one is certain that the ultrafast charging point is available, the less attractive it becomes. This might have to do with the relative value towards the 'no preference' alternative (which is the reference level). This way of thinking implies that being sure of an available charging point is a kind of prerequisite for most EV drivers. Interestingly, in practice, charging availability problems occur repeatedly in the Netherlands (see for example NOS (2018)). For slow and fast charging, the positive values for the certainty variable imply that once one is certain of an available slow or fast charging point, the more attractive that alternative becomes.

Having to make a detour would most likely discourage people from choosing that particular alternative. The fact that this *detour* parameter is insignificant for the slow charging alternative, indicates that people would not mind making a small detour in order to reach a destination charger. This is logical since they will usually leave their car at such a spot for a longer period of time. On the other hand, the *detour* parameter is negative and significant for the ultrafast alternative, indicating that when people have to make a detour, the ultrafast charging alternative becomes more attractive. This is rather unlikely, however it is possible that other unobserved factors or circumstances influence such a notable value. Further research is required to draw conclusions on the effect of having to make a detour for ultrafast charging.

As expected, the variable *price* is a significant factor in influencing the choice for all considered charging types for EV users in the Netherlands. A generic parameter was estimated, which has a negative sign. This implies that the higher the price, the less attractive the alternative becomes, and vice versa. This confirms the price hypothesis mentioned earlier and is in line with logical assumptions, which would usually be to prefer the cheaper option.

For the slow charging alternative, the *proximity to a shopping area* parameter has a positive and significant value. This indicates that the presence of a shopping area at these locations increases people's tendency to opt for this alternative. This matches logical assumptions, since slow charging takes more time than fast and ultrafast charging, so the desire for a shopping area where one can spend time is larger. Interestingly, the opposite is true for the presence of a small shop or cafe, according to the model. This implies that when there is only a small shop or cafe at a slow charging point, it makes the charging point less attractive, all else equal. Another notable finding is the positive parameter for *no facilities* for the slow and fast charging alternatives. This indicates that, given all other variables are held the same, people have higher odds of choosing slow or fast charging when there are no facilities. This could have to do with the idea that people who use slow or fast charging may do this at their final destinations. Currently it is the case that EV users prefer to charge at their destination rather than on their way, especially due to current charging speeds (Hardman et al., 2018; Spoelstra, 2014). These final destinations are most likely not regarded as 'facilities' when asked in this research. It is however not possible to draw conclusions on this with the currently available data of this study, since no question was asked about the respondents' interpretation of destinations and facilities.

The next parameter value in Table 5 implies that a higher *current frequency of fast charging* indicates a higher tendency to opt for fast charging in the choice experiment. A possible explanation might be habitual behaviour that may substantially influence people's choices (Verplanken and Aarts, 1999). In line with this habitual behaviour theory, it was expected that when one has access to a homecharger on their private parking spot, one is more likely to opt for slow charging in the experiment. However, interestingly, the *homecharger* variable that was examined, was not significant. In addition, the variable *access to private parking (S)* is positive and significant, meaning that when one has access to a private parking spot, the utility of slow charging decreases. This is contrary to what was expected in the hypotheses.

The *income* parameters in this MNL model are all found to have a very small negative value, indicating a weak negative relationship between income and the utility that is associated with each charging alternative. There may exist several moderating variables that have not been researched in this study, so follow-up research is advised. The *income* variable has a weak positive correlation with *access to private parking* (Pearson correlation=0.117, p=0.002) and a weak negative one with the variable *regular trip length* (Pearson correlation=-0.168, p=0.000). That people with a higher income more often have access to private parking and drive less kilometres on a regular trip may influence their lower tendency to opt for any of the three public charging alternatives.

In the survey, five attitude statements were included so they could be used to answer the research question on to what extent these user-related factors influence charging behaviour of EV users in the Netherlands. Respondents were asked to report how important they find sustainability, comfort, travel time, travel cost, and being up to date with new technologies on a scale from 1-5. These variables make up the 'Attitudes' box of the UTAUT framework in Figure 6. Of all these variables, only the *importance of comfort (U)* parameter is significant in the MNL model. The more important one finds comfort, the more likely one is to opt for ultrafast charging. This is in line with expectations, as ultrafast charging is possibly the most comfortable option, especially in terms of time, availability and location. That no significant parameter is found for travel time means that no conclusions can be drawn about a relationship between how important one finds travel time and the utilities of the charging alternatives. This hypothesis can therefore not be confirmed.

5.2. ML models (1) and (2)

In retrieving ML model (1) and (2), all parameters were estimated again in the same manner as for the MNL model: adding variables one by one and using their significance as criterion whether the variable is kept in the model. These models (1) and (2) are estimated in the process of arriving at the final model with the best fit, and they are shown to provide insight in this process. Respectively 17 and 18 parameters were significant (at a 90% significant level) for the reported models. Model (2) is retrieved after improving model (1). Several socio-economic variables were significant in ML model (1), including a generic parameter for *age*, *education* for ultrafast charging and the *importance of travel time* for ultrafast charging. In the ML models, error components (the sigmas) are added to be able to estimate possible panel effects. These sigma parameters, together with the ASCs, explain part of the error (ε) in the utility function as mentioned in Eq. 1. This error term ensures that the model is not biased, which is why also insignificant error components are kept in the models. Only the error component for ultrafast charging is significant and positive (ε_{U2}=0.548), indicating the presence of preference heterogeneity in the sampled population for this alternative (Hensher and Greene, 2003). This implies that respondents have a certain 'loyalty' to this alternative. This could be due to the fact that ultrafast charging is not yet possible but that it seems an attractive new technology. Such respondent loyalty is not found for slow and fast charging. The estimated parameters can be seen in Table 5.

In ML model (2), the ASC for the ultrafast alternative is not significant anymore, however it is kept in the model because it is a necessary and important part of the utility function. The values of the ASCs for all alternatives increased in ML model (1) compared to the MNL model, but decreased again in ML model (2). This decrease of ASCs indicates that a larger part of the utility of the alternatives is explained by the variables added to the model, but the opposite is true for ML model (1) as compared to the earlier estimated MNL model.

In both ML model (1) and (2), a generic parameter for *no facilities* was estimated. Its positive value indicates that for all charging types, the likelihood of choosing a certain charging type increases when there are no facilities present. As explained before, for slow and fast charging this could be due to EV drivers' preferences to charge at their final destinations, and for ultrafast charging, no facilities are necessary due to the very short charging sessions. In ML model (1), the *importance of comfort (U)* parameter was not significant, but *importance of travel time (U)* was. However when further developing the model, this was reversed again in ML model (2), resulting in the same interpretation as given for this parameter in the MNL model.

A generic parameter for *age* was significant in ML model (1), indicating that when people are older, they are less likely to opt for any of the three alternatives. Since this is hard to believe, the parameter was split into several alternative-specific parameters for *age* in ML model (2). This resulted in a negative parameter for the slow and ultrafast alternatives. These values imply that the younger people are, the higher their tendency is to choose slow or ultrafast charging types, and the other way around. For fast charging, no conclusions can be drawn anymore, since the parameter was not found to be significant in this model.

Concerning the level of education, a positive parameter value for ultrafast charging indicates that one is more likely to opt for ultrafast charging when one has a higher level of education, and vice versa. Care should be taken when interpreting these results, since the sample in this study has an above average education level (ANWB, 2019).

5.3. Final ML model

The final ML model provides the best fit to the data ($\rho^2 = 0.241$), which is said to be a good model fit (Louviere et al., 2000). In Table 5 it can be seen that in the final model one error component (ε_{U2}) is found to be significant, which means there is preference heterogeneity of respondents towards the ultrafast charging alternative. The positive sigma value for ultrafast charging ($\varepsilon_{U2} = 0.548$) indicates that respondents opted for the same alternative in different situations. It can be concluded that there is a panel effect for the ultrafast alternative, but this is not the case for the slow and fast alternatives. The sigma values for the latter two are insignificant, indicating that it is impossible to draw any conclusions on plausible panel effects.

The significant ASC values for slow and fast charging are lower than in the previous ML models, which means that more explanatory power is captured by the other estimated parameters in the model.

Comparing the final ML model to the earlier models, the *age* parameter is no longer significant, the *income* parameters are included and significant, and the generic parameter for *no facilities* has been replaced by two significant *no facilities* parameters for slow and fast charging, as can be seen in Table 5. Higher income implies a lower tendency to opt for all three alternatives. This possibly indicates that public charging, compared to other (undefined) alternatives, is preferred less by people with a higher income. The final model also shows that both slow and fast charging become more attractive when no facilities are present.

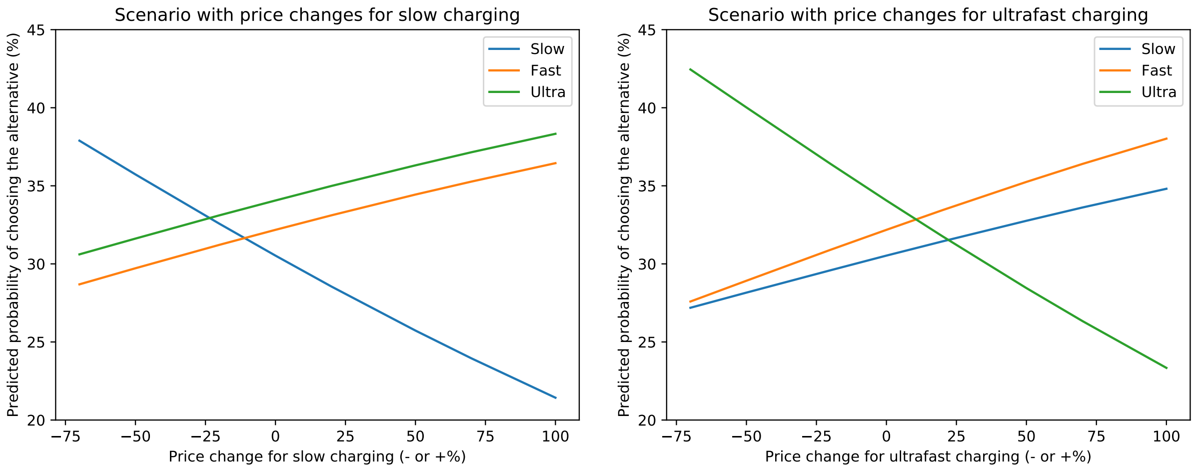
No significant values were found for *gender* and *urban density* in the models, and also *age* is no longer significant in the final ML model. This is encouraging because in policymaking, it avoids the dilemma of which interest to serve when it comes to these aspects. Government and other stakeholders can ensure the installation of charging infrastructure in such a way that

EV drivers consider all charging types as viable alternatives. The found values for income and education do indicate that a difference between income and education groups exist. However, this should be taken with care as the sample includes many high-income and highly-educated individuals.

5.4. Model application

The final mixed logit model was used to evaluate different scenarios with changing levels of the *price* and *detour* attributes. These attributes are chosen since price as well as location are most easily influenced by stakeholders, so they are the most relevant to explore. Firstly, scenarios in which the price for slow charging and the price for ultrafast charging change were explored. Both scenarios are possible future situations in which a price change of either two alternatives pushes EV users into opting for another charging point type. The base scenario includes similar pricing for all three alternatives. Both direct-point and cross-point elasticities are calculated. Direct-point elasticities look at the impact of a change of an attribute of alternative j on the choice probability of the same alternative; cross-point elasticities measure the sensitivity of the model for alternative j with respect to a modification of the attribute of another alternative (Bierlaire, 2017). These predicted probabilities of choice can be seen in Figures 7a and 7b. It can be seen that price has a substantial influence on the predicted probabilities of the sample, keeping all other parameters constant. A price decrease for a certain alternative results in a higher predicted probability for the respective alternative. All else equal, the figures show that it is predicted that people are willing to pay slightly more for ultrafast charging than for slow charging, since the intersection of all alternatives occurs at a price increase of 25% for ultrafast charging and at a price decrease of approximately 25% for slow charging. This price sensitivity should be kept in mind when installing charging stations. When for example high land prices will increase slow charging prices, this will affect the choice probabilities of people opting for that alternative. Price change could be used as steering mechanism by several stakeholders.

Figure 7: Predicted probabilities for scenarios with price changes per alternative.



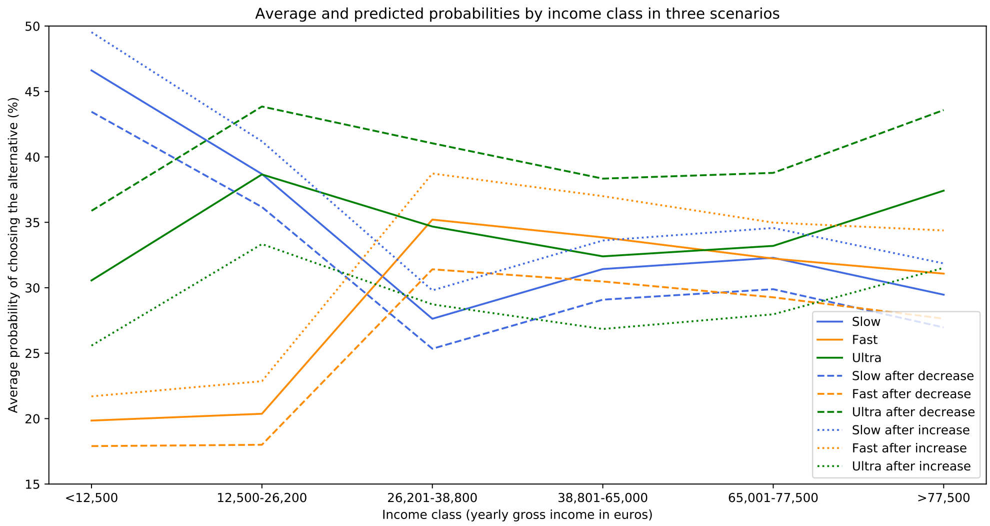
(a) Price changes for slow charging

(b) Price changes for ultrafast charging

After this exploration of the influence of price changes in general, it is also interesting to look at socio-economic characteristics. Since *income* was one of the socio-economic variables found to be significant in the final model, the probability distribution for different alternatives among income classes is examined. This can be seen in Figure 8. The income class ‘unknown’ is not included. The other six defined income classes can be found on the horizontal axis of Figure 8.

The influence of ultrafast price changes per income class can be clearly observed in the figures. All else equal, when ultrafast charging becomes 50% cheaper, it has the highest predicted probability for all income classes except the lowest class. When ultrafast charging becomes 50% more expensive, it is a lot less attractive for the lowest income classes, as is logically expected. For the higher income classes, the predicted choice probabilities in Figure 8 are similar for all three alternatives when ultrafast prices increase. The most important conclusion from this is that possibly quite a large difference exists between different income classes. It is interesting to see that mainly for gross yearly incomes of 26,201-38,000 euros and higher, a different market leading alternative can emerge due to price variations. When the Dutch EV driver population (and the used sample) will be more diverse, this possible difference should be further explored.

Figure 8: Probabilities per income class for scenarios with price changes for ultrafast charging. The scenarios include a 50% price decrease for ultrafast charging, the base scenario and a 50% price increase for ultrafast charging.



Next, detour scenarios are explored. In Figure 9, three scenarios are shown: one in which people do not have to make a detour to get to an ultrafast charging point, the base scenario in which people sometimes have to make a detour, and one in which people always have to make a detour to reach a charging point. The detour has a set length of five minutes in the model. The hypothetical scenario that no one ever has to make a detour for ultrafast charging indicates a future with an immense penetration rate of ultrafast charging points. In this case, the predicted probability that people opt for ultrafast charging along their route, taken all else equal, is 45.5% compared to 34% in the base scenario. Always having to make a detour makes the alternative a lot less attractive, looking at the predicted probability of only 23%. This implies that for the installation of new charging points, it is advised to look at the most used roads and routes to determine optimal locations for charging.

5.5. Stakeholder perspectives

To obtain information about opinions and visions of stakeholders in the field of EV, the researcher has spoken with six Dutch organisations and companies that are currently involved in the EV-sector. Both the user views on charging and whether a feasible scenario for ultrafast charging in the Netherlands exists, were part of the semi-structured interviews. All interviews were held in February 2019 and lasted approximately 30 to 70 minutes per interview.

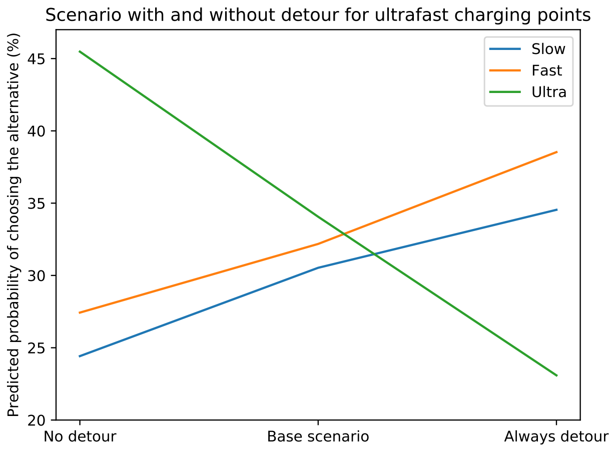


Figure 9: Predicted probabilities for a scenario with and without having to make a 5 minute detour for an ultrafast charging point.

All stakeholders that were spoken to regard the user view as very relevant to take into account. Despite this, the user perspective is not put first in their considerations as this takes a lot of research and it is found difficult to consider different user types equally. For businesses, it is the most interesting to find out what types of charging users prefer, since they can then adjust their business model accordingly. For the government stakeholders, the primary interest is to achieve a covering and fully functioning charging infrastructure, almost independent of which charging types this comprises. Both types of stakeholders share the idea that interpretations of user preferences for charging are important, since the choices of these users will influence their goals and strategies. Several noticeable findings on stakeholder views compared to the user perspective are discussed next.

One important contrast between what users seem to want versus what local government *thinks* users want, concerns the relationship between current behaviour and future choices. For the data-driven strategies on the installation of charging infrastructure, the government relies on the measured occupancy rate as main key performance indicator [Interview sources]. Interestingly, in the models, the only variable regarding current charging behaviour that was significant is *current frequency of using fast charging*. The current frequency of charging at several locations and the current usage of a homecharger (if applicable) were not significant. This means that from this research, there is no evidence that the current charging behaviour reflects future choices of users, implying that more ways or additional indicators should be used to determine the number of to-be-installed charging points.

Secondly, a charging infrastructure exploitation party indicates that they follow their own vision, but that they believe what they do is in the interest of the EV user [Interview sources]. This stakeholder is planning to add small shops to some of the fast charging points they exploit, since they believe this is what the EV user wants. Recent literature shows that when users have to choose from leisure facilities, shopping facilities, motorway service stations, gas stations, workplaces or educational institutes, indeed shopping facilities were found the most important (Philipsen et al., 2016). A no-facilities option was however not included. The model results reported in Section 5 indicate that fast charging stations are found more attractive when there are no facilities present. In contrast to this research, the respondents of the study by Philipsen et al. (2016) also included non-EV users. It cannot be concluded whether this impacts the results substantially. Based on these findings, the advise would be to investigate user needs regarding shops more extensively, since otherwise resources may be spent on something that is not directly desired.

Thirdly, some stakeholders expect that ultrafast charging may be overdimensioned for the average Dutch EV user. They state that such high charging speeds are not necessary for a regular user, but only for example for taxis, with very high mileages, or for high segment cars that can reach top speeds [Interview sources]. From this research, no conclusions can be drawn about taxis since they were not part of the target group. However, vehicle-related variables like *range (km)* were included in the models, but were insignificant. This implies that there is no confirmed relationship between higher range cars and a higher (or lower) tendency to ultrafast charge, or vice versa. Looking at the choices made by the respondents, it can be concluded that in the presented choice scenarios, people regarded ultrafast charging as a viable and realistic alternative, since it was chosen in 34% of the scenarios. This finding does not align with the stakeholders' view on the ultrafast charging developments.

Lastly, several stakeholders acknowledge that it is hard to take into account different user profiles equally. This research shows that the current group of Dutch EV users is rather homogeneous, indicating that the confrontation with different user types may not yet be a very pressing issue. However this will probably change in the near future due to the growing popularity of EV (CEDelft, 2017; Ecofys, 2016). The larger the group of EV users, the more important the stakeholder perceptions of user preferences become. Clear is that both user preferences and stakeholders' perceptions indicate that (low) costs and (suitable) locations (and thus comfort) are prerequisites for well-used charging points [Interview sources].

6. Discussion

The results of this study about whether ultrafast charging can be the future for EV in the Netherlands from a user perspective should be carefully evaluated. It has been shown that price, not having to make a detour, certainty of availability, proximity to shopping facilities or the absence of facilities, income, education and comfort are important for the users' choice for certain charging speed types. Several of these variables are in accordance with a previous study on user criteria for EV fast-charging locations, in which detours and shopping facilities were proven to be very important to users (Philipsen et al., 2016). It should be noted that shopping facilities were chosen from several options where a no-facilities option was not included. In the following sections, the interpretation of results, putting these results in a broader perspective and the limitations of this study are discussed.

6.1. Interpretation of results

Users generally do not show a conclusive clear preference for ultrafast charging (chosen 34.1% of the time), indicating that this is at least not the one and only charging method to implement in the Netherlands. Part of this may be due to the currently well-functioning and covering destination charging infrastructure, shown by the current ratio of only 0.97 BEVs per public or semi-public charging point (RVO, 2018). This may be subject to change when the number of BEVs will continue to increase the coming years (CEDelft, 2017; Ecofys, 2016; Gnann et al., 2018). In this research, it is found that some preference heterogeneity for ultrafast charging (panel effect) plays a role in the users' choice, which is likely to be explained by the influence of habits on decisions as mentioned in the literature (Verplanken and Aarts, 1999). However, even though this might be true, only a significant value was found for the current usage frequency of fast charging influencing the tendency to opt for fast charging. Other variables concerning the current usage frequency of charging points at different locations were not significant.

The estimated parameter values for *certainty of availability* are interesting to look at, since their sign is not similar across alternatives. The reasons for this cannot be explained just by looking at the model results. The response of people about this parameter might be due to their current main reason to use fast charging, as investigated by Wolbertus et al. (2018a). This reason is 'Time left and possibility to charge', indicating that people use faster charging only when it is available. This may distort the results of the choice model as people might take availability as a prerequisite and only look at other parameters when making their choice. This is a noticeable result, as charging availability issues occur repeatedly in the Netherlands (e.g. NOS (2018)). Such issues are assumed to be less apparent for faster charging, since the duration of the sessions is much shorter. This leads to the expectation that the availability should be most important for slow charging, however this was not the case in the model.

The parameter *not having to make a detour* is negative for ultrafast charging, implying that when no detour has to be made, the alternative becomes less attractive, which is not in line with expectations. It is also contradictory to what is found in earlier studies on fuelling locations: drivers prefer to recharge along their frequently used routes (Kelley and Kuby, 2013). It can be said that, also considering the significant results of *proximity to a shopping area*, *proximity to a small shop or cafe* and *no facilities* for some alternatives, that the location of the charging point is important to the user. Also, when people find *comfort* important, this increases their tendency to opt for ultrafast charging, indicating that the comfort associated with ultrafast charging is valued highly by Dutch EV users.

A sensitivity analysis is executed on the models used in this research. Since linear models are estimated, simple elasticity calculations could be applied to retrieve results. As expected, price and whether or not having to make a detour influence choice probabilities of the alternatives in the expected directions. Interestingly, income classes do not follow a straightforward pattern, indicating that there probably are other moderating or explanatory variables that impact the probabilities found. Comparing this finding to the result of the final ML model, it is also possible that higher income classes have a lower preference for public charging at all. Private homecharging could well be their first choice. Unfortunately these results cannot be retrieved from this study alone, which leaves it for further research.

6.2. Placing results in a broader perspective

To answer the question about the feasibility of ultrafast charging in the Netherlands, it is important to put this user-focused research into a broader perspective. The stakeholder interviews provide valuable input for this. The current situation in the Netherlands is one with a rather good network of destination chargers (37,000 public and semi-public charging points as of January 2019). This could possibly be a drawback to the development of a ultrafast charging network, since this new technology has to compete with the existing ones. The current Dutch charging behaviour is summarised quite well as: 'You don't stop to charge, you charge when you stop' [Interview sources], to which fast charging simply does not live up. The interviewed stakeholders predict that (ultra)fast charging will become much cheaper in the future, making it more attractive. Since price is considered important by the respondents in this research, this can be confirmed. A considerate remark is made that no behavioural change would be required for drivers that currently drive a conventional vehicle since ultrafast charging will be similar to conventional refuelling. As habits may substantially influence people's choices (Verplanken and Aarts, 1999), this could have some impact positively related to ultrafast charging preferences. This might boost the ultrafast charging point market eventually. To examine this, further research could focus on drivers who do not (yet) drive an EV.

Furthermore, fast changes in the automotive industry concerning both cars and batteries might have large impacts on the future use of charging infrastructure types. Satisfaction levels of current infrastructure may decrease, and ultrafast charging might rise as a plausible alternative. A possible contextual variable might be the generally short distances driven in the

Netherlands, which might not be the ideal environment to implement a network of ultrafast chargers. Regular fast or destination charging might just be enough. However, when price and location are selected well, ultrafast charging is certainly an option for EV drivers as can be deduced from the models. Such pricing and location decisions can be influenced by businesses as well as government stakeholders, making ultrafast charging an interesting alternative.

Future developments that are hard to predict will likely impact the success of ultrafast charging in the Netherlands. An example of such a development is smart charging in combination with vehicle-to-grid or vehicle-to-home technologies (ElaadNL, 2019), which is only useful for slow charging. Automotive industry innovations in cars and batteries will also impact the level playing field. In addition, developments in costs per kWh as well as costs for newly to be installed infrastructure (hardware and grid connections) will influence the feasibility of ultrafast charging as primary charging mode. A future consideration that puts ultrafast charging in a positive light, is the impact charging infrastructure has on public space. When the masses start driving BEVs, it is questionable whether primarily slow charging could cover the charging needs of all users. Since faster charging points can serve more customers in less time, this would be more practical and additionally put less pressure on public space.

6.3. Limitations and further research

The main limitations of this research on EV drivers' charging preferences include the following:

- The sample size in this study is just 171 respondents or 672 observations. Sample sizes of this kind allow only drawing preliminary results;
- The choice context for lease drivers may not be realistic, since it was asked that the respondents consider paying for charging themselves, which is usually not the case. This could have made the choice scenarios less realistic for lease drivers;
- This research rests on several assumptions about charging, including the usual locations and the time it takes to charge (this is in fact dependent on many factors). These assumptions may impact the results of this study by overlooking (and thus underestimating) the importance of such assumed variable values;
- Linked to the previously mentioned limitation, a large significant alternative-specific constant for fast charging in the ML model indicates that there are variables influencing the choice for this alternative that are not included in the model. This could be improved in follow-up research by studying additional variables in the choice models.

Further research could focus on using a larger sample size, trying different attribute(s) (levels) in a similar choice experiment (for instance time of the day or week), or combining such data with a revealed preference survey. More specifically, future research into user preferences for ultrafast charging could focus on the impact of charging locations, relating to possible necessary detours and installed facilities. The difference between facilities and final destinations should be incorporated in any follow-up research. The influence of income on charging choices is also interesting to further explore, since from this research it seems likely that there are more variables that have an impact on this relationship. Related to this is the recommendation to aim for a more diverse sample in a similar choice experiment, especially regarding educational level, income, and (a lower) frequency of EV use. The inclusion of private charging in such research would be very interesting.

Quite a large group of respondents was excluded from analysis, mainly because the respondents opted for the same alternative in all four choice scenarios. It was assumed that the choice context for these EV users was not properly defined, so estimating the models with these results would not make sense. In follow-up research, more attention could be paid to seeking a balance between realistic but distinctive enough choice sets. Including broader price ranges as attribute levels is one way to achieve this. Another option is to use an adaptive choice experiment, so the attribute levels change depending on answers given to previous questions in the survey.

Lastly, it would also be interesting to study non-EV drivers, however the presence of required pre-knowledge on EV charging should be carefully considered. Linking to the remark by an interviewee about the possible future of smart charging, it would be very interesting to focus follow-up research on this topic.

7. Conclusion

The aim of this research was to investigate the feasibility of ultrafast charging in the Netherlands, from a user perspective. In a choice modelling procedure, several MNL and ML models were estimated to retrieve the quantitative influence of various factors on the EV driver choices for different charging types. Concluding this thesis, the research questions are answered one by one.

What does current charging behaviour of EV users in the Netherlands look like?

Looking at the descriptive analysis of the sample of EV users of this research, several remarks can be made about the current charging behaviour in addition to what is known from recent literature. Most of the EV users have regular trip lengths between 5 and 100 kilometres, with some outliers in the direction of 300 kilometre-trips. The majority of the sample (84.5%) drives an EV four or more days a week, indicating a substantial charging need. Slow charging at work or on-street, and fast charging are used more than once a week by 25-55% of the respondents. Interesting is that almost 40% of the respondents uses fast charging 11 days or less per year, indicating that a very large part of the EV drivers is not a regular fast charger. Both EV owners (77.6%) and leasedrivers (88.9%) who have private parking often also have access to a homecharger. Of the people who have a homecharger, the majority (67.5%) uses it four or more times per week. 27.3% of the EV owners in the sample does not have private parking, against 40.5% of the leasedrivers, making them dependent on public and semi-public infrastructure. As much as 75% of Dutch households does not have access to private parking, which is why the future use of (semi-) public charging points will likely increase when the number of Dutch EV drivers grows.

What are the factors that influence charging behaviour of EV users in the Netherlands?

The results of the MNL and ML choice models are used for answering this question. All variables as outlined in the conceptual framework based on the UTAUT model (see Figure 6) were added to and tested in the model. It can be concluded that this conceptual framework adequately presents the theoretical model used for this research, even though not all factors were found to be significant. Using this framework, all charging point characteristics (which were attributes in the choice sets) were found to have significant influence in the estimated models. The other part of the framework, concerning user characteristics, partly applies. One attitude variable, several socio-economic variables and one charging behaviour variable were found to be significant in the final ML model. This means that satisfaction levels, travel behaviour variables and vehicle characteristics did not have a substantial influence on the user choice, as found in this research.

All researched charging point characteristics are found to be significant, including price and proximity to facilities. *Price* is found to have a negative relationship with the utility of ultrafast, fast and slow charging alternatives ($\beta_5 = -0.0511$). This means that a lower price for an alternative makes that alternative more attractive. A slow charging point location next to a shopping area boosts the utility of this charging alternative ($\beta_6 = 0.979$). However, respondents also have a higher tendency to opt for fast and slow charging points without facilities. Noticeable is a decrease in utility of slow charging linked to access to private parking, when one would have expected the opposite.

Comfort is the only attitude variable that was significant in the model. When someone finds comfort important, his assigned utility to ultrafast charging becomes larger. This can be explained by the fact that ultrafast charging sessions are usually en route, have the shortest waiting times and charging durations and therefore add to charging comfort. Interestingly, *awareness of new technology* and *importance of sustainability* did not have a significant value, while this was expected. A (preliminary) conclusion from this could be that the market focus should be more on the comfort of a charging type, rather than on its 'new tech' or 'sustainable' image, according to the final ML model.

Both the socio-economic factors *income* and *education* were found to have significant influence on the utility of several alternatives. Higher income levels decrease people's tendency to opt for any of the alternatives, while a higher level of education increases one's likelihood to choose ultrafast charging. Urban density, gender, and age were not significant in the final ML model, indicating that no conclusions can be drawn concerning the influence of these socio-economic aspects.

Regarding the variables on current charging behaviour, it was expected that when people drive more kilometres, they would prefer to charge ultrafast more often. However, this could not be confirmed by the models in this research. Based on the finding that people who currently frequently fast charge have a higher tendency to choose fast charging in the choice scenarios, it can be expected that when people will use ultrafast charging in the future, they will use it regularly. The preference heterogeneity found for ultrafast charging ($\varepsilon_{U2} = 0.548$) confirms this expectation. Theoretically, the significant error component may have a distorting effect on the estimated parameters, but this seems not to be the case (see Table 5). The best model, which is the final ML model, has a model fit of $\rho^2 = 0.241$. This means that the model explains almost 25% of the variability. This can be classified as a good model fit (Louviere et al., 2000).

What happens to the likelihood of EV users' choices for charging types subject to parameter changes?

A sensitivity analysis was executed, looking at what happens to choice probabilities of different alternatives when parameter changes occur. It is found that price has a substantial influence on the predicted probabilities of the sample, keeping all other parameters constant. A price decrease for a certain alternative results in a higher predicted probability for the respective alternative and in lower predicted probabilities for the other alternatives. All else equal, the results show that it is predicted that people are willing to pay slightly more for ultrafast charging than for slow charging. This is because the predicted choice probabilities for these alternatives are equal at a price increase of 25% for ultrafast charging and at a price decrease of approximately 25% for slow charging. This price sensitivity should be kept in mind when installing charging stations. When for example high land prices will increase slow charging prices, this will affect the choice probabilities of people opting for that alternative. So price changes - whether as a result of market interactions or put in place by government regulations - will impact user choices substantially and can therefore be used as a steering mechanism if required.

Comparing scenarios in which no detour or a detour of five minutes has to be made to reach an ultrafast charging point, it is found that a required detour for ultrafast charging lowers the respondents' tendency to choose this option by as much as 11% as compared to the base scenario.

For the installation of new charging points, it is advised to look at the most used roads and routes to determine optimal locations for charging.

Interesting is to see whether an answer can be formulated to the question at what point people will switch from their current charging habits to ultrafast charging. Based on the sensitivity analysis, ultrafast charging is currently seen as viable and competitive alternative. For this to be the case, the price of ultrafast charging should not be more than approximately 20% higher than the prices of other alternatives. In addition, an incidental detour of five minutes is acceptable.

What are EV stakeholders' perspectives regarding user preferences for different charging types?

For both business and government stakeholders, the user perspective is important to take into account, as was acknowledged by the interviewees. Several differences between what users want (from the model outcomes) and what EV stakeholders *think* users want, were found in this research. The first concerns the relationship between current behaviour and future choices, which is not as clear as stakeholders expect. Secondly, different opinions based on the model outcomes and stakeholders' input on the presence of facilities at charging point locations do not provide conclusive answers as to whether to install which facilities. Thirdly, in this research it appears that Dutch EV users regard ultrafast charging as a plausible alternative (chosen 34% of the time), while some stakeholders address that ultrafast charging may be well overdimensioned for the average Dutch EV user.

Businesses may adjust their business models to be able to provide the charging types users prefer. The results from this study include that price, comfort and availability are found important. This should be taken into consideration by market parties when setting out their future strategies in the developing world of EV. Government stakeholders will want to act in accordance with user preferences, in order to achieve a covering and well-used charging infrastructure network. The availability of public space and suitable grid connections are possible issues to be aware of. Once this is not regulated well, this may impact the user experience of charging, since malfunctions can occur. From the interviews it can be concluded that EV stakeholders share the idea that interpretations of user preferences for charging are important, since the choices of these users will influence their goals and strategies.

Feasibility of ultrafast charging in the Netherlands, based on a user perspective

Looking at the model outcomes and stakeholder attitudes, a feasible scenario exists for the development of ultrafast charging in the Netherlands. However, it might not become the dominant charging type in the Netherlands. The results of this research may have implications on charging infrastructure policy in the Netherlands. Due to the size of the sample, policy implications are limited, however some preliminary results can be provided. The results indicate that a sole focus on ultrafast charging is not the ideal way to go, since people also express their preference for regular fast and destination (slow) charging. A mix of these options is recommended. All else equal, when building charging infrastructure from scratch, it is definitely interesting to consider focusing on ultrafast charging. It should furthermore be stressed that as of this moment, many different developments will likely influence the feasibility of ultrafast charging which were out of the scope of this study. These developments include the effects of the habits of new EV drivers (who are currently used to conventionally fuelling their ICEV); possible benefits of smart charging for EV users, which promote slow charging; and cost fluctuations for usage as well as for newly to be installed infrastructure.

All in all, coming back to the main research goal of *investigating the feasibility of ultrafast charging in the Netherlands, from a user perspective*, this research leads to believe that ultrafast charging has a bright future as additional charging technology, given it is provided at a decent price and at suitable locations.

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REFERENCES

Allego, 2018. First mega-e high power charging network site opened in europe. https://www.allego.eu/first-mega-e-high-power-charging-network-site-opened-in-europe/, accessed: 2018-11-20.

ANWB, 2019. Anwb elektrisch rijden monitor. https://www.anwb.nl/binaries/content/assets/anwb/pdf/belangenbehartiging/mobiliteit/rapport-erm-def.pdf, accessed: 2019-07.

Axsen, J., Kurani, K., 2013. Hybrid, plug-in hybrid, or electric - what do car buyers want? Energy Policy 61 (2013), 532–543.

Bakker, S., Maat, K., Van Wee, B., 2014. Stakeholders interests, expectations, and strategies regarding the development and implementation of electric vehicles: The case of the netherlands. Transportation Research Part A 66 (2014), 52–64.

Bierlaire, M., 2003. Biogeme. Paper presented at the 3rd Swiss Transportation Research Conference, Ascona, Switzerland.

Bierlaire, M., 2017. Calculating indicators with pythonbiogeme. Series on Biogeme 2017, 1–38.

Björnsson, L., Karlsson, S., 2015. Plug-in hybrid electric vehicles: How individual movement patterns affect battery requirements, the potential to replace conventional fuels, and economic viability. Applied Energy 143 (2015), 336–347.

Caperello, N., Tyreehageman, J., Davies, J., 2015. I am not an environmental wacko! getting from early plug-in vehicle owners to potential later buyers. Paper presented at the Transportation Research Board 94th Annual Meeting, Washington D.C., United States.

CBS, 2019. Aantal volledig elektrische auto's verdubbeld. https://www.cbs.nl/nl-nl/nieuws/2019/19/aantal-volledig-elektrische-auto-s-verdubbeld, accessed: 2019-07.

CEDelft, 2017. Uitbreiding publieke laadinfrastructuur tot 2020. inschatting van het aantal benodigde publieke laadpunten voor elektrische auto's. https://www.cbs.nl/nl-nl/maatschappij/verkeer-en-vervoer/transport-en-mobiliteit/infra-vervoermiddelen/vervoermiddelen/categorie-vervoermiddelen/personenauto-s, accessed: 2018-12.

Davis, F., 1989. A technology acceptance model for empirically testing new end-user information systems: theory and results. Massachusetts Institute of Technology, United States.

Dong, J., Liu, C., Lin, Z., 2014. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. Transportation Research Part C: Emerging Technologies 38 (2014), 44–55.

Ecofys, 2016. Toekomstverkenning elektrisch vervoer. https://www.rijksoverheid.nl/documenten/rapporten/2016/12/06/eindrapport-toekomstverkenning-elektrisch-vervoer, accessed: 2019-01.

ElaadNL, 2019. Interview on ev user preferences. Interview, date: 2019-02-18.

EU, 2014. Directive 2014/94/eu of the european parliament and of the council of 22 october 2014 on the deployment of alternative fuels infrastructure.

Figenbaum, E., 2017. Perspectives on norways supercharged electric vehicle policy. Environmental Innovation and Societal Transitions 25 (2017), 14–34.

Flowcharging, 2019. Kosten opladen elektrische auto. https://www.flowcharging.com/tarieven-openbaar-laden/, accessed: 2019-04.

Franke, T., Krems, J., 2013. Understanding charging behaviour of electric vehicle users. Transportation Research Part F 21 (2013), 75–89.

Funke, S., Plotz, P., 2017. A techno-economic analysis of fast charging needs in germany for different ranges of battery electric vehicles. Paper presented at the European Battery, Hybrid and Fuel Cell Electric Vehicle Congress, Geneva.

Gkiotsalitis, K., Stathopoulos, A., 2015. A utility-maximization model for retrieving users willingness to travel for participating in activities from big-data. Transportation Research Part C: Emerging Technologies 58 (2015), 265–277.

Gnann, T., Funke, S., Jakobsson, N., Plotz, P., Sprei, F., Bennehag, A., 2018. Fast charging infrastructure for electric vehicles: Today's situation and future needs. Transportation Research Part D 62 (2018), 314–329.

Hardman, S., Jenn, A., Tal, G., Axsen, J., Beard, G., Daina, N., Witkamp, B., 2018. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transportation Research Part D 62 (2018), 508–523.

Hensher, D., Greene, W., 2003. The mixed logit model: The state of practice. Transportation 30 (2), 133–176.

Hensher, D., Rose, J., Greene, W., 2015. Applied Choice Analysis: A Primer. Cambridge: University Press.

Hoekstra, A., Refa, N., 2017. Characteristics of dutch ev drivers. Paper presented at the EVS30 Symposium, Stuttgart, Germany, October 9-11, 2017.

IBM, 2019. Two-step cluster analysis. https://www.ibm.com/support/knowledgecenter/en/SSLVMB_24.0.0/spss/base/idh_twostep_main.html, accessed: 2019-04.

InsideEVs, 2019. 76% of charging points in europe are concentrated in just 4 countries. https://insideevs.com/news/340641/76-of-charging-points-in-europe-are-concentrated-in-just-4-countries/, accessed: 2019-01.

Kelley, S., Kuby, M., 2013. On the way or around the corner? observed refueling choices of alternative-fuel drivers in southern california. Journal of Transport Geography 33 (2013), 258–267.

Klimaatakkoord, 2018. Voorstel voor hoofdlijnen van het klimaatakkoord, 10 juli 2018. https://www.klimaatakkoord.nl/documenten/publicaties/2018/07/10/hoofdlijnen-compleet, accessed: 2019-01.

Kuhfeld, W., 2010. Experimental design: Efficiency, coding, and choice designs. Marketing Research Methods in SAS, 53–233.

Lancaster, K., 1966. A new approach to consumer theory. The Journal of Political Economy 74 (2), 132–157.

Louviere, J., Hensher, D., Swait, J., 2000. Stated Choice Methods: Analysis and Application. Cambridge: University Press.

McClave, J. T., Benson, P. G., Sincich, T., Knypstra, S., 2011. Statistiek: een inleiding. Amsterdam: Pearson.

McFadden, D., Train, K., 2000. Mixed mnl models for discrete response. Journal of Applied Econometrics 15 (2000), 447–470.

Morrisey, P., Weldon, P., OMahony, M., 2016. Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour. Energy Policy 89 (2016), 257–270.

Neaimeh, M., Salisbury, S. D., Hill, G. A., Blythe, P. T., Scoffield, D. R., Francfort, J. E., 2017. Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. Energy Policy 108 (2017), 474–486.

Nicholas, M., Tal, G., 2014. Charging for charging at work: Increasing the availability of charging through pricing. Paper presented at the Transportation Research Board 94th Annual Meeting, Washington DC, United States.

NKL, 2018. Factsheet Anders Laden — Financieel, januari 2018. www.nklnederland.nl.

NOS, 2018. Laadpaalklevers moeten een boetetarief gaan betalen. https://nos.nl/artikel/2261179-laadpaalklevers-moeten-een-boetetarief-gaan-betalen.html, accessed: 2018-12.

Ortúzar, J., Willumsen, L. G., 2011. Modelling transport. United Kingdom: John Wiley Sons, Ltd.

Philipsen, R., Schmidt, T., Van Heek, J., Ziefle, M., 2016. Fast-charging station here, please! user criteria for electric vehicle fast-charging locations. Transportation Research Part F 40 (2016), 119–129.

RDW, 2019. Open data elektrische voertuigen. https://opendata.rdw.nl/Voertuigen/Elektrische-voertuigen/w4rt-e856, accessed: 2019-07.

Robinson, A. P., Blythe, P. T., Bell, M. C., Hubner, Y., Hill, G. A., 2013. Analysis of electric vehicle driver recharging demand profiles and subsequent impacts on the carbon content of electric vehicle trips. Energy Policy 61 (2013), 337–348.

Rogers, E., 1983. Diffusion of innovations. Macmillan Publishing Co., Inc: New York.

RVO, 2018. Statistics electric vehicles and charging in the netherlands up to and including october 2018. https://www.rvo.nl/file/statistics-electric-vehicles-and-charging-netherlands-and-including-october-2018, accessed: 2018-11-18.

Samaradiwakara, G. D. M. N., Gunawardena, C. G., 2014. Comparison of existing technology acceptance theories and models to suggest a well improved model. International Technical Sciences Journal 1 (2014), 21–36.

SAS, 2019. Jmp14 statistical discovery from sas. https://www.jmp.com/en_be/software/download-jmp-free-trial.html, accessed: 2019-01.

Spoelstra, J., 2014. Charging behaviour of dutch ev drivers. https://www.rvo.nl/file/master-thesis-charging-behaviour-dutch-ev-drivers, accessed: 2018-11.

Train, K., 2002. Discrete Choice Methods with Simulation. Cambridge: University Press.

Verplanken, B., Aarts, H., 1999. Habit, attitude, and planned behaviour: Is habit an empty construct or an interesting case of goal-directed automaticity?. European Review of Social Psychology 10 (1999), 101–134.

Wolbertus, R., Helmus, J., Maase, S. J. F. M., Van den Hoed, R., 2018a. Modes of fast charging: Rolling out fast chargers in cities and along corridors to meet the heterogeneity of needs among ev drivers. Paper presented at the EVS 31, Kobe, Japan.

Wolbertus, R., Kroesen, M., Van den Hoed, R., Chorus, C., 2018b. Fully charged: An empirical study into the factors that influence connection times at ev-charging stations. Energy Policy 123 (2018), 1–7.

Wolbertus, R., Kroesen, M., Van den Hoed, R., Chorus, C., 2018c. Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments. Transportation Research Part D 62 (2018), 283–297.

Yoo, C., Kwon, S., Na, H., Chang, B., 2017. Factors affecting the adoption of gamified smart tourism applications: An integrative approach. Sustainability 9 (12), 2162–2183.