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Analysing Public Charging Infrastructure Operations:

- Consumer Profiles of Electric Vehicle Drivers

Table of Contents

Table of figures

Preface

Abbreviations

Abbreviations	Description
CSP	Charging service provider is a company that supplies the service of charging stations and the required hardware to the public.
DSM	Demand side management, also known as Energy demand management, is the modification of consumer demand for energy through various methods such as financial incentives and education.
EV	An electric vehicle, also referred to as an electric drive vehicle or battery electric vehicle (BEV), uses one or more electric motors or traction motors for propulsion.
ICE	The internal combustion engine is an engine in which the combustion of a fuel (normally a fossil fuel) occurs with an oxidizer (usually air) in a combustion chamber that is an integral part of the working fluid flow circuit. In an internal combustion engine the expansion of the high-temperature and high-pressure gases produced by combustion apply direct force to some component of the engine.
GSM	GSM (Global System for Mobile Communications, originally Groupe Spécial Mobile), is a standard set developed by the European Telecommunications Standards Institute (ETSI) to describe protocols for second generation (2G) digital cellular networks used by mobile phones.
PEV	A plug-in electric vehicle (PEV) is any motor vehicle that can be recharged from any external source of electricity, such as wall sockets, and the electricity stored in the rechargeable battery packs drives or contributes to drive the wheels.
PHEV	A plug-in hybrid electric vehicle, plug-in hybrid vehicle (PHV), or plug-in hybrid is a hybrid vehicle which utilizes rechargeable batteries, or another energy storage device, that can be restored to full charge by connecting a plug to an external electric power source (usually a normal electric wall socket). A PHEV shares the characteristics of both a conventional hybrid electric vehicle, having an electric motor and an internal combustion engine (ICE); and of an all-electric vehicle, having a plug to connect to the electrical grid.
TOU	Time-of-use pricing is a time-based pricing of services, whereby electricity prices are set for a specific time period on an advance or forward basis, typically not changing more often than twice a year.

1 Executive Summary

Electric vehicle transportation and its relevant infrastructure are topics that gain increasing traction in economic, ICT and further branches of academia. This study analyses the charging behaviour of electric vehicle drivers and deduces relevant factors for its frequency of usage. Based on the relevant factors a clustering procedure of the users is conducted to obtain consumer groups of public charging stations. The results allow making assertions about whether current consumer behaviour integrates with DSM methods. Managerial implications condense the results into strategic steps for charging station providers.

Electric energy has advantages for transportation; it is instantly distributed within a grid and requires no physical transportation, after it is generated. Future energy grids based on renewable energy alleviate the need for fossil fuels to be processed in various ways and can offer a potential for sustainable transport.

These future grids or “smart grids” need to distribute and price energy effectively, because the energy from renewable sources is fluctuating. As a consequence the demand-side of these grids should mimic the fluctuating supply-side of the renewable sources. The balancing act of these grids is done with the help of demand side management systems, which also optimize the charging processes of electric vehicles.

So far in academia DSM systems for charging electric vehicles have been mostly reviewed from the supply side, this study analyses the user side of the system. In this way it adds granularity to the DSM research domain.

In collaboration with the distribution system operator of Cologne this study investigates EV-owners and their charging habits. The firm called RheinEnergie AG maintains a network of charging stations, supplies the data for an analysis of the charging network, and grants the right to conduct a survey among its clients.

The first stream of information for this study comes from the survey. The survey aims at eliciting important factors that influence the frequency of usage of public charging stations. The factors are based on an extensive literature review, which collects significant dimensions in the field of electric vehicle research.

Regressions and bivariate analyses permit to make judgements about the relevant factors that influence EV drivers’ decision making process.

Based on the regression data the study presents consumer groups that differ according to their behaviour. A combination of Ward's method and k-means is used to generate the groups, which are subsequently statistically compared.

The second stream of information comes from the charging data, which is obtained from multiple databases. The data shows arrival-times, end-times, kWh meter-values and other vital data points for the analysis of the charging behaviour.

A classification the databases according to charging durations is conducted. The study presents the amount of charging instances which have a longer parking time than the actual charging time of the battery. These cases are particularly interesting for DSM measures.

The charging data reveals that drivers frequently park for durations of 0 to 3hours and 12 to 24 hours. The data shows that 50% of the people who charge their car between 0 and 3 hours do not require a fast-charging connection. Their cars are fully recharged after one hour of average parking time. These results are favorable for smart charging solutions and other DSM related procedures.

The results from the survey show that there is a connection between the frequency of usage and the kilometers that an EV drives on average. However, it indicates that users who drive more kilometers use public charging infrastructure less often. Additionally the results show that fast-charging becomes particularly important for users who drive longer distances. Fast-charging also has an enhancing effect on the perception of convenience of public charging infrastructure. The survey further underscores the influence of the type of dwelling on the frequency of charging. Especially those respondents who do not live in detached houses with private parking spaces have a tendency to use charging stations more frequently. Users with multiple subscriptions for public charging services also use public charging stations more frequently.

The consumers are clustered in groups, which reflect their distinctive attributes. Three groups are obtained from the sample, the short city commuters, long commuters, and long haul drivers.

Short city commuters show the highest frequency of usage, more than half of them charge at least once a month at public charging stations. Long commuters tend to accept longer charging periods in order to pay lower prices. They also show the highest intensity and occurrence of range anxiety. Long haul drivers have a stronger preference for fast-charging infrastructure and have the most subscriptions of all groups.

A combination of the survey data and the charging database illustrates that the users of public charging infrastructure mostly charge and park below three hours at the stations. The survey further demonstrates that most EV drivers charge their vehicles after a driving-distance of 25km to 50km. These two sources explain the short charging duration of the vehicles that park below three hours. The second biggest user-group in the charging data (20%) parks the car between twelve and 24 hours, which means that they are mostly overnight parkers. According to the survey at least 13% of the sample belongs to this group. Both indications are a significant benefit for DSM systems. Overall this study underlines the potential for DSM systems in the realm of public charging infrastructure.

In terms management and strategy this means that operators of charging infrastructure must be aware of the hidden potential to optimize their networks. The implementation of smart charging solutions can reduce the operation cost of a charging network without affecting customer satisfaction. On the contrary, the system becomes more efficient and saves natural resources, a message that is also considerable for marketing campaigns.

The positive effects of fast-charging should also be taken seriously by managers in this industry. The implementations of such facilities can boost the perception of the convenience of the infrastructure and hence have positive effects on a brand's image. However the management should realize that fast-charging must be balanced with regular chargers to achieve equilibrium in prices for the different groups of consumers.

A strategic result that follows the research is the special situation of drivers living in attached multi-unit housing. Additionally, mangers should continue to monitor consumer behavior in order to detect changes in the customers' perception.

The results show that it is possible to explain the behavior and motivations of EV drivers to use public charging infrastructure. The study can help to explain the industry that begins to evolve around electric vehicle transportation. The analyses find important factors that influence satisfaction and profitability from a consumer's point of view. It is expected that this study adds knowledge to the discussion around these technologies and to the creation of more environmentally sustainable business-models.

2 Introduction

The transportation sector currently explores many different technologies that can help to overcome the dependence on fossil fuels. Part of this wave of technologies are electric vehicles (EVs), which allow for a more effective distribution of energy than regular petrol driven internal combustion engines (ICE’s) (Argueta, 2010). Part of this is due to the fact that electric energy is instantly distributed within a grid and requires no physical transportation, after it is generated (Stoft, 2002, p.45). Petrol on the other hand needs to be extracted, refined, and distributed among millions of gas-stations. A future energy grid based on renewable energy alleviates the need for fossil fuels to be processed in various ways. Therefore it has a strong potential to increase the effectiveness of energy distribution for transportation purposes. Currently scholars consider many different ways to intelligently integrate individual personal transport into the energy grid (Kahlen et al., 2013; Kempton[a], 2005;Kempton[b], 2005;Turton et al., 2008;). Once the energy networks are able to react to shifts in supply and demand curves reciprocally, we call them “smart energy grids”. Those grids can distribute and price energy effectively, as they manage the varying energy volumes coming from fluctuating renewable sources (Ketter, 2010, p.3). This agile management strongly requires the inclusion of end-consumers, which is achieved in so called demand side management (DSM) systems. The consumer inclusion is inevitable, because ”electricity supply must always equal demand” (Aghaei & Alizadeh, 2013). This fact imposes that demand must change in order to adapt the supply curve, i.e. costumers must shift their consumption patterns to affect the supply. The shift can either be achieved by means of price augmentation or incentive payments, which encourage lower consumption (Aghaei & Alizadeh, 2013). DSM systems try to attain 100% energy efficiency by using methods that create an equilibrium between off-peak and on-peak periods (Balijepalli et al., 2011). Finn et al. 2012 describe methods to effectively integrate electric cars into DSM systems, by shifting charging cycles. Other scholars also recognize that smart-grid solutions and DSM technologies are necessary to optimize electric vehicle charging processes (Tian et al., 2010). Yet, consumer profiles and sensitivities related to the charging of EVs have received marginal interest in academia and management sciences so far.

Many governments world-wide push for a move towards more electrified transportation. Governmental support schemes for EVs reduce taxes on vehicle purchases and create investment programs for public charging infrastructure (Bundesministerium für Wirtschaft und Technologie, 2011; République Française, 2012; GOV.uk, 2013; Rijksoverheid, 2011; IRS, 2009). These policies aim at convincing consumers to make their buying decision in favour of EVs.

Whole industries are created that gravitate around the production of charging infrastructure and electric vehicles within the eco-system of e-mobility. These firms currently strongly rely on public investment projects (Projektträger ETN, 2013). However, these businesses must ensure their survival after the financial help of the government ceases. In order to allow for this to happen, the services in the ecosystem must become profitable.

To analyse the situation of public charging infrastructure, this study is strongly supported by Rheinenegie AG, a German energy distribution system operator, which conducts a network of EV charging stations in the city of Cologne.[1]

We investigate the possibility to generate comprehensive consumer profiles of EV-owners who use public charging infrastructure. The overall goal of this paper is to produce profiles, based on a survey- and charging-data, which detail the various types of EV-drivers. This identification helps to define how the infrastructure needs to be organized from a user’s perspective to fulfil a purpose in DSM systems. It also permits to create pricing schemes for public charging stations. Moreover it serves to answer the question whether it is possible to conduct such a framework profitably.

The research question that follows from this concept can be formulated as follows: “How do consumers utilize public charging infrastructure? Is it possible to group consumer behaviour in order to create comprehensive user profiles?”

Building on these research questions the paper applies clustering methods and regression statistics to determine the user profiles. With this approach we contribute to the discourse in this field of research. We conduct a detailed analysis of the actual usage patterns and relevant factors for consumers to use public charging stations. Analysing how the actual demand integrates in such a system adds granularity to the DSM field of research.

