EVS30 Symposium
Stuttgart, Germany, October 9 - 11, 2017

Current and potential future EV driver charging needs

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Abstract

To pave the way for a widespread diffusion of electric mobility, both electric vehicles and their charging infrastructure need to fit drivers' needs. Thus, two surveys targeting different driver groups are conducted. On the one hand, a voluntary online survey among current EV drivers (n=2,088) serves to understand the inconveniences that early-adopters of the technology already perceive today. On the other hand, a large-scale online survey among current non-EV-drivers (n=5,283) reveals what convenience potential future EV drivers expect from the charging process.

1 Introduction

1.1 Motivation & prior research

According to the German Federal Motor Transport Authority (*KBA, Kraftfahrt-Bundesamt*), only about 11,400 new electric vehicles have been admitted in Germany in 2016 [1]. Thus, according to this reference, the total number of EV admissions in 2016 is lower than the 12,363 electric vehicles admitted in 2015. This is despite a government-funded sponsorship scheme that has been passed on May 18th, 2016 providing a buyer's premium of up to 4,000 € per newly licensed electric vehicle [2]. Thus, it seems worthwhile to analyze what the reasons for this reluctant market uptake could be.

Several prior works have already surveyed quite a spectrum of e-mobility related questions. Two of the most in-depth studies (TØI reports 2014 and 2016) have been published by the Institute of Transport Economics in Norway [3, 4]. Both studies surveyed EV drivers (2014: n_{EV}=1,721 / 2016: n=5,176) as well as ICE drivers (2014: n=2,241 / 2016: n=3,080), and looked for differences between these user groups, ranging from sociodemographic data over differences in driving behavior (trip purposes, trip distances, travel patterns, yearly mileage) to motives when buying a vehicle (information sources, EV incentives). Moreover, EV drivers were specifically asked about their charging behavior and the problems they face when charging their vehicle, and how they deal with the challenges of e-mobility in general (e.g. foresightful itinerary planning). A major limitation of both TØI reports is their exclusive focus on the Norwegian market. The same restriction also applies to a recent study that has been published within the framework of the German showcase program "Schaufenster Elektromobilität" [5], where 299 BEV and 23 PHEV drivers from Germany have been surveyed. The study put an emphasis on current charging behavior (frequencies, locations, challenges) and user preferences regarding charging infrastructure including authentication and payment methods as well as willingness to pay for (fast) charging. Similar topics (with less focus on EV charging) have been covered by an earlier DLR-survey among 3,111 EV drivers [6]. However, the population of this large-scale survey was again limited to Germany.

Major transnational studies on EV users' behavior and attitudes have only been published recently and after the work on the present study had started. A report published by McKinsey [7] in 2017 is based on survey answers of 7,000 EV and ICE drivers from the US, Germany, Norway and China. While the study emphasizes the comparison between perceptions of EV owners and "EV considerers" as well as other groups of non-EV-drivers, it does not at all cover the topics of charging behavior and charging preferences. In turn, a (commercial) study created by CleanTechnica [8] based on a survey among 2,324 EV drivers from the US, Canada and several European countries seems to cover these subjects. However, the corresponding section ("EV Charging Use, Convenience, & Needs") is not freely accessible to the public.

1.2 Goals of this study

As outlined above, there is hardly any existing research on EV user behavior and preferences on a transnational level. Within the EU-funded infrastructure project "fast-E" however, it was required to gain a border-crossing picture of the perceptions of current and future EV drivers. Financed by the European Union, fast-E aims to build a network of 278 EV fast charging stations in Germany and Belgium. Therefore, these two countries have been selected as main research target. Accounting for the notion of European transport corridors, the Netherlands as a country neighboring both Belgium and Germany has been selected as a secondary research target. Significant differences between the EV driver communities in these countries provide first indications on what can be done to increase the acceptance of electric vehicles.

The goal of the EV user survey is to capture an updated picture of EV drivers' habits and usage patterns, looking at factors such as car ownership, trip purposes and usual trip distances. A specific focus of the survey is set on charging behaviour and experiences, i.e. how often EV drivers use different kinds of private or public charging alternatives and what pricing models they prefer, as well as what difficulties they face in their regular charging activities. In order to not overstrain the patience of EV drivers, a detailed assessment of their willingness to pay for charging has not been part of the voluntary (online) EV user survey. Instead, a second survey among a paid-for panel of consumers from Belgium, Germany and the Netherlands has been conducted. As the majority of this representative panel does not drive an electric vehicle, this survey is called "Non-EV-user survey" throughout this paper. Its major goal is to understand how much of a premium people are willing to spend for increased charging comfort. This includes reduced charging times (i.e. a higher charging power), smaller detours from the planned route, and additional amenities at the charging station, such as a supermarket or a restaurant. Additionally, EV drivers' and non-EV-drivers' demographics should be compared to identify attributes that distinguish early from later adopters.

Finally, to relate the demand side (i.e. the results of the EV user survey) to the supply side of the market, an overview of major (fast) charging offers from several European countries has been created.

2 Methodology

2.1 EV user survey

2.1.1 Selection of method: online survey

The research design in form of an online survey was chosen as it represents a systematic information-gathering method for the purpose of constructing quantitative descriptors of the attributes of especially larger populations. Moreover, web surveys offer the possibility of supplementing question text with visual and interactive elements. An adequate provision of visual support for the survey instrument assures increased design efficiency and data quality [9].

2.1.2 Survey design

In order to guarantee a precise survey design, at first, it was defined which relationships could exist between different dependent and independent variables (see section 2.1.5). Subsequently, corresponding survey questions were developed in order back up each hypothesis with sufficient character-based variables of analysis. This procedure resulted in a questionnaire consisting of the following sections of interest:

Your EV and charging behavior: this section comprises questions on the participants' electric vehicle(s) such as the type, model and build year as well as driving distances, trip purposes, charging and payment habits.

Charging infrastructure design: this section was designed in order to reveal attitudes towards certain location configurations, charging station features and the most crucial problems concerning the network infrastructure.

Demographics: the last section comprises a traditional set of socio-economic questions including information on participants' residence, household, employment and income.

Next to the inclusion of a data privacy statement, all participants were offered an incentive of winning a charging voucher for the fast-E fast charging network and one of 50 power banks. This incentive was offered in order to increase response rates

2.1.3 Data acquisition

As the project is particularly interested in the attitudes and behavior of EV drivers in Germany and Belgium, the questionnaire was translated to German, French and Dutch. However, an English version was also made available to allow EV drivers from other countries to participate in the survey as well. It went online at the beginning of January 2017 and was extensively distributed for the first time on January 12th via a German e-mobility related newsletter (electrive.net). Additionally, the survey link was posted on leading online forums (e.g. Going-Electric in Germany). Due to an initially small number of results from Belgium, a further notification was published via the international electrive.com-newsletter and a major Belgian e-mobility website (www.egear.be). As of May 8th, a sample of n=2,088 was achieved. This sample is the basis of the following descriptive and statistical analyses.

2.1.4 Description of subgroups: independent variables for further analysis

Based on a general analysis of all survey participants (n=2,088), specific subgroups were defined. In order to simplify group comparisons many groups were generated along with a respective counter-group. The first, most intuitive comparison represents the difference between BEV (n=1,862) and PHEV (n=226) drivers. Moreover, variances were expected for default smartphone users (n=1,378) vs. default RFID card users (n=251). As electric vehicles are already commonly used for business trips, another distinction was made between company (n=593) and private (n=1,495) car drivers. Concerning the participants' country of residence, sufficiently large enough subgroups have been identified for Austria, Belgium, Germany, France, the Netherlands, and Switzerland. As another demographic component, six distinct age groups have been created. Further groups were defined by classifying participants based on their driving and charging habits:

Table 1: Overview of subgroups in EV user survey

Subgroup	Size	Description
Long distance drivers	n=708	EV drivers that do trips of more than 150km at least monthly.
Short distance drivers	n=1,380	EV drivers that do trips of more than 150km only yearly or never.
Tesla drivers	n=329	EV drivers that stated to use a Tesla as their primary vehicle.
Non-Tesla-drivers	n=1,759	EV drivers that stated to use a non-Tesla EV as their primary vehicle.
Fast chargers	n=996	EV drivers that use public fast charging at least monthly.
Anti–fast-chargers	n=1,092	EV drivers that never or only yearly use public fast charging.

Real fast chargers	n=1,471	EV drivers that have a car that is available with/without fast charging and use public fast charging at least yearly.
Slow chargers	n=617	EV drivers that have a car that is available with/without fast charging but never use public fast charging, and EV drivers that have a car that is only available without fast charging.
Exclusive home/work chargers	n=480	EV drivers that never or only yearly use a public charging (regular, semi-fast, fast).
Exclusive public chargers	n=158	EV drivers that never or only yearly charge their car at home or at work.
Fast chargers	n=996	EV drivers that use public fast charging at least monthly.

2.1.5 Hypothesis development: anticipated relationships completed by exploratory analysis

Based on experience with previous projects (e.g. SLAM), hypotheses have been built that connect the independent variables (subgroups) as explained above to dependent variables of interest. Three hypothesis are explained here:

> H1: Tesla drivers were expected to do trips of >150km more often than other EV drivers, as Tesla cars have a significantly higher range.
>
> H2: Long distance drivers (>150km at least monthly) were expected to use fast charging more often than short distance drivers, as they need to recharge their car on these long trips.
>
> H3: People that commonly pay by RFID card were expected to have less price awareness than people that mostly pay via smartphone, because the latter can check the charging prices in the payment app on their smartphone.

In addition to hypothesis development based on prior research, data mining approaches were used to explore further independent variables. Moreover, the preference for different authentication methods has been selected as fourth dependent variable for an exploratory analysis.

2.1.6 Hypothesis testing: statistical analysis & machine learning algorithms

Although descriptive modeling and visualization represent a significantly large amount of the overall analysis, statistical estimations were drawn in order to test the hypotheses introduced above. Thereby, several techniques were performed in order to explain the four dependent variables of interest: driving behavior (H1), charging behavior (H2), price awareness (H3) and authentication methods (exploratory analysis). While the first two represent interval variables, the third and fourth are categorical. Each variable was observed by the two following central statistical methods.

First insights were drawn from simple ordinary least-squares regressions (OLS), which represent a generalized linear modelling method for the analysis of multiple independent variables including dichotomous (e.g. country of residence), ordinal (e.g. rating of locations for fast charging) and numeric data (e.g. yearly mileage) [10]. This method corresponds to minimizing the sum of square differences between observed and predicted values. The simplest linear model is:

$$\mathbf{Y} = \boldsymbol{\beta}_0 + \boldsymbol{\Sigma}_{j=1\ldots p}\, \boldsymbol{\beta}_j \mathbf{X}_j + \boldsymbol{\varepsilon}. \qquad (1)$$

After specifying the independent and dependent variables, possible transformations of such were conducted. The common approach of additionally estimating robust regressions was integrated in the analysis in order to provide a more precise observation especially in regard to outlier difficulties. Robust regression estimation therefore is understood to be a form of weighted and reweighted least squares regression which initially was conducted [11]. The investigation of OLS estimates however often does not satisfy researchers' expectations as they often have low bias but large variance. As first regressions were drawn solely based on the introduced hypotheses and as OLS do entail some implications, further analysis focused on machine learning techniques such as the stepwise model selection function or best subset regression selection. Basically, these methods are used for the automatic generation of a regression model which provides information on which variables (of all variables included in the dataset) should be included in the statistical model. While stepwise regression selects variables sequentially, best subset regression finds for each $\mathbf{k} \in \mathbf{0}, \mathbf{1}, \mathbf{2}, \dots, \mathbf{pk} \in \mathbf{0}, \mathbf{1}, \mathbf{2}, \dots, \mathbf{p}$ the subset of size k that gives the smallest residual sum of squares. Latter compares all possible models that can be modeled based upon an identified set of predictors. Therefore, it aims "to select the best fit model from all possible subset models by evaluating such to a goodness-of-fit criterion" [12]. Solely the estimation results driven from the best subset regression selection are reported in chapter 3.

2.2 Non-EV-user survey

2.2.1 Selection of method and research design

Fast charging is offered as a product or service consisting of several attributes that may provide different value to the customer. For instance, a slower charging speed (and longer charging time accordingly) may be more acceptable than a significant detour from the planned route. To find out how consumers trade off these different attributes against each other, a conjoint analysis as main survey method was developed. Conjoint models are most common within behavioral science and play a major role for market research. Such research designs calculate values/utilities which customers base their decision on and therefore provide the analysis of demand depending on a specific product or service. The use of a choice-based conjoint analysis (CBC) which is also known as a discrete-choice conjoint analysis (DCA) allows to gather information through respondents' choice of the most preferred full-profile service. Such choices are made repeatedly within the survey in order to guarantee a sensitive analysis of small influences on customers' choices [13]. This method is particularly popular for transportation studies including the analysis of preferences between airlines, trains and cars [14]. The quality of the output heavily depends on the design development and its final qualities [13]. Thus, three main conjoint designs have been developed. While the third design clearly differs content-wise, the first two designs are identical with the simple differentiation of scenario variation. Therefore, the first and second design are labeled as "conjoint 1A" and "conjoint 1B", and the third design is labeled as "conjoint 2".

Table 2: Overview of conjoint designs

Conjoint	Scenario	Attributes	Attribute levels
1	A / B	Price	3€, 6€, 9€, 12€, 15€, 18€
		Charging time (speed)	4min, 9min, 25min
		Detour (one-way)	0km, 2km, 6km
		Number of charging poles	4, 2, 1
2	-	Price	0€, 4€, 8€, 12€, 16€
		Time	9min, 25min, 40min
		Energy source	No green energy, grid green energy, local green energy
		Amenities/facilities	Consulting (e.g. bank), electronics/hardware/furniture store, restaurant, parking lot, pedestrian area (city center), shopping center)

Several trip purposes such as business day trips and short holidays have daily driving distances of up to about 250 km. With a current range of EVs of 100-300 km, one of the main use cases will be a needed additional charge of about 100 km on-route. The first and second scenario (1A and 1B) represent exactly this use case. Therefore, the charging speeds 50kW (25 min), 150kW (9 min) and 350kW (4 min) are included as attributes for the time spent at the charging station. Moreover, the detour that is required from the planned route is defined as another attribute, including manifestations that also exist in reality: 0km (highway service station), 2km (travel center / truck stop / “Autohof”) and 6km (industrial parks nearby the highway). Finally, different numbers of charging poles represent the likelihood of waiting time before charging (1, 2 or 4 charging poles): Four charging poles therefore represent a decisive shorter waiting time than only one available pole. The difference between C1A and C1B relates to the circumstances of the trip. In C1A, the “leisure” scenario, respondents are said to travel with family and friends, for instance heading southward for vacation, and they do not have any time pressure. In C2B, the “pressure” scenario, respondents are said to travel all by themselves to an appointment in another city, and thus are in some kind of a hurry.

The design of the single choice sets was generated by a dedicated statistical software solution.[1] In order to guarantee a precise design with the best possible efficiency, several pre-tests were carried out. Based on the above mentioned conjoint criteria and common efficiency indices implemented in the software, the final choice designs were created. Two exemplary choice sets are shown below.

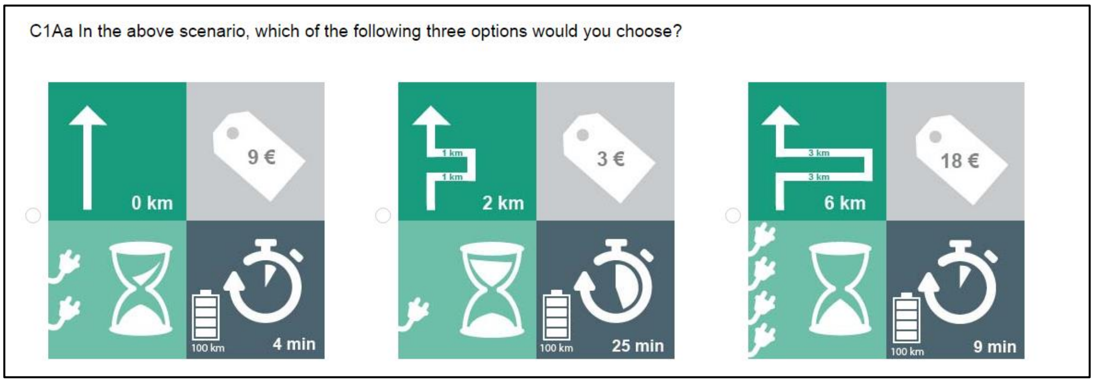

Figure 1: An exemplary choice set from conjoint 1

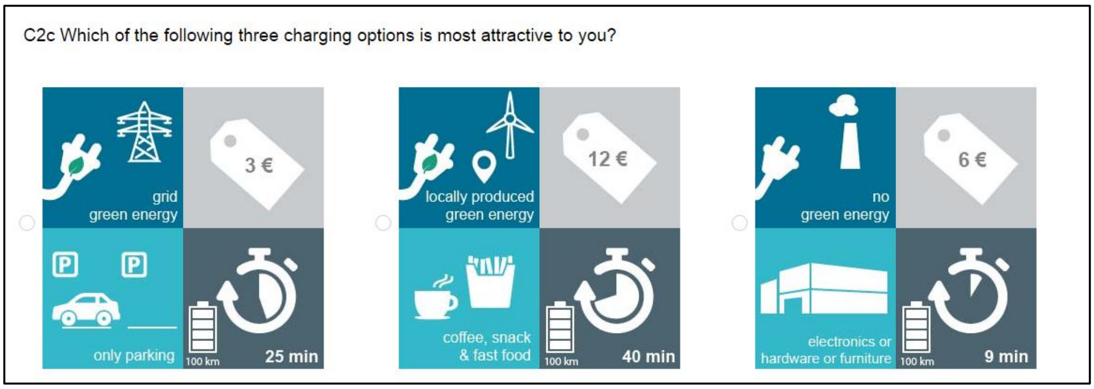

Figure 2: An exemplary choice set from conjoint 2

2.2.2 Survey design

Like the EV user survey, the non-EV-user survey has been implemented as an online survey. Next to the conjoint questions, the questionnaire included classical survey queries as well as vignette questions that describe several options and ask the respondent to rate these [15]. All data in the non-EV-user-survey was gathered via an online survey, which was structured as follows:

Current ownership & usage: current owned vehicle(s) concerning type, model, yearly driving distance, distance between home and work as well as travel purposes

Future ownership & usage: considerations of buying an EV, participants experiences with EVs and (fast) charging stations

[1] JMP®, Version 13. SAS Institute Inc., Cary, NC, 1989-2007

Conjoint C1A, C1B & C2: direct assessment of pre-defined charging options, revelation of preferences about single attributes embodied in charging offers

Demographics: age, gender and employment, parking arrangements and living situation

2.2.3 Data acquisition

For this study, an online sampling company was assigned to provide 6,000 survey participants from Germany, Belgium and the Netherlands. For the purpose of this study, these drivers were considered non-EV-users. By providing a financial incentive, the online sampling company insured that respondents finish the entire survey, which in turn enabled the analysis of a gapless dataset. As it was assumed that a proper completion of the survey would take at least 10 minutes, complete survey answers that have been finished within less than 10 minutes have been excluded from the sample. Eventually, a sample of n=5,283 survey answers was used for the analysis.

2.2.4 Statistical models & data analysis

For the estimation of the conjoint attributes various analysis techniques were performed. Next to the use of standard robust regressions, the conjoint data was analyzed by the means of multi-level and maximum likelihood estimation of logistic modelling. The latter competes with discriminant analysis as a method for analyzing categorical-response variables. Logistic regression studies the association between a categorical dependent variable and a set of independent variables. It overcomes inefficiencies of other methods such as the analysis of dichotomous variables (0, 1), describing when a service product was chosen (1) and when not (0). Y (1, 0) is thereby transformed into a logit which captures the odds of a choice falling into the "1" category. This maximum likelihood estimation aims to find relevant parameters for which the probability of the data is greatest [16]:

$$\log\left(\frac{p}{1-p}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p \tag{2}$$

The analysis of both unstandardized and standardized logits permits the estimation of independent variables' effect directions and strength [16]. As mentioned above, the direct impact of these variables on the choice of service product is thereby captured.

Multi-level models were run as they offer the possibility of incorporating random effects as well as conventional fixed regression coefficients. It provides the estimation of participants' willingness to pay while simultaneously taking context effects into account. Specific methodological configurations permitted the analysis of regression coefficients that are permitted to vary from participant to participant. As the hierarchical data structure allows the analysis of differences in group averages, several statistical models with varying configurations of intercepts and slopes were conducted. The dependent variable is to be observed at the lowest level. In regard to residuals on both levels, a basic multi-level model is noted as followed:

$$Y_{ij} = \beta_0 + \beta_1 + X_{ij} + u_j + e_{ij} \tag{3}$$

2.3 Market research charging offers

As offers for public fast charging are pretty much directed at the general public, the information on available products and services are gathered by exploring the most common channel for B2C sales today: the internet. In case of missing information, the respective provider is contacted via phone and/or e-mail. If information was not provided neither by the company's website, nor by e-mail, nor by a potential customer hotline, is was labeled as "not available".

In a pre-study, a web search has been done to create a long list of companies that offer charging services in the fast-E countries (Belgium, Germany, Czech Republic and Slovakia) or other countries that are of interest due to their lead market position (Netherlands, Norway) or proximity (Austria, Denmark, France, Slovenia, Switzerland, UK). Based on discussions with experts, the collection has been reduced to a short list of about 20 companies. Simple calculations of the occurrence of different pricing models and ad-hoc authentication methods were done to analyze the prevalence of different approaches within the sample.

3 Findings

3.1 Demographics of EV users vs. non-EV-users

The analysis of demographic characteristic of EV users (n=2,088) and non-EV-users (n=5,283) displays some differences. Firstly, non-EV-users tend to be younger than EV users. 31% of non-EV-users are between 18 and 34 years old, whereas only 16% of EV drivers are younger than 34 years. Most of EV drivers (63%) are between 35 and 54 years old.

Furthermore, EV users seem to have a higher annual gross household income than non-EV-users. 31% of non-EV-users have less than 34,999 € at disposal compared to 10% of EV-users. 21% of EV users have an annual income exceeding 100,000 €. Only 5% of non-EV-users have a similar income. This indicates that EV driving currently is a pleasure for the rich, while it is not affordable for average income households.

3.2 Driving behavior of EV users vs. non-EV-users

EV users (n=2,088) seem to drive more kilometers per year (stated yearly mileage) than non-EV-drivers (N=5,283) do. However, trips of more than 150km only account for 26% of all EV mileage, while they account for 47% of non-EV-users' mileage. Both insights are intuitive: EV have high acquisition cost, but low operating costs. Therefore, it makes sense that EV drivers drive more than non-EV-drivers do. The small amount of long distance trips in turn can be explained by the relatively small batteries of currently available electric vehicles. Still, there are EV users that drive more than 150km at least monthly (n=708). Based on H1, one would assume that most of these are Tesla drivers.

Corresponding regression analyses verify these results: the probability of Tesla drivers driving distances of >150 km is higher than that of non-Tesla-drivers (0.40). Further significant results were found when including a binary variable which categorized users into BEV and PHEV drivers. Whereas the results show that PHEV drivers are much more likely to drive longer distances than BEV drivers (0.23), the estimate for Tesla drivers increased even more (0.43). Thus, hypotheses 1 is confirmed.

3.3 Charging behavior of EV users

For long-distance trips in particular, fast charging is an important factor. In fact, public fast charging sessions account for 10% of all charging sessions of EV users in the survey. For people that do trips of more than 150km frequently, fast charging even accounts for 14% of all charging sessions. Tesla drivers, most of which can use Tesla's supercharger network for free, fast charge their car at least monthly. However, there is also a quite big group of EV drivers (52% of sample) that never or only yearly use a public fast charger.

The regression based on the stepwise selection model confirms the descriptive statistics. Tesla drivers use fast charging ten times more per year than non-Tesla-drivers. Similar results are found for long distance drivers (n=708), confirming H2. These drivers use fast charging approximately 27 times more often than users driving shorter distances. Taking a closer look at short distance drivers reveals that the more often EV drivers use their vehicle for shopping (0.04) and work (0.02) the more often they use fast charging. While the impact might not be as strong as of the other variables, the results illustrate the relevance of available fast charging infrastructure nearby shopping and business facilities.

3.4 Authentication methods

Concerning the authentication process at public charging stations, EV users have been asked to assess different methods on a 4-point scale ranging from "perfect solution" to "bad solution". While for ad-hoc payment the clear majority of EV users would prefer to pay via an EC or credit card terminal, even more people think that Plug&Charge is the best authentication method for contract-based payment. In fact, when only looking what people consider the perfect solution, Plug&Charge (58%) leaves all other authentication methods far behind – even if Tesla drivers are excluded from the analysis (56%). However, if "good solution" and "perfect solution" are considered together, the credit card terminal catches up significantly and scores just 12 percentage points behind (64% vs. 76%). Moreover, considerable country-specific differences exist with regard to authentication via RFID card for contract-based payment: While 85% of Dutch EV drivers and 63% of Belgian EV drivers think it is at least a "good solution", the majority of Austrian and German

EV drivers think that is it only an ‘okay’ method. This difference could be related to the long-established central interoperability register (CIR) that ensures trouble-free usage of RFID cards in the Netherlands. The regression analysis, however, did not yield any significant relationships.

Going from authentication method preferences to the actually used payment methods, 66% of EV drivers stated that they most commonly use an RFID car for authentication, while only 12% of the drivers use their smartphone. This also means that at least 66% of drivers commonly use contract-based payment. Therefore, ad-hoc payment is not specifically considered in the pricing models section below.

3.5 Price awareness according to EV users

Besides payment and authentication methods, actual price awareness is a crucial factor. In fact, 46% of all EV users rarely or never know the exact price at a public charging station. The share of people that always or mostly know the charging price is higher among smartphone payers (71%) than among RFID card payers (50%). The regression analysis confirms this observation: People who commonly pay by RFID card know the prices less (0.35) than people who use a smartphone app (0.57). Therefore, H3 is confirmed.

The regressions run for country-specific differences generated rather mixed results. While similar results were found for Germans (-0.18) and Belgians (-0.61), statistical results showed that Dutch (-0.72) users know the prices the least of all. Further interesting results were found for the age group from 18-25 years (0.30). The subgroups EV vs. BEV drivers and fast chargers vs. anti-fast-chargers were also imbedded in the model. While EV users are significantly aware of charging prices (0.27), no significant results were found for PHEV drivers (n=226). Similar results are found for fast chargers and anti-fast-chargers (n=1092): users who were categorized as fast chargers know the prices better than anti-fast chargers, which again is no surprising result.

Table 3: Results of stepwise selection model regression for price awareness

Independent variables	Price awareness
RFID card users	**0.348****** (0.047)
Smartphone users	**0.571****** (0.067
Belgians	**-0.611****** (0.076)
Dutch	**-0.724****** (0.070)
Germans	**-0.184*** (**0.043)
Age group: 18-25	**0.303****** (0.109)
Fast chargers	**0.148****** (0.039)
EV drivers	**0.275****** (0.071)
Constant	**1.010****** (0.090)
Observations	2,088
R^2	0.163
Adjusted R^2	0.160
F Statistic	44.573*** (df = 9; 2057)

*Note: *p<0.1; ** p<0.05; *** p<0.01*

3.6 Pricing models for contract-based payment

Regarding pricing models, EV users have a clear preference: 93% believe that “only pay per kWh” is a perfect or good solution. This attitude contrasts strongly with the pricing models that are actually offered by European CPO and MSP players. While EV users always prefer kWh-based over time-based pricing, the latter is much more common across all kinds of contract-based charging offers in the market (kWh-based: 29% / time-based: 59%). The second most popular pricing model out of a total of ten inquired models is the payment of an only one-time fee (42%). Table 3 illustrates the remaining pricing models ranked after popularity by EV users. For further comparisons it also lists current market offers shares which demonstrate larger disparities between these offers and users’ preferences.

Table 4: pricing model preferences vs. actual market offers

"Perfect" or "good" pricing models according to EV users (n=2,088)		Pricing models prevalent in sample of charging offers (contract-based payment)
pay per kWh only	93%	17%
one-time fee only	42%	-
pay per kWh + pay per min	35%	-
monthly fee only	26%	12%
start fee + per kWh	26%	-
pay per min only	20%	38%
monthly fee + per kWh	17%	12%
start fee only (fixed fee per session)	13%	-
start fee + pay per min	7%	-
monthly fee + pay per min	5%	21%

3.7 Willingness to pay according to non-EV-users (conjoint analysis)

By a longitudinal two-level regression, it was possible to translate the respondents' choices into an estimation of price tags for specific configurations of a charging station. After all the data was prepared, ambiguous results were found for the variable "detour". As these ambiguous results are traced back to a bias in the survey design, it was decided to leave them out of this report. According to the results of conjoint 1A and 1B, non-EV-users would on average pay 3.90€ for a charge of 100km range (equals ~17kWh) at a 50kW charging station (charging time: 25 minutes). They would pay 5.00 € more to reduce the charging time from 25 to 9 minutes (equals ~150kW charging), and another 1.60 € (6.60 € in total) to reduce it to 4 minutes (equals ~350kW charging). Furthermore, non-EV-users would pay 0.20 € more if there were two instead of only one charging pole, and 0.60 € if there were four instead of one charging pole. Another interesting insight is that people who have experience with EV and/or charging stations show a higher willingness to pay than people that do not have any experience.

Due to the relatively easy installation and the low need for construction work of charging stations compared to conventional gas stations, charging poles can be installed in many different locations. Based on the conjoint analysis and other questions from the non-EV-user survey, it was possible to prioritize various locations. The results show that shopping centers should be the preferred location to build fast charging stations followed by grocery stores and fast food restaurants. For all but one location category (consulting services) more than 50% of people consider changing their current vendor if a similarly accessible one would offer charging opportunities. When the traveler is offered a bundle of price, energy type, charging speed and location category, the main factor influencing their choice is the price asked for the charging session. The second most important factor is the specification of the location (amenities) – the charging time (speed) and energy source only play a minor role. In fact, within the conjoint analysis, the revealed preferences regarding the influence of green energy are ambiguous: While green energy that is locally produced rates better than conventional energy from the grid, certified green energy from the grid rates worse.

3.8 Charging infrastructure design

3.8.1 Top 3 features & way of finding a public charging station

Being asked about the top 3 features of a fast charging station EV users and non-EV-users agree on the most important one: "24/7 access to the charging station" with 96% approval among users and 82% among non-EV-users. However, "Green energy" is the second most important feature for EV users (54%), compared to only 33% of non-EV-users, which consider "Plug&Charge" to be the second most important feature (51%).

Asked what participants think would be an ideal way of finding a charging station, 56% of respondents prefer to have this function integrated into their navigation system. While a smartphone app is considered an ideal solution by 33%, a website that is accessed via smartphone or a computer is only selected by 8%.

3.8.2 Favorite locations for additional fast charging stations

To understand where additional fast chargers are most urgently needed, EV users were asked to assess different locations on a 4-point scale ranging from “most important” to “not important”. Additionally, four types of locations were presented in different variations of available facilities. According to respondents, the extension of the fast charging network should clearly focus on highway locations that are equipped with a shop, a restaurant and toilets: 74% see this as “most important”. Only if “important” and “most important” votes are counted together, the big shopping mall located in the city outskirts levels up. Intermodality hubs (airports and train stations) are not seen as an important or most important location for fast charging by the majority of respondents (64% and 60% respectively).

3.8.3 Crucial problems

Current EV users already experience today what is in store for the generality of car drivers tomorrow. The inconveniences and problems perceived by this pioneering group can be a valuable input for improving the market model. Therefore, EV users have been directly asked what they think are the top three problems with regard to (fast) charging infrastructure. Five main issues can been identified as crucial across the entire sample:

1. Charging station is blocked by non-EV (a »top three«-problem for 16% of EV users)
2. Not enough fast charging stations (16%)
3. Not enough charge points or wrong standard (15%)
4. Contract/card not always accepted (13%)
5. Price system is too complicated (11%)

Variations from this general perception can be observed in some countries. For instance, in Austria and the Netherlands, “charging is slower than specified” seems to be a bigger problem than elsewhere. However, across all countries, three topics are not seen as particularly problematic: “Cables are not long enough”, “Insufficient status info during charging” and “No hotline service or not useful”.

4 Discussion

4.1 Conclusion & recommendations for action

Based on the results presented above, several immediate EV user needs can be identified:

Firstly, to make electric vehicles suitable for long-distance travel, they need to get closer to the “Tesla system”, i.e. the cars need bigger batteries and there needs to be a comprehensive fast charging network. Especially charging stations at highway locations that are equipped with a shop, a restaurant and toilets are what EV drivers require more of. To avoid that the scarcity of public (fast) charging stations is even made worse by ICE vehicles blocking the station, a mechanism needs to be found that solves this most urgent problem of EV drivers.

Secondly, charging needs to be made easy: A vast majority of EV users sees Plug&Charge as the perfect authentication method; both EV drivers and non-EV-drivers consider this technology a Top 3 feature for charging stations. In fact, this preference goes together well with the current predominance of contract-based payments via RFID card. However, the industry needs to make sure to address the issue of lacking pricing awareness when developing future authentication methods (such as Plug&Charge).

Thirdly, acceptance of public charging prices could be increased if more operators switched to a kWh-based instead of a time-based billing. Regarding the willingness to pay for fast charging, it looks like the additional value of a higher charging speed diminishes at some point. Therefore, it should be checked whether future high power charging (HPC) stations really need to be equipped with power levels of up to 350kW.

Finally, for electric vehicles to become a mainstream product, the industry needs to come up with solutions that make EV driving affordable for young people and lower income households.

4.2 Limitations and further research

Even though the fast-E user survey covered EV drivers in Belgium, Germany, the Netherlands and some of their neighboring countries, it does still not provide a fully Europe-wide or even global picture of EV user habits and preferences. Moreover, the specific relationship between driving and behavior, i.e. which charging options are used for which trip distances and purposes, has not been analyzed in detail. Therefore, a future survey should look at this connection and potentially target an even broader audience. Another shortcoming of the EV user survey could be a certain self-selection bias that results from fact that the research was designed as a voluntary online survey. Overcoming this limitation, however, is difficult, as it is quite challenging to recruit a representative sample of EV drivers.

The non-EV-user survey in turn fulfilled the requirement of a representative sample. However, the research design of the conjoint analysis had weaknesses, too: Against literature recommendations, three attributes of the conjoint design (charging power; detour; potential waiting time) had a fairly high correlation, as all of them in some way or the other relate to the time that people need to invest in the charging session. This restriction was known at the outset of the work, yet this "imperfect" design seemed to be the best compromise to meet the goals of the research. Further studies could look for ways to reduce the influence of this correlation and/or use other methods to understand user preferences regarding these different "dimensions of speed". Finally, it should be stated that societal as well as political and environmental awareness have become dominant factors within an evaluation of attitudes at the individual level. By the inclusion of item batteries questioning such rather latent attitudes, more detailed analysis is provided and the probability of generating accurate data could increase drastically.

Acknowledgements

The authors would like to extend their gratitude to all fast-E consortium members. The research leading to these results has received funding from a TEN-T project funded by the EU under the Connecting Europe Facility (CEF) program. Yet, this research only reflects the authors' view and the European Union is not liable for any use that may be made of the information contained therein.

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