The paper is structured in the following way. First an introduction to the electric vehicle market and the topic of public charging infrastructure is given. Then the research model for the underlying investigation is presented. Subsequently a literature review reveals the relevant streams of information related to the research. The ensuing description of the charging data gives an overview of the information that we obtain from RheinEnergie’s operations. Afterwards the dependent and independent variables of the research model are explained, followed by the methodology used for the classification and grouping of the variables. The results of the survey and the charging data, their discussion, and a final conclusion are going to consummate this paper.

[1] http://www.RheinEnergie.com/tanken

The results section combines the survey results and the charging data to reveal conclusive consumer-profiles. It equally shows whether the profitable operation of public charging stations is attainable.

The overall conclusion will consequently answer the research questions and summarize the findings and results. Additionally we mention ideas for potential future research.

3 Charging EVs: Challenges

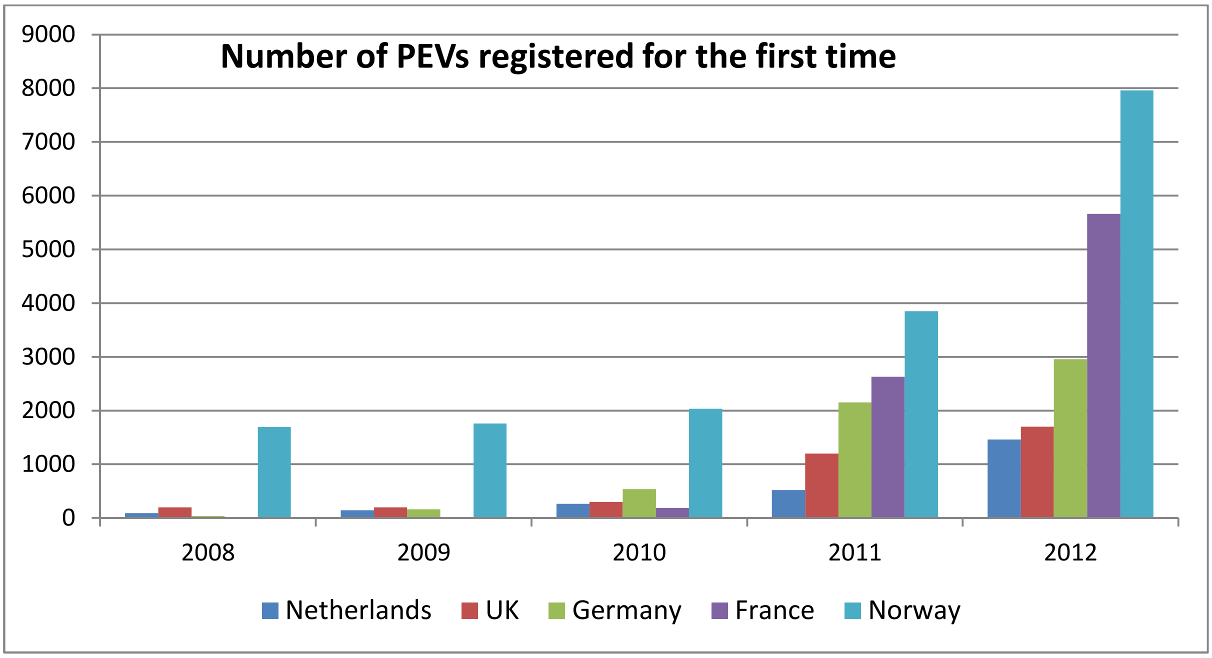
EVs have positive attributes for the means of urban transportation (Chan, 2001, p.278). Yet, the demand for electric vehicles is still strongly below the levels of cars propelled by internal combustion engines (Kraftfahrt-Bundesamt, 2013). This has a wide array of reasons related to the technological and infrastructural changes these types of vehicles bring about. The minuteness of sales in Europe makes this market a niche market. EVs currently offer less range than gasoline engines (Pearre et al, 2011, p.1172) and fully charging the batteries normally takes at least two hours (Schroeder, 2011).In the following section we present the challenges and achievements of the electric vehicle market and the respective charging infrastructure.

3.1 The Electric Vehicle Market

This paper concentrates on Europe with a particular focus on the German market. This is grounded on the fact that we conduct the underlying survey among costumers of RheinEnergie AG in the Cologne area. As a consequence, the herein obtained results are specific to the geo-political factors in this area. Every country in the European Union, but also the USA and others, has created specific laws and regulations for the investment, subsidization and operation of EVs and their infrastructure. On certain levels countries have already recognized that a harmonization of these deviating systems is necessary. This led for instance to a unified plug-system for the European market (ACEA, 2011). We explain this accord more detailed in the following chapter. (Bundesministerium für Wirtschaft und Technologie, 2011) (République Française, 2012) (GOV.uk, 2013) (Rijksoverheid, 2011) (IRS, 2009)

We focus on the EV market in Germany, but a wider comparison of additional markets helps to put it into perspective. Therefore we present the sales figures for electric vehicles in Germany and other major European countries below. The following figure shows the numbers of electric vehicles being registered for the first time in the respective country.

Figure 1: Number of PEVs registered for the first time



Sources:CBS, GOV.uk, Kraftfahrt-Bundesamt, Ministère de l'Ecologie, Statistics Norway,

The figures underpin that the sales of plug-in electric vehicles (PEV) are still very marginal when compared to the overall sales in the personal vehicle sector. When comparing the sales of regular cars with those of EVs on the German market, we notice that EVs have a market share of about 0.1%[2]. In Norway this market share already amounts to 0.3%[3]. The low shares mark the situation for the electric vehicle industry in these countries. The marginal interest of clients is currently too little to spur large scale investments in infrastructure. That is why all of the above mentioned countries set up investment and subsidy programs to support the development of the industry and therewith infrastructure development.

The biggest projects to promote e-mobility are mostly related to governmental tax reductions and subsidies. The governments of the large European countries such as Germany and France support the research and development of EV technology. Germany is said to invest around one billion Euros until 2013 (Bundesministerium für Wirtschaft und Technologie, 2011). It is the German governments proclaimed aim to have one million electric vehicles on the roads by 2020, and six million by 2030 (Bundesministerium für Wirtschaft und Technologie, 2011). France has similar projects, with a stronger focus on infrastructure. Here the government plans to subsidize the research and development of vehicles and infrastructure in order to achieve sales of two million plug-in electric vehicles (PEV) and Plug-in hybrid electric vehicles (PHEV) by the year of 2020. Additionally the French

[2]Total sales in 2012 of 3,082,504 cars, 2,956 of those are electric vehicles (Kraftfahrt-Bundesamt).
[3]Total sales in 2012 of 2,442,964 cars, 7,961 of those are electric vehicles (Statistics Norway).

government continues to subsidize each purchase of an electric vehicle with a bonus of 7,000 Euros (RépubliqueFrançaise, 2012) until the end of 2013. Other European governments such as the Netherlands or the UK have similar projects to subsidize and promote the purchase of EVs and the construction of charging stations (GOV.uk, 2013; Rijksoverheid, 2011).

In the USA the governmental support initiatives are distributed among federal and state incentives. A federal tax rebate incentivises the purchase of an electric vehicle with up to $7,500. This amount is paid out to the first 200,000 electric vehicles on the US market (IRS, 2009). For example, the state of California adds an additional rebate of $2,500 for eligible vehicles (DriveClean.CA, 2013). So that consumers purchasing a vehicle can save significant amounts for the acquisition of an EV.

3.2 EV Charging Infrastructure

Building the charging infrastructure and maintaining it, is probably as vital as the actual spread of EVs in the market. As long as consumers do not perceive environment as being secure for the use of EVs, they will shirk the purchase of such cars (Franke et al., 2012, p.386). As a consequence governments equally support the creation of infrastructure projects. The French government plans specific investments to encourage the construction of charging infrastructure. The government passed legislation to invest 181 million Euros until 2015 and 303 million Euros until 2020, focussing on 3kVA chargers in licensed locations (Negre, 2011).

A vital part for the successful deployment of infrastructure in Europe is a unified plug-system. This was achieved when the European Automobile Manufacturers Association (ACEA) agreed to support the so-called “Type-2” plug for alternating currents and direct currents (ACEA, 2011). The firm Mennekes developed the Type-2 plug, a flattened plug that protects against polarity reversal (Mennekes Elektrotechnik GmbH & Co. KG, 2011). The plug has seven connectors, four for AC as well as DC charges, one for the earth lug, and two for the communication with the charging infrastructure (proximity and control). The plug allows bidirectional energy flows. This makes V2G technologies possible for this type of plug. (Mennekes Elektrotechnik GmbH & Co. KG, 2013)

For future implementations of fast-charging stations the ACEA recommends the use of the unified “Combo2” plug, which can combine regular charging and fast charging via alternating and direct currents. This harmonization is a first step into the direction towards unified e-mobility systems in Europe. It contributes to the convenience of the charging stations. However discrepancies remain. One of the most fundamental differences in these countries is the concept for pricing the charging services[4]. In this paper we investigate the consumer perspective in order to derive profiles in terms of preference types. The preferences of consumers have an effect on the convenience of the charging structure and the frequency of usage. The convenience of the charging stations depends on several preferences, which we discuss in section 3.

In order to gain an overview of the current public infrastructure in the different European countries, it is a straight-forward approach to count the number of available charging stations. For this purpose we consult the website Chargemap.com. The website does not deliver a fully accurate and objective comparison, but it can give an indication about the development of the infrastructure networks per country. The following table shows the number of charging stations per country. Here we quote the actual number of charging poles and not the number of plugs that are connected to each station.

Table 1: EV Charging Stations per Country

Country	Number of stations
Netherlands	4,039
France	2,045
Norway	1,198
United Kingdom	1,094
Germany	1,078

As of 10.07.2013, Source: Chargemap.com

The table shows that the development per country varies depending on the support programs of the government and sales of electric vehicles. The Netherlands show the lowest number of new EV registrations per year in Figure 1, yet the country offers 4,039 charging stations. This can make it more attractive for motorists to change from an ICE vehicle to an EV, as they can rely on wide-spread (charging-) service network.

3.2.1 The Difference between AC and DC Charging Infrastructure

For users and suppliers of charging infrastructure it is important to know that there are significant differences between the various types of charging systems. A very practical factor that strongly depends on the applied charging technology is the charging-time. It can have strong effects on the perceived convenience when using a charging station (Botsford & Sczcepanek, 2009, p.7). Additionally the prices for the different kinds of charging equipment vary significantly (Schroeder, 2011). The main distinction between the charging stations is the usage of alternating (AC) or direct currents (DC) (Schroeder, 2011). A station that uses alternating currents has a direct connection to

[4] See for example http://e-laad.nl/oplaadpas-aanvragen, https://www.rwe-mobility.com/web/cms/de/1311934/produkte-services/rwe-epower/rwe-epower-sms/, or https://www.autolib.eu/fr/offres-et-tarifs/tarifs-charges-particuliers/

the AC-grid and transmits the energy to the car's inverter. The inverter transforms the energy into a direct current to charge the battery. For a more efficient charge, DC-inverters are directly built into the stations. They can transform the AC current into a DC current more efficiently and hence charge the batteries with a much stronger direct current than the car's internal devices. As a consequence DC charging stations are capable of recharging the batteries significantly faster than AC stations (Schroeder, 2012, p.138; Botsford & Sczcepanek, 2009, p.2). However this effectiveness comes at price. The following table lists the different types of charging equipment and their respective procurement prices.

Table 2: Comparison of Charging Equipment Performance and Costs

	"Super-Fast" DC public	Level III DC public	Level III AC public	Level II AC public 3ϕ	Level II AC public	Level II AC home
Load Limit (Volt)	2,000	500	400 (3 phase)	230 (1 phase)	230 (1 phase)	230 (1 phase)
Load Limit (Ampere)	125	125	96	32	16	16
Current	DC	DC	AC	AC	AC	AC
Power (kW)	250	63	50	7	4	4
Duration of a 20kWh charge cycle (min)	5	19	24	164	333	333
Total investment cost (EUR)	125,000	95,000	90,000	4,000	2,000	500

Source: Schroeder, 2011, p.138

The table shows the price and charging-time variations according to the charging technology. It underlines the simple connection between charging speeds, energy and prices. The higher the desired charging speed, the more indispensible it becomes to apply DC solutions. The quicker solutions also bring about a higher cost of the infrastructure. When drivers charge their EVs at home, they use the regular residential AC grid connection. For home-charging processes most energy providers charge the regular residential energy-prices (Axsen & Kurani, 2012). The potential to offer charging services at a higher price point than the residential energy prices is hence rather possible for outside-the-home occasions. When the charging equipment is significantly reducing the charging duration at an external location, it "seems" possible to define it as a distinct product, which is detached from residential energy-prices. Naturally this equally depends on the consumer's willingness to pay for this additional charging service. In this paper we attempt to cluster consumer sentiment according to the utilization of the public charging infrastructure. Information of that kind helps to define pricing-models and to understand how consumers perceive the service of public charging infrastructure as compared to home-charging. This ultimately helps for the definition of external fast-charging infrastructure as a unique product.

3.3 EV Market Challenges

The previous chapters described the EV market and the infrastructure that currently comprises this niche market. However, they also reveal the challenges that this new transport ecosystem still faces. Despite the governments' proclaimed goals, low sales numbers still cause consumers and suppliers to be doubtful about the future prospects of EV transportation (Kleber, 2011). The uncertainty that originates from these effects lets the market participants question the future profitability of EVs and the associated infrastructure. Due to the governmental subsidies that are pushed into this market, an undistorted picture of the situation is not available. The missing objectivity makes it hard to judge whether this ecosystem is self-sustaining and profitable in the long-term. We aim to find factors of consumer behaviour that are vital for an effective construction of EV infrastructure in public locations. Based on these factors we classify different user-groups for EV charging services, which eventually helps to reduce the missing objectivity and shows whether this sector has a profitable future. We conduct our analysis according to statistical methods that we present in the course of this paper.

3.4 RheinEnergie Charging Stations

In collaboration with the distribution system operator of Cologne we are able to study EV-owners and their charging habits. The firm called RheinEnergie AG maintains a network of charging stations within the city of Cologne (Germany), which makes the conception of consumer profiles possible. RheinEnergie AG[5] conducts the network and generously supplies the data for this research. The firm's charging stations are located at central locations, for example at the airport, albeit it also supplies home-charging solutions to its local clients.

Rheinenegie AG is a German energy distribution system operator that was a part of the municipal utility of Cologne from 1863 until 2002 (RheinEnergieAG[b], 2013). In 2002 the municipal utility split up into several individual companies initiated by European market regulations (RheinEnergieAG[b], 2013).

RheinEnergie AG was founded as a public limited company and is currently owned by RWE AG (20%) and GEW Köln AG (80%) (RheinEnergie AG[a], 2013). GEW is a holding company of the municipality of Cologne (RheinEnergie AG[a], 2013).

Today RheinEnergie AG is responsible for the management of the local gas, water, and energy infrastructure and is obliged to make the network available to all market participants (Deutsches Energiewirtschaftsgesetz, §12).

[5] On the internet: http://www.RheinEnergie.com

RheinEnergie currently conducts nine charging stations in the Cologne area in public locations. Many more are installed, but are privately owned. The data of the private stations is not available to our research. Their access can be restricted to certain types of user-groups, e.g. employees of a particular company, which can also bias research results. The nine publicly installed charging stations are situated in the city and at the airport.

Picture 1: One of RheinEnergie's Charging Stations in the City-Center of Cologne (Lungengasse)

Source: Rheinenergie AG

Table 3: Table 3: EV-Charging Stations in the Cologne Region

Location	Charging spots and opening hours	Address
Cologne City (Nähe Neumarkt)	2 Charging slots+ + 2 CarSharing (24 hrs)	Parkhaus Lungengasse 33/Ecke Clemensstraße, 50676 Cologne
Flughafen Cologne-Bonn	3 Charging slots (24 hrs)	Heinrich-Steinmann-Straße 12, 51147 Cologne
e-WOLF	1 Charging slot (during working hours)	Ernst-Heinrich-Geist-Straße 5, 50266 Frechen, vor dem Haupteingang der Firma e-WOLF
TÜV Rheinland	2 Charging slots (24 hrs)	Konstantin-Wille-Straße, 51105 Cologne
RheinEnergie AG Verwaltung	1 Charing slot (during working hours)	Parkgürtel 24, 50823 Cologne
Procter&Gamble	2 Charging slots (during working hours)	Wilhelm-Mauser-Straße 40, 50827 Cologne
KVB P+R Weiden-West	6 Charigng slots (24 hrs)	Aachener Straße/Bonnstraße, 50859 Cologne-Weiden
RVK Meckenheim	2 Charging slots (24 Stunden geöffnet)	Kalkofenstraße 1, 53340 Meckenheim
Kreissparkasse Cologne Parkplatz	2 Charging slots (Wokring hours)	Richmodstraße 13, 50667 Cologne

Source: RheinEnergie AG[c], 2013

Each charging pole is open for public access and features two Type-2 plugs and two Schuko plugs. The utilized Type-2 plugs limit the charging capacity of the stations to 32 Ampere and their specifications correspond to the "Level II AC public 3ϕ" charger in Table 2. The supplied Schuko plugs correspond to the "Level II AC public" charger. The users can decide to use either of the two connections to recharge their vehicle's battery. In order to be able to recharge their vehicles at one of the stations, users need to register on the company's website[6]. After the registration process the users can charge their vehicles at any of publicly available stations. They can decide to either send an SMS to a free service number or to use an RFID card to start the charging process. The process is stopped by unplugging the vehicle.

3.5 The Research-Model

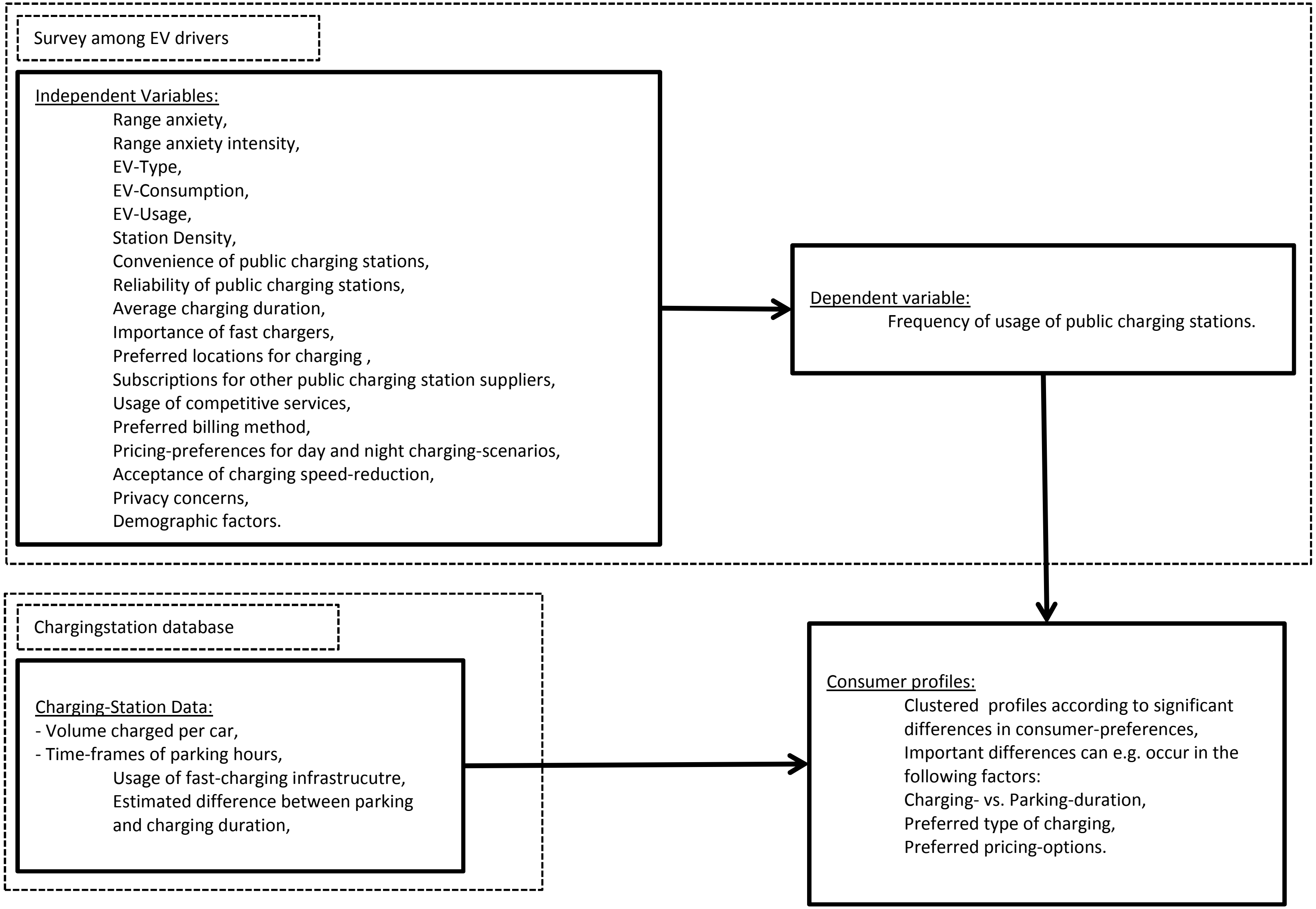
The research model for this paper avails information from two sources. We conduct a survey among EV drivers who are registered in RheinEnergie's database to obtain measurements of consumer behaviour. Additionally we use a database that contains usage-information of the charging stations to gain a more complete picture of the consumer preferences and behaviour linked to public charging infrastructure. RheinEnergie's stations record most of the operating-information for each charging process. We use the charging station data to validate the data that we obtain from the survey. This means that if controversial results arise from the survey, we use the charging data to compare the respondents' assertions with the actual charging data. The ability to reflect on or verify the results of the survey with an objective quantitative dataset enables us to create more reliable results.

The overall goal of the research model is to analyse the effects of consumer behaviour and the characteristics of charging stations on the frequency of usage of public charging infrastructure. We want to integrate the charging behaviour of EV owners in the academic context of electric vehicles and DSM systems. Additionally, we create comprehensive homogenous consumer profiles for public charging infrastructure. Our contribution to the discourse in this field of research is a detailed analysis of the actual usage patterns and relevant factors for consumers to use public charging stations. By analysing how the actual users integrate in such a system, we hope to add granularity to DSM research. The knowledge about specific consumer profiles can conceivably make a smart grid even smarter and move it closer to the actual consumer. This eventually leads to a more effective energy distribution, which contributes to an improved carbon footprint and better integration of renewable energy-sources. (Gangale, 2013)

[6]RheinEnergie Registration form:
http://www.RheinEnergie.com/de/unternehmensportal/technik_zukunft/elektromobilitaet_1/registrierung_2/index.php

The next chapter introduces relevant literature. Subsequently we present the different data sources. Afterwards we explain the dependent and independent variables. Thereafter we describe the conception of the survey and methodology.

Figure 2: The Research Model



3.6 Relevant Literature for the Clustering of Consumer Groups and the Pricing of EV Infrastructure

The literature review for our study concentrates on research with a focus on market segmentation, consumer behaviour and electric vehicles. The ensuing paragraphs present the literature related to these fields of research.

3.6.1 Consumer Profiles and their Relevance for Demand Side Management

Many energy utility companies and distribution network operators like RheinEnergie AG are beginning to investigate a more effective usage of their grids, as renewable energies make it more and more difficult to exactly match supply and demand (Ketter, 2010, p.3). As a consequence DSM systems are of great importance to these players in the market. The support of DSM solutions also requires these firms to observe the demand-side of the energy grid. This interest fosters the research of consumer profiles. As a way to create these profiles we, first of all, need to understand how consumers perceive the delivered service. Second of all, we need to analyse how users integrate the infrastructure in their lives and how they use it. And, third of all, we need to understand how they react to price changes that a possible DSM system brings about. Firms can subsequently implement this information into DSM systems to achieve a more optimized and balanced load curve.

Academic manuscripts in the domain of electric vehicles and demand side management refer to the analysis of consumer perception as an element of future research (Pearre et al., 2011; Schroeder, 2011; Turton & Moura, 2008). Their recognition is the foundation of the academic relevance of this paper. Correspondingly, the classification of consumer profiles for public charging infrastructure is not accomplished in the literature thus far. The recharging of EVs can have a significant impact on the grid and hence DSM management systems (Finn et al., 2012). It is therefore relevant to understand the impact of EV-drivers' charging-habits. Schroeder (2011) indicates that further research in the area of charging economics and user behaviour is necessary. He hypothesises that charging infrastructure might "be used as a perk to attract consumers while the main revenue is generated from the sale of other products, for instance parking space or commodities (Schroeder, 2011, p.144)". The author indicates that "EV users could possibly prefer simpler rates over erratic TOU (time-of-use) tariffs (Schroeder, 2011, p.144)". This further demonstrates that consumer profiles for charging infrastructure are pertinent for the creation of economically feasible charging solutions.

Similar approaches have already been conducted by Shafiei et al. (2012), who apply behavioral data in an agent based methodology. The authors apply this technique to predict the market share of electric vehicles on the Icelandic market. Pearre et al. (2011) analyze driving patterns of ICE vehicles to establish range requirements for electric cars. In their analysis the authors acknowledge that "a form of driver travel adaptation (…..) is charging during the day (Pearre et al., 2011)".They notice that future articles “will analyse each trip rather than each day, and the frequency with which vehicles park at locations likely to be effective vehicle charging sites (Pearre et al., 2011)”. Moreover they underline that research that focuses on the EV market acceptance needs to investigate the perception of customers rather than the needs which are dictated by travel patterns (in their case travel patterns of gasoline cars). Lastly the scholars point out that even automakers show little evidence that they understand the relationship between driving and market segmentation. This relationship equivalently affects charging processes and thereby DSM systems. Turton & Moura (2008, p.1105) mention that knowledge about consumers’ acceptance and enthusiasm is key for the provision of charging and discharging (V2G) services.

In synopsis we can assess that the assertions by Pearre et al. and Shafiei et al. corroborate the research of consumer profiles for public charging infrastructure and the ensuing effects for DSM implementations. Kotler (2005) points out that in order to create consumer profiles that actual users have to be identified. The identification of users includes values and perceived benefits that convince them to use these services (Kotler, 2005, p.674).

We contribute to this literature by adding a consumer perspective and associated values to the demand side-management context. We use market research methodologies to cluster consumers and assess their capacity and will to contribute to DSM systems for electric vehicle charging. This approach fills the analytical omissions that the above mentioned authors left in their research.

3.6.2 The Pricing and Economics of Charging Infrastructure

The economics and pricing possibilities of charging infrastructure can vary significantly depending on the geographic location and the political framework in which they are analysed. As a consequence the varying results of the studies need to be evaluated with respect to these facts. A direct comparison is sometimes not feasible.

Schroeder (2011) presents a full economic rationale for public fast chargers. After defining the relevant input parameters “Investment costs”, “EV market-penetration”, “demand for fast-charging”, “use-patterns”, “electricity prices and tariffs”, and “electricity generation”, he shows how the mark-up and the demand affect the ROI of fast-charging stations. Based on a EUR 95,000 expenditure (capital and operating expenses) and a mark-up of 30% over regular European Energy Exchange prices (EEX) (estimated at 23.7ct/kWh on average), an independent charging station operator would require 30 vehicles per day in order to break even. In a second example with 55,000 EUR total investment expenditure and the same mark-up a reduction of 10 cars per day is feasible to achieve a positive ROI. A rate of 10 vehicles per day in the same scenario would require an energy price of at least 36.7 ct/kWh on average to recoup the costs. 36.7ct/kWh can be converted into variable costs of roughly EUR 5.50 per 100km, which is comparable to state-of-the-art gasoline cars. Additionally he finds that time of use rates improve the revenue stream by 3% - 5%. However Schroeder also recognizes that simpler tariffs are more likely to be better understood by consumers. In his estimation the author assumed that independent operators run the charging stations. These firms are liable for paying grid-tariffs. About 25% of the electricity costs for commercial services are ascribed to these tariffs. The grid-tariffs can be avoided, if German utility companies run the charging stations instead of independent operators. This can ultimately result in a 30% reduction in costs. (Schroeder, 2011)

These sample cases drawn by Schroder (2011) underline the dependency of the current EV infrastructure on governmental policies (such as tax exemptions) and stable energy prices. Moreover he mentions that knowledge about consumer behaviour related to charging stations is a vital factor for the widespread adoption of EVs (Schroder, 2011).

Another study underlines the fragility of the EV infrastructure's success. Li (2011) makes an ROI calculation based on information from Beijing, China. As cost factors he considers the surface area of the charging stations, rent, equipment costs, construction costs, and the operational costs for batteries. Additionally he defines five time-of-use rates for Beijing per day (valley, flat, high, peak), where flat tariffs occur twice from 12:00 – 18:00 and 22:00 – 24:00. Li bases his calculation on an equally distributed demand over the five tariff periods. This yields an average purchase price of 0.978 RMB Yuan per kWh for charging station suppliers. Due to strong correlation between oil and energy prices in China, he expects this price to rise. Li shows that Bejing charging stations would require at least 1.478 RMB Yuan per kWh in order to be profitable. The cost-structure of the stations and the energy prices are the cause for this effect. However EV drivers in China can solely accept a maximum price of 0.695 RMB Yuan per kWh. The inclusion of the battery costs and the higher expenditure of an EV as compared to a regular ICE vehicle create this price-ceiling for Chinese consumers. Therefore consumers do not have a price incentive to purchase an EV, as the capital and operating expenses on a regular vehicle are still cheaper. The result is a shortfall of 0.783 RMB Yuan per kWh for a profitable operation of the charging stations. If Chinese oil and energy prices increase by 25%, the scenario attains a break-even position. Additionally, Li points out that a healthy balance between EVs and charging stations is essential to achieve a station load that maximizes profits. Applied to Beijing's situation this amounts to 672 charging stations. The author notices that utilities or associations of independent charging station operators have cost advantages over single suppliers.

In this study Li does not fully consider the ratio of charging instances at home and at public charging stations. He presumes that there is no arbitrage between the two electricity prices. In this sense the author does not fully consider the added service of fast-charging infrastructure. He assumes that consumers are unwilling to pay higher prices at public charging stations.

Other papers in this stream of literature equally emphasise the importance of off-peak hours for the charging of EVs. Lyon et al. (2011) show that load shifting to off-peak hours can have a significant impact on the charging costs for EVs. A simple timer that initiates charging from 0.00 – 8.00 o'clock yields very effective results and does not justify the implementation of a highly optimized solution. Full optimizations would yield modest additional savings. These do not rationalize the additional infrastructure costs that are required to implement such systems. Lyon et al (2011) conduct their study on two American independent system operators (ISO's), which need to commit significant amounts of costly resources (mostly gas) to respond to daily peak demand.

Our work differentiates itself from the above presented stream of literature in that we investigate the demand-side of the public charging infrastructure. Schroeder (2011), Li (2011) and Lyon et al. (2011) take the supply side as their point of view and calculate the respective costs of the system assuming certain degrees of system workload. Our method is to take a different perspective and measure the system workload and its characteristics. In this sense we add an additional point of view to the evaluation of charging stations. We conduct a survey and analyse EV drivers and their actual usage of the charging infrastructure. Based on these analyses we infer system requirements and consequences for DSM systems. Our approach complements the economic picture of public charging infrastructure and this stream of research.

3.6.3 Clustering of Consumer Groups according to Preference Profiles

Consumer segmentation is the means of adapting products and prices to a diversified heterogeneous base of consumers. "A firm segmenting its market is seeking to group potential customers into homogenous groups that are large enough to be profitably cultivated (Churchill et al., 2005)." Firms use this approach to match their products and services with consumers' unique needs, characteristics and behaviours (Kotler, 2005). These unique attributes can be clustered along various types of parameters including socioeconomic, psychological, geo-demographic, and buyer behaviour variables (Churchill et al., 2005). Essentially one could hence recognize each individual buyer as a separate market; however a complete segmentation is not always worthwhile. Instead it is more goal-oriented to create broader classes of buyers who differ significantly in their product needs or buying responses. (Kotler, 2005)

A particular type of segmentation takes place in niche markets. These markets are normally relatively small and attract only few competitors. Niche markets have to be well understood, so that clients are willing to pay a price premium (Kotler, 2005). In this respect an additional type of marketing is micromarketing, where products and services are tailored to specific individuals and locations.

Niche marketing approaches for EV charging stations are of a more limited nature. The product offers marginal amounts of tailoring to specific users groups. This is because the location and services (parking and charging) of the stations are fixed. However, the network of charging stations and the pricing system are adjustable factors for charging services.

The concept of consumer profiles and segmentation is applied in many different industries classifying the respective clientele. Hallmann and Wicker (2012) use the notion of consumer profiling to determine important factors for the intention to revisit marathon events. They apply a logistic regression analysis, which reveals that the intention to revisit a marathon is influenced by the length and the daily spending of the trip, as well as, the overall satisfaction with the event. The authors use an online survey and capture a large sample of marathon runners (n = 1,370). Subsequently Hallmann & Wicker apply Ward's method on half of the sample. This method ascertains three clusters. They analyse the full sample using a "quick cluster technique based on k-means" (Hallmann & Wicker, 2012). This confirms the three pre-defined clusters. Finally the authors use a logistic regression to measure the impact of the profiles on the intention to revisit the event (Hallmann and Wicker, 2012). Although their field of research differs greatly from the one investigated in this study, the authors' methodological approach seems suitable for the investigation of consumer groups of EV charging stations. Just as the marathoners revisit an event based on certain factors; EV-drivers revisit specific charging stations based on their experience of pervious charging occasions.

Hanson et al. (1994) take a similar approach to cluster consumers of sea food. The authors apply a logistic regression on the data of 3,600 telephone interviews, which leads them to define five consumer groups. The results reveal that the geographic location of the consumer plays a strong role on the consumption, as well as, several other factors such as race, seasonality, price, and consumption-related indicators (e.g. boniness). On the basis of these results the authors are able to suggest foci for sea food marketing and pricing. For instance, they attest restaurants to concentrate marketing efforts on high income clients with few children.

In this work we apply the method of consumer clustering to users of public charging infrastructure. With our work we contribute to this stream of literature by adding a new type of consumer to the clustering field. Additionally we show that clustering is an appropriate way to analyse new types of consumers. The scholars that we present above rather focus on very established types of consumers. However we point out that these clustering procedures need to be repeated in order to capture the changes in the consumer group and their environment.

3.6.4 Involvement and Consumer Behaviour

The concept of involvement plays an important role in the studies of consumer theory. Laurent & Kapferer (1985) describe involvement as “causal or motivating variable with a number of consequences on the consumer's purchase and communication behaviour (Laurent & Kapferer, 1985)”. Different levels of involvement can strongly affect the way consumers make their purchase decisions. In their study Laurent & Kapferer assess that a single “involvement”-score is neither achievable nor meaningful. Instead they define several facets of involvement that can describe the engagement of a consumer with a product. These facets comprise for instance the perceived importance of the product, the probability of mispurchase, and the perceived sign value of the product. In this context sign value refers to the symbolic value of a product and its “psychological risk” (Laurent & Kapferer, 1985). Building on these facets the authors define a survey-method to describe consumer profiles. These require antecedent conditions of involvement in order to predict behaviour. They conclude that the term, if used alone, is too imprecise and requires a word specifying the kind of involvement (Laurent & Kapferer, 1985).

Laurent & Kapferer use a survey to measure the facets. Their survey is mainly focused on appliances and fast moving consumer goods (FMCG’s) among a sample of housewives. As a consequence, it is not possible to directly relate their research to a topic involving EV charging stations. The expectations of consumers towards the product and the functioning of the stations differ strongly from those of FMCG’s. Additionally, the charging stations rather constitute a service than an appliance or product. As a consequence we consult other studies related to the subject of involvement.

Scherer & Lane (1997) describe a type of involvement that they refer to as attribute involvement. This facet of involvement concentrates on the perceived importance of a product’s attributes that are salient to an individual consumer (Scherer & Lane, 1997). It focuses on the function, usefulness, quality and services associated with the product (Scherer & Lane, 1997). “According to the usability hierarchy, attribute involvement would be most involved at the time of product selection when device appeal becomes a key influence on a product's ultimate usability (Scherer &Lane, 1997)”.

We try to use the insights gained by the above mentioned scholars to estimate the involvement of EV drivers with public charging infrastructure. We contribute to this debate by adding an additional product-group to the framework of involvement.

4 Description of the Data

The following section introduces the data sources for this study. We obtain behavioural data from two sources. The first source is the charging data, which is provided by RheinEnergie AG. The second source of data is the survey that is conducted among RheinEnergie's EV-clients. We cross-verify these two sources to create comprehensive consumer profiles. First the charging data reveals the time horizons, charged energy-quantities and parking durations of the consumers. Second the questionnaire probes deeper for behavioural information related to charging processes. Below we present the variables of the data sources.

4.1 Charging Station Consumption Data

RheinEnergie utilizes two types of charging stations; one produced by "Mennekes Elektrotechnik GmbH & Co. KG"; the second type is produced by "Elektro-Bauelemente GmbH" (EBG). Mennekes charging stations use a proprietary system (a PC-terminal and software) to record the data. EBG charging stations use an open API for the communication, which RheinEnergie engineers use to create the firm's own control software. Each client with an electric vehicle has an account with RheinEnergie, which includes the client's mobile phone number. Before each charging process a client needs to send a text-message to the central registration number to identify her - himself at one of the poles or use her/his respective RFID card. The server subscribes the user to the charging pole and sends a text-message to the respective station via the GSM network. After the charging pole received the text message from the server, the charging process begins. In the case of an RFID, the charging pole first sends a text message to the server. After the server confirms the user it sends a text message back to the pole to start the charging process. The charging instance stops once the car's battery is full or the plug is pulled from the car's socket. When the cable is unplugged, the charging pole sends a text message to the server notifying it that the charging process has stopped. The server acts as a mediator recording the interactions between the users and the charging stations. The software records each individual event that occurs at the stations. Additionally it records several supplementary parameters of the charging events. These parameters differ according to the manufacturer of the charging station. RheinEnergie used EBG charging stations from January 2010 to July 2013. The company started to use Mennekes charging stations in January 2013 and they are currently still in use. Table 3 and 4 show the lists of the recorded information.

Table 4: EBG Charging-Stations, recorded Information from January 2010 to July2013

Parameter	Description
Meter value	Records the amount of energy that was transferred to the car's battery. The values are stored in kWh.
Time-stamp	This column registers each moment in time that an operation takes place.
Flag	Indicates whether the charging stations sent or received data via the broadband connection.
Serial number	Gives a serial number for each recorded operation.
Socket	Indicates the type of socket that is used for the charging process. (left or right side of the charging pole)
SMS-Text	This column quotes the transmitted text that was either send by the charging station to the server and vice-versa.
Initialization switch	The column quotes either "ON" or "OFF" depending on whether the charging stations initiated or ended the electric current.
Client ID	Shows the ID of the client membership-card that was used to start the charging process.
Client-Type	Here the following distinctions are made: private, professional and internal.
Charging Station ID	Quotes the charging stations ID.
Charging Station Installation Date	Quotes the initial installation date of the charging station
Charging Station Manufacturer	Quotes the manufacturer of the charging station.
Charging Station Description	Quotes the exact positioning of a charging pole, e.g.: "left charging station".
Location	Quotes the address of the entire charging station.

Source: Rheinenegie AG, IT Department, Porsch, P.

Table 5: Mennekes Charging-Stations, recorded Information, from January 2013 to September 2013

Parameter	Description
Location	Records the amount of energy that was transferred to the car's battery. The values are stored in kWh.
Transaction ID	This column registers each moment in time that an operation takes place.
Identification medium	Gives a serial number for each recorded operation.
ID number	Indicates the type of socket that is used for the charging process. (left or right side of the charging pole)
SMS-Text	This column quotes the transmitted text that was either send by the charging station to the server and vice-versa.
Authentication result	The column quotes either "ON" or "OFF" depending on whether the charging stations initiated or ended the electric current.
Authentication timestamp	Shows the ID of the client membership-card that was used to start the charging process.
Bill timestamp	Here the following distinctions are made: private, professional and internal.
Authentication meter	Quotes the charging stations ID.
Bill meter	Quotes the initial installation date of the charging station

Source: Rheinenegie AG, Technik Department, Lars Spitzlei.

4.2 Relevant Variables in the Context of Consumer-oriented Public Charging Infrastructure

Next to the data from the charging stations, we conduct a survey to analyse consumer behaviour related to charging processes. In the following paragraphs we present the dependent and independent variables for the analysis of the survey. First we illustrate the dependent variable "frequency of usage". Afterwards we explain the independent variables, which we apply on the basis of literature reviews for each concept. We include concepts that are most relevant in the context of public charging stations and EVs. These comprise the notions of range anxiety, station density, consumption-factors, demographics, preferred locations, billing methods, willingness to delay a charge, privacy concerns, attribute involvement, and measurements related to the providers of charging stations.

4.3 Dependent Variable for the Creation of Consumer Profiles

The two dependent variables that are explained by the independent variables in the regression formula have to reflect the overall level of satisfaction with the infrastructure. To achieve this we choose the variables "frequency of usage" as the dependent variable for the model.

The indicator "frequency of usage" shows how often EV drivers actually use the infrastructure on a scale of "once a day" to "once a year" or "never". The more frequently an EV-driver uses the charging stations, the stronger should be the influence of the independent variables. A similar dependent variable has been used in studies to investigate the long-term success of reoccurring sports events or satisfaction with food products (Hanson et al., 1994; Hallmann & Wicker, 2012).

4.4 Independent Variables in the Context of Consumer-oriented Public Charging Infrastructure

In the following section we introduce and explain the independent variables of the research model. It is worthwhile to point out, that we do not necessarily include all of these variables in the final regression and clustering models, as we will solely include those with strong explanatory power. We will first asses their impact on the dependent variable using bivariate and regression analyses. Afterwards we create the clusters according to the results.

4.4.1 Range Anxiety

Range anxiety describes as driver's feeling of being afraid to deplete the battery power before arriving at the actual destination (Tate et al., 2008). Range anxiety is a variable that is particularly important in the field of electric vehicles. Franke et al. (2012) conduct a longitudinal study with 40 EV drivers and measure the psychological effects of range anxiety. They devise four levels that influence the transition from the objective physical situation to the subjective psychological one. They refer to the first level as "cycle range", which they measure according to the vehicle's standard specifications; it acts as an objective point of reference for the other three levels. The second level is called "competent range" and refers to the range that each individual can obtain given their eco-driving competence (Franke et al., 2012). Driving styles can affect the achievable range of an EV. It follows that the competent range of an individual driver differs from the cycle range of the EV. The third level is "performant range". It measures the driver's motivational strength and habits of eco-driving.

“Driving behavior is influenced by various motives with range optimization being only one among others and, hence, performant range will likely be lower than competent range (Franke et al., 2012)”. The fourth level is termed “comfortable range” and describes the range that users actually utilize. It is defined as the highest trip distance between two charging occasions or the lowest charge level which a user still considers comfortable. The authors’ results reveal that range is a central attribute for the satisfaction with an electric vehicle. Most users in the study (29 of 36) indicate that the range of their test vehicle (BMW Mini Cooper with a cycle range of 250km) was sufficient. Nevertheless the users never mention range in a positive context when talking about the EV. The authors describe this as a “Zeitgeist effect because today, the range of an ICE vehicle is a primary anchor from which users evaluate the range (Franke et al., 2012)”. Some users are also disappointed due to their inability to match their performant range with the actual cycle range of the vehicle. As a consequence to this problem users start to evaluate range in terms of subjective typical trips, e.g. “Twice to work and back”. Some users (17 of 36) devise methods to circumvent the range-problem. They avoid certain trips or carry out frequent battery top-ups. “More users (19 of 36) were categorized as regarding range as a challenge or problem-solving task to be solved, rather than a threatening encounter to be avoided (Franke et al., 2012)”. Users also believe that many factors influencing range are beyond their predictive capabilities. This creates uncertainty, which stands central in this study and only a few subjects are able to resolve this problem with an accurate mental model. (Franke et al., 2012)

Other studies further corroborate these findings and apply them to the purchase of EVs. These EV purchasing habits of a population need to be considered, when trying to assess the market and its potential. Shafiei et al. (2012) present scenarios for these habits and use the Icelandic market as an example. They estimate the market-penetration-rate of EVs to vary between 20% and 60% by 2024. This percentage also depends on the development of petrol and electricity prices. Their estimation also includes vital factors such as the prices of EVs and the driver’s range anxiety. Despite the inclusion of the concept of range anxiety in their study, the authors assume that drivers do not frequently experience range anxiety. This however does not seem to be the case when considering the results of Franke et al.. Bakker (2011) further emphasizes the significance of range anxiety as a factor for the development of consumer profiles. He points out that “experiments have shown that public charging infrastructure reliefs the electric vehicle driver from this range anxiety (Bakker, 2011)”. Notwithstanding that this can only be achieved if there are enough charging facilities available to the drivers. Consequently drivers who experience range anxiety top up their vehicles’ batteries more often than those who feel more confident to drive longer distances on a single charge.

We measure range anxiety in two ways in the survey. The survey asks EV owners to rate their experience concerning this variable in terms of frequency and intensity. We record both concepts on semantic scales 1 – 7 (“fully agree” to “fully disagree”). We expect that drivers who “agree” with the range anxiety question show a higher frequency of usage of charging stations.

An aspect that is closely related to the concept of range anxiety is the density of charging stations in a geographical sense. The following paragraph discusses the variable station density.

> **H1:** Range anxiety has a positive relationship with the frequency of usage of public charging infrastructure.

4.4.2 Station Density

To gain a deeper insight and to refine consumer profiles more accurately we ask the respondents to classify the level of station density in Cologne. The variable adds to the interplay of station-density and range anxiety and allows for a more accurate clustering of consumer profiles. As a consequence it is possible to judge whether range anxiety as a personal feeling, or the density of stations as geographic actuality, is of more importance when designing the profiles.

We use these two indicators to reflect daily situations and obstacles related to individual passenger traffic using EVs. It is helpful to know which one of these two variables (density or range anxiety) has a stronger effect, because this study is the first attempt to segment EV-drivers and can affect future research.

Therefore the density of stations adds granularity to the clustering of EV-drivers. It allows to distinct the respondents according to their charging habits and range anxiety. The station density can have effects on the frequency of usage because the more stations are available the more likely it is that they are in a suitable location for the individual driver.

Clemenz (2006) further underlines the importance of spatial dimensions in a study investigating the locational choice of gasoline stations. He reveals that the competition among gasoline stations is affected by the density of local competition. “That is, the density of stations rises less than proportionally with population density, since fiercer competition drives price down (Clemenz, 2006)”. So despite the necessity to create local charging stations, the occurrence of competition can drive prices down, making it less attractive and profitable for firms to invest in more charging stations. We discuss the issue of competition in one of the next paragraphs.

We anticipate that a high score for density of stations positively affects the frequency. We measure station density on a semantic scale 1 -7 (“fully agree” – “fully disagree”)

H2: Station-density has a positive relationship with the frequency of usage of public charging infrastructure.

4.4.3 Technical Factors that influence EV Transportation

There are three main technical aspects that influence the transportation convenience of electric vehicles. Despite the type of vehicle, the factors “consumption” and “usage” are of paramount importance to integrate an EV into one’s daily life. Subsequently we explain these three factors.

The type of EV is a relevant variable, because there are various manufacturers who produce many different types of vehicles. The respective vehicles are a vital part, when clustering consumers according to their handling of public charging infrastructure. The consumption, charging speed, or brand influences the consumer’s satisfaction with the vehicle. As a consequence these variables are valuable to include. They add scope to create a comprehensive picture of a consumer’s perception of the charging infrastructure.

The Energy-consumption of an EV is dependent on the type of car (manufacturer), engine, and the driving-patterns of the owners. We obtain the data on EV charging from RheinEnergie’s database. The importance of the consumption is underlined in studies that investigate the price elasticity of demand for car fuel. In a study by Romero-Jorda et al. the authors find that a reduced vehicle-consumption does not necessarily imply a reduced demand for the product (Romero-Jorda et al., 2010, p.3905). Brons et al. use the consumption per car as a variable in their model and are able to show that it influences the price elasticity of demand for gasoline (Brons et al., 2007, p.2107). In the survey we ask respondents to quote their type of EV, their average weekly mileage, and how their EV’s consumption (in kWh / 100km). We expect that the more energy an EV consumes the more likely it is that the drivers need to use public charging infrastructure.

To complement the variable “range anxiety”, we add a further question concerning the mileage of a vehicle. We ask respondents to indicate the average amount of kilometers they drive between two charging instances. This information is based on indications by Franke et al. (2011), who define this distance as comfortable range.

We estimate that a high score for the consumption and a low score for the average distance between two charging occasions positively affects the score for the frequency of usage of charging stations.

We predict that a low score for the average weekly mileage negatively influences the frequency of usage. We ask nominal questions to indicate the consumption, distance between two charges, and the weekly mileage.

H3: EV-consumption has a positive relationship with the frequency of usage of public charging infrastructure.

H4: The distance between two charging instances has a negative relationship with the frequency of usage of public charging infrastructure.

H5: The average weekly mileage has a positive relationship with the frequency of usage of public charging infrastructure.

4.4.4 Demographic Factors of EV Owners

The theory of consumer segmentation suggests the inclusion of demographic factors for the clustering consumer profiles. Demographic factors are essential for the grouping of consumers, because the "needs, wants and usage rates often vary closely with the demographic variables (Kotler, 2005)".

We expect that the demographic data of respondents for this research differs from the population average. The "infancy" of the EV market and the high purchase costs of electric vehicles cause the probable divergence from the average. As a consequence, we compare these factors with the population average in order to show the deviation of the sample from the actual population. The data for the average population is retrieved from the German Federal Statistic Office.

The survey compiles the following demographic aspects: Income, Age, Gender, Education, Marital status, Children and Type of dwelling. Hidrue (2011) equally applies the variables for income, age, gender, and education in a research about the willingness to pay for EVs. The results of the survey show that the largest part of the sample (41.6%) has an income of $35,000 to $74,999, wherein the majority is in the bracket between $50,000 and $74,999 (22.5%) (Hidrue, 2011). Given this outcome, we expect a similarly high income for the respondents of this research. The age statistics in Hidrue's study demonstrate that the age group with the highest interest in EVs is between 25 and 44 years old (39.4% of the sample). 43% of the sample are male and almost 73% live in detached houses (Hidrue, 2011). The housing situation is relevant for the EV context and we elaborate it in a later chapter. Education reveals equally high results in Hidrue's study. Circa 39% of the sample finished high school and 36% have a BA or higher degree. Only 2% have an incomplete high school degree (Hidrue, 2011). Again, we expect a similar distribution for the survey among RheinEnergie's clients

The variables marital status and children are of interest, because nobody tested the integration of EVs in families' lives, yet. Hence this paper includes these variables as possible impact-factors on the consumer profiles.

4.4.5 Preferred Types of Charging-Speed and Locations, the Convenience of Public Charging Infrastructure

Especially from a consumer’s point of view it is important to be aware of the different types of charging infrastructure. The engineers Botsford & Sczcepanek define slow charging as an “overnight-charge” of 6 to 8 hours. It makes use of the on-board charging equipment of the vehicle (Botsford & Sczcepanek, 2009). Furthermore Botsford & Sczcepanek use the definition of the California Air Resources Board (ARB), which declares “fast-charging as a ten-minute charge that enables the vehicle to travel 100 miles (Botsford & Sczcepanek, 2009)” (Botsford & Sczcepanek, 2009). However this definition of fast-charging appears excessive when comparing it to the available infrastructure in the area of Cologne (see Table 2 and chapter 2.4). As a consequence, we define slow charging as a charging-process that utilizes the on-board charging equipment and a Schuko-plug. We define fast-charging, on the other hand, as a process that applies Type-2 plugs and external AC charging equipment, such as charging poles or wall-chargers. Currently RheinEnergie does not supply any DC charging stations, which essentially renders the definition of the ARB void for our purpose. Our separate definition of “fast” charging is employed throughout this paper and the survey. The distinction between fast and slow charging is vital for the clustering of consumer groups, because it constitutes an essential difference in the service propositions. We presume that the charging speed actively affects the perceived convenience of the charging stations.

Support for the distinction between charging-speeds and their importance is developed by Hidrue (2011). He found that one of the main concerns that consumers have when considering the purchase of an EV are the long charging periods (Hidrue, 2011). He finds that consumers are willing to pay an additional amount of between $425 and $3250 for an EV, if the general charging time is reduced by one hour. For every additional mile of range consumers are willing to add $35 to $75 to the invoice amount of their EV. The author quantifies the buyer’s willingness to pay for a reduction in charging time when he/she purchases the vehicle. He finds that buyers willing to pay $5646 for a charging-time-reduction from 10h to 1h for 50 mile recharge (Hidrue, 2011). These figures emphasize the relevance of charging-speeds for the public infrastructure. Hence the factor is included in the survey. EV-drivers are asked to indicate the importance of such infrastructure in public places. We expect that high scores for the speed of charging positively affects the convenience score of the stations.

An additional aspect, next to the speed of charging stations, is the location. Axsen & Kurani[a] (2012) find that about 48% of US households do not have direct access to level 1 (110V/120V) charging facilities. In San Diego county about one third of the new vehicle buyers have access to a level 2 (220V/240V) home charging. Besides the lack of higher voltage connections, in another study the authors also reveal that 4.4% have outlets at their work-place and 9.1% find outlets in other nonwork location (Axsen & Kurani[b], 2010). 45.3% of the respondents in Axsen & Kurani's research identify their home as a viable recharge location.

The results signify that the distribution, density and availability for charging stations are vital in order to ensure the integration of this technology into drivers' lives. Another noteworthy element regarding the location of charging stations is the type of dwelling. In the US around 10% percent of the population lives in apartment buildings that deny the possibility to install home-charging equipment (Axsen & Kurani, 2012). In Europe the percentage increases to 41.5%, and is particularly high in urban areas such as Cologne (The European Commission, 2013). In metropolitan areas less than 30% of vehicle owners have access to off-street parking facilities (Schroeder, 2012). These complex conditions render home-charging solutions impossible for a larger part of the population and require local public charging infrastructure. In the survey we ask respondents to indicate their preferred location for public charging infrastructure (home, city, countryside and periphery). We also ask respondents to indicate the type of dwelling that they live in. They can choose from three nominal options: "detached- and semi-detached houses", "attached multi-unit housing with a parking space", and "attached multi-unit housing without a parking space" We deduce that scores for detached or semi-detached houses negatively influence the frequency of public charging. We measure the importance of charging speed on a semantic scale 1-7 ("fully agree" to "fully disagree").

> **H6:** Fast-charging has a positive relationship with the convenience of public charging infrastructure.

> **H7:** Living in detached- and semi-detached houses has a negative relationship with the frequency of usage of public charging infrastructure.

4.4.6 Preferred Billing Method

Payment-and billing-methods are further relevant variables that concern the usage of public charging infrastructure. They have an influence on the purchase occasion and usage rate of the service, as well as, the attitude of the consumer towards the product. The factors include two levels of interaction. The first level is the technical setup of the payment and billing method, which we discuss in this paragraph. The second level is the interaction with the client and relates to the privacy of the process. We discuss the subject of privacy in the following section.

The technical side of the payment process leaves many different types of billing methods open to the preferences of the firm and the consumer.

Charging station suppliers often have to rent public parking spaces from municipalities and other institutions in order to offer their charging services to the public. To achieve a profitable business model, the provider of charging infrastructure has to recoup the cost for the parking space, the charging equipment and the transferred energy. Schroeder (2011) and Li (2011) described these issues in their work, which we present in the literature review. The cost structure translates into four different billing methods to calculate a unit price. Firstly, charging suppliers can bill EV drivers per kWh that they transfer to the car's battery. This approach requires the supplier to elevate the price per kWh to such a level so that he can cover the costs for the equipment and the parking space. Secondly, the supplier can charge clients on a time basis (e.g. per hour, or any other unit of time). Here the same logic applies as before, the supplier needs to recover all his costs by adding them to the hourly rate. Thirdly, it is possible to combine these two cost-drivers into a billing method that charges per time unit parked and kWh transferred. Kahlen et al. (2013) support the notion that EV-fleets can charge profitably using vehicle-to grid technologies.

In the survey we ask consumers to indicate their preferred billing method. The indication adds higher granularity in terms of behavioral aspects and the consumers' attitude towards the product. Additionally, the responses to this question can help in the definition of pricing models. We measure the preference for billing methods on a nominal scale, which proposes three billing methods: Billing per kWh, according parking duration, or per kWh and parking duration.

4.4.7 Willingness to Delay a Charge

As a part of the integration of DSM systems, energy consumers equally have to play their part in the eco-system. We mentioned before that DSM systems can only reach their full potential, if the demand side is integrated into the context. This requires that consumption shifts according to the availability of the respective loads (Lyon et al., 2011). For EVs this means that the time of a charge can change according to the load curve in order to optimize the equilibrium of the grid. However users need an incentive in order to act in line with such a system. To incentivize advantageous behaviors for public charging infrastructure there are basically three options. One; a price difference between on-peak and off-peak charging tariffs. Two; a difference in charging speeds between on-peak and off-peak hours. Or three, a combination of these two options. Scholars who publish academic works on the topic of DSM and charge-shifting mostly focus on plug-in hybrid electric vehicles (PHEVs). Weiller (2011) points out that circa "4% of all vehicles driven in the USA are on the road at any one time (Weiller, 2011, p. 3767)" and 85% - 90% are parked in various locations (home, work, commercial places). This leaves a strong potential for time-shifting technologies, because of the low amount of actively driving vehicles. She shows that the installation of charging infrastructure at home, work and in public places improves the balance of the overall load-curve. "During peak hours of the day, home energy demand, when people only charge at home, is 24% - 29.4% higher than when they can charge anywhere and 4.7% – 9.3% higher than when charging is possible only at work (Weiller, 2011, p.3772)". However Finn et al. (2012) also point out that the shifting of a charge depends on the "timeframe within which the load could be time-shifted without interfering with the user's need for the car (p.360)". They demonstrate that it is achievable to create financial savings for consumers and providers, if consumers are willing to engage into time-shifting technologies. Additionally Lyon et al. (2011) mention that the costs of making users charge the vehicles during the optimal timeframe has to weigh against the savings. In their model the authors show that the net present value (NPV) of the savings achieved with an optimal shifting technology is $10 more effective than the utilization of a timer that charges vehicles from 12AM – 8AM. The timer generates about $224 in savings. The difference in NPV between these two methods does not justify the installation of the optimal shifting technology. Other scholars, such as Hadley & Tsvetkova (2009), Lam et al. (2011), and Göransson et al. (2010) also acknowledge and support the shift of charging periods from on-peak to off-peak hours. They also sustain the potential savings that are associated with such schemes, and their effect to even out the overall load curve. For the clustering of EV-drivers we add the notion of delaying the charge of a vehicle due the assertion by Finn et al. (2012) that the delaying procedure should not interfere with the consumers need for the car. We add three questions to the questionnaire related to the concept of charge-shifting. Two questions investigate whether the EV-driver is willing to delay the charge due to cost-savings. Another question asks the respondents to indicate whether they are willing to accept the reduction of charging speeds when many users are connected at the same time. We measure the acceptance of a reduced charging speed on a semantic scale 1-7 ("fully agree" – "fully disagree").

We create two charging scenarios in order to ask for preferred pricing options. In the first charging scenario, which focuses on short-term visits of charging stations (e.g. in the city-center), we ask respondents to evaluate three options of a hypothetical charging situation. The first option proposes a high price for a full charge of their battery within 2 hours, the second option has a medium price and charges their car enough so they can safely drive home, and the third option suggest a very low price in return for a longer charging-period. Each option is evaluated on a semantic scale 1-7 ("fully agree" – "fully disagree"). In the second scenario we ask a similar question for overnight charges. In this scenario we offer two answer possibilities. The first option has a higher price and fills the cars battery within two hours. The second option has a low price but requires the car to be connected to the charging station the whole night.

We estimate that positive answers for the acceptance and willingness of these load-shifting technologies positively affect the frequency of usage of the charging stations. This is because users who do not like to engage in such technologies simply charge their vehicles at home, where no such burden intervenes with their charging-preferences.

4.4.8 Subscriptions for Public Charging Stations

We cluster consumers in the local market of Cologne. For this purpose we need to consider spatial and competitive factors. Clemenz (2006) shows that the spatial factor of competition has effects on prices, which inevitably means that it affects consumers. The competition for charging stations in the Cologne area is not fierce. There is one competitor next to RheinEnergie AG who offers public charging services. After the consultation of two websites (www.chargemap.com and www.e-tankstellen-finder.com) which offer databases with the locations of public charging stations, we found a total of six competitive stations. RWE runs all six of them and offers two types of payment methods for the usage of its services (RWE Effizienz GmbH, 2013). Clients can either opt for a contractual basis or hourly payments. The contract has a minimum term of 12 months and costs €4.95 per month; each kWh that a client charges consequently costs €0.30 (RWE Effizienz GmbH, 2013). Without the contract users can charge their vehicles at the RWE stations using the SMS service. This service costs €3.95 per hour for a 16 Ampere charge. RWE's stations are not situated in the city-center but rather in the urban area and periphery of Cologne.

The survey asks consumers to indicate whether they have one or more subscriptions for competing services. A second question aims to elicit the frequency at which consumers use these services. We estimate that a higher number of subscriptions positively affect the frequency of usage of public charging stations. The first question asks EV drivers to indicate the types of subscriptions that they have, e.g. different service providers and other firms (scale 1-7, "fully agree" – "fully disagree"). The second question measures on a scale 1-7 ("fully agree" – "fully disagree"), the user's agreement with the statement that they frequently charge their cars at different service providers.

> **H8:** The possession of subscriptions has a positive relationship with the frequency of usage of public charging infrastructure.
>
> **H9:** The use of different charging services has a positive relationship with the frequency of usage of public charging infrastructure.

4.4.9 Privacy Concerns, User-Identification

The identification of users at the charging stations can pose a security risk, because the user's data is shifted and transmitted via various nodes (charging stations) and the server of the charging service provider. Therefore we need to consider the privacy concerns among consumers. Drivers that subscribe to charging services can be tracked in the system, as every public charging instance is recorded. We conduct the survey for this study in Germany, where privacy feelings are historically particularly strong in the population and legislation (Flaherty, 1992, p.21 ff). Hence a future academic comparison of the results needs to take the different attitudes of consumers towards privacy into account. The European Union recognizes similar concerns with regard to smart metering. In a statement the European data protection supervisor notes that: "…unless adequate safeguards are established to ensure that only authorized third parties may access and process data for clearly specified purposes and in compliance with applicable data protection law, deployment of smart metering may lead to tracking the everyday lives of people in their own homes and building detailed profiles of all individuals based on their domestic activities (Buttarelli, 2012)".

In the survey we ask consumers to indicate whether the activation of a charging process with a mobile phone or other device poses a privacy risk to them. A possible distinction along this variable allows us to cluster EV-drivers into groups of contract-preferring and contract-rejecting customers. We expect that high scores for privacy concerns reduce the frequency of charging station usage. We measure the privacy usage on a semantic scale 1 - 7 ("fully agree" – "fully disagree").

> **H10:** Privacy concerns have a negative relationship with the frequency of usage of public charging infrastructure.

4.4.10 Measurement of Attribute Involvement

As described in section 2.6.3 the concept of attribute involvement is the most applicable one in the context of public charging infrastructure. Scherer & Lane (1997) define several dimensions along which they test attribute involvement. Several of these dimensions do not apply in the field of public charging infrastructure and are thus omitted in the survey. The variables from Scherer & Lane (1997) that are not applicable are: affordability, portability, durability, learnability, and maintenance. Most of the variables that equally apply to context of charging stations are already integrated in the concepts introduced above. The dimensions "Securability" and "Safety" are part of the privacy variable. The dimension of "comfort / acceptance" is part of the independent variable "convenience" and the dependent variable "frequency of usage". We convert the dimension "operability" to "density of stations" and "preferred charging location". Scherer & Lane (1997) describe the dimension as the "extent the device is easy to use", we apply this to the operability of the whole infrastructure network. The actual ease of use and handling of the charging stations is not measured in this survey. We assume a similar handling and ease-of use for all charging stations, because of the unification of the charging process and plugs, which we described in the preceding chapters. We add the dimensions of "Effectiveness" and "Reliability" as additional questions to the survey. Scherer & Lane (1997) describe these as "how much the device improves one's living situation" and "the degree to which the device is dependable", respectively. We convert "Effectiveness" to define "how much the charging stations improve one's battery-situation" and ask consumers if they are satisfied with the charging speed of the stations. The reliability dimension remains as is and we consequently question consumers to indicate the reliability of the stations. We estimate that a high score for the charging speed satisfaction positively influences the frequency of usage. We measure the concepts for reliability, convenience and charging speed on semantic scales 1-7 (“fully agree” – “fully disagree”).

> **H11:** The satisfaction with the charging speed has a positive relationship with the frequency of usage.

> **H12:** The reliability of the charging stations has a positive relationship with the frequency of usage.

In the subsequent section we present the methodology to test the hypotheses that we derived from various sources in this chapter. Each hypothesis is a building block of the consumer behavior related to the usage of public charging stations. We use these building blocks to create a comprehensive picture describing how consumers perceive and use public charging stations in order to augment the understanding of the framework around DSM systems.

5 Methodology

The methodology has four sections that explain the approach to derive the consumer profiles. First, we present the method to analyse the charging station data. This reveals usage-patterns and particular types of clients or vehicles that use the charging structure more or less frequently. Second, we present the design and structure of the survey. Third, we introduce the clustering methods that we use to group the clients according to their responses. The fourth step presents the regression analysis. The final consumer profiles rest on the combination of the regression analysis and the clustering method. This combination assures a segmentation that defines profiles along the most significant variables.

5.1 Data Analysis

We conduct two big-data analyses of the charging information, as the types of information differ between the EBG and the Mennekes database. For both databases we split the data according to charging durations and list the respective quantity of users as well as the charged amounts of energy for each time horizon. For the EBG dataset we are also able to divide the data according to charging speeds. This division is possible, because the EBG system limits charging speeds to 2.2kW and 3.7kW for Schuko and Type-2 plugs, respectively (Spitzlei et al., 2013). Additionally we obtain a reference list for the EBG database, which associates user IDs and car-types. We use the reference list to create a table revealing the frequency of usage per car-type. For the Mennekes database the analysis of different charging speeds is unavailable. This is because the system regulates charging speed in tandem with the respective car's inverter. Additionally the frequency of usage per car-type is not attainable for this database, because there is no reference list for car-types available.

The results of the big-data analysis reveal particular patterns that help to adapt the questionnaire. Additionally we are able to cross-verify the results of charging database and the survey results. The review of both information-streams aids in the derivation of consumer profiles. It can for example show whether particular results from the survey are confirmed in the charging data or vice versa. The two data sources hence corroborate the validity of consumer behaviour.

5.2 Survey Structure

In the following section we present the methods for the scales, survey techniques and the sample. The purpose of the survey is to cluster the drivers into comprehensive groups of homogeneous consumers. It is hence not the aim of the survey to elicit specific variables that influence purchase intention, but rather to find patterns that permit clustering according to usage.

5.2.1 Measurement and Scaling

Articles on purchase intention that are consulted for this paper mostly suggest binary point-scales of 5, 7, 9 or 11. Kalwani & Silk (1982) state that the reliability of a scale increases with the number of points used on its spectrum, especially when the intentions are beta binomially distributed (Morwitza,V., et al., 2007,p.351). Additionally papers on the methodology of surveys suggest that one constant Likert-scale size throughout one questionnaire can lead to measuring different constructs with similar scale formats (Podsakoff et al., 2003, p.884). “This may also increase the possibility that some of the covariation observed among the constructs examined may be the result of the consistency in the scale properties rather than the content of the items (Podsakoff et al., 2003, p.884)”. Moreover other research in the area proposes the use of vertical Likert-scales instead of horizontal ones. This is “because, in some cases where either arrangement is feasible, confusion can arise when a horizontal one is employed” (Bryman, 2011). Due to technical limitations of the online-survey tool, we apply seven point horizontal Likert scales.

The stem questions are based on the previously defined variables. We adapt these questions to the respondents. The respondents for the questionnaire at hand are about 200 persons of diverse lifestyles. To assure an objective economic view, we construct the stem questions as neutral as possible. The survey asks for plain facts, and precisely defines the concepts that we require for the creation of consumer profiles. Due to the occurrence of response errors, the survey requires a high reliability. The survey has 38 questions and it consequently takes the respondents several minutes to fill-in and carefully read the concepts. We omit conforming questions, as they significantly affect the length of the survey. Long surveys compel respondents to quit before the end (Malhotra & Birks, 2007, p.396).

The survey mostly applies seven point semantic scales with some exceptions. We avoid the application of Standard Likert scales, because research suggests that scales without specified labels increase a respondent's proneness to answer in an extreme way (Weijters, et al., 2009, p.242). Specified labels are for example “fully agree”, “agree”, “rather agree”, etc.; as opposed to the standard bipolar labels of Likert scales, “strongly agree” and “strongly disagree”. Weijters et al. identify several other significant results for the effects of rating scales on response-styles and suggest improved measurements. The scholars find that labelling all response categories reduces the level of misresponse to reversed item scales and extreme response style. More gradations of (dis-) agreement decrease extreme response style. Higher response gradation equally reduces the amount of misresponse to reversed items scales when a midpoint is present. However, their research also yields that the usage of midpoints and the labelling of all response categories increases net acquiescence response styles. The authors show that fully labelled scales including a midpoint increase the negative effects of a midpoint on the misrespone to reverse item scales. (Weijters, et al., 2009, p.242)

Following Weijters et al. (2009, p.242) and Malhotra & Birks (2007, p.353), fully labelled scales reduce extreme response styles, misresponse to reversed item scales, and scale ambiguity.

We apply semantic differentials with fully labelled seven-point rating scales in the survey. The seven point scale ensures that the users are able to have a "neutral" response to each of the concepts (Malhotra & Birks, 2007, p.352). The scales are labelled with bipolar terms of agreement/disagreement and gradual descriptions towards each pole. We omit the reversal of the items on the scale to decrease the tendency of respondents to drop out of survey.

5.2.2 Survey Design and Pre-Testing

The literature on survey design suggests clear guidelines for the setup of questionnaires among a knowledgeable audience. We refrain from the usage of filtering questions, because all respondents are electric vehicle drivers and are hence familiar with the topic (Malhotra & Birks, 2007, p.378). Most of the EV drivers are registered with their emails in RheinEnergie's database. We presume that most of the EV vehicle drivers are familiar with internet technologies and possess mobile internet connections. A hyperlink to the survey is sent to each driver's email account. The drivers can subsequently access the survey using their mobile phones' or PCs' browser.

In the introduction of the survey we define the purpose of the research to obtain legitimacy from the respondent (Malhotra & Birks, 2007, p.380). The survey is structured along four sections. The sections are ordered according to the sensitivity of the underlying subject. The reviewed literature suggests posing the most sensitive group of questions at the end of a survey (Malhotra & Birks, 2007, p.380). The four sections are: (1) EV properties, (2) Charging stations, (3) Driver preferences and feelings, and (4) Demographic factors. We follow the funnelling approach where general questions are posed before specific ones (Malhotra & Birks, 2007, p.389). We apply an unstructured question at the beginning of the survey, to ease the respondents into the topic of e-mobility (Malhotra & Birks, 2007, p.381).

We conduct a pilot-test of the survey among an audience of 15 electric vehicle enthusiasts who have an established body of knowledge related to the topic. Only some of them have electric vehicles themselves. During the pilot-test all aspects of the questionnaire are tested, "including question content, wording, sequence, form and layout, question difficulty, and instructions (Malhotra & Birks, 2007, p.391)". We organize the pilot-test as personal interviews, "because interviewers can observe respondents' reactions and attitudes (Malhotra & Birks, 2007, p.391)". We adjust the survey according to the results of the pilot-testing session. Appendix 1.1 presents a sample survey in English, the original survey is in German.

5.2.3 Sample of EV-Drivers

The sample of the survey consists of 140 EV drivers who are all clients of RheinEnergie AG. We obtain the sample using a one stage clustering method. Cluster sampling assumes a maximum of heterogeneity in the sample (Churchill, 2005). Our type of sampling is a non-probability convenience sampling method. Literature defines a convenience sample as "one that is simply available to the researcher by virtue of its accessibility (Bryman, 2011)". The sampling frame consists of the attribute of owning an electric vehicle. Due to the distortion of this sample, we benchmark it against the overall German population in terms of demographic factors.

5.3 Applied Clustering Methodology

After receiving the results from the survey, we analyse the data in several steps to achieve comprehensive clusters. Firstly we analyse mean comparison and correlation tables in the results section. Subsequently we cluster the sample into groups of respondents that have a minimum distance between their attributes. In the literature many types of taxonomic methods are discussed, and lend themselves to the clustering of EV-drivers. Mojena (1977) tests Johnson's min, Johnson's max, simple average, group weighted average, Median, Centroid and Ward's error sum squares according to their performance on 12 data sets. His results for an incidence matrix show that "Ward's error sum of squares gave a superior performance across all data sets (Mojena, 1977)". Mojena uses matching coefficients to measure the disparity between the known incidence matrix and the one given by the clustering method. Punj & Stewart (1983) conduct a meta-analysis of 12 studies that use different clustering techniques. In either of the reviewed studies Ward's method outperforms or is on par with comparative processes (Punj & Stewart, 1983, p.142). Similar quality of the method is attested by Padilla et al. (2007). Punj & Stewart equally mention one of the main caveats of Ward's method: "...as a clustering algorithm includes more and more observations, its performance tends to deteriorate, particularly at high levels of coverage, 90% and above (Punj & Stewart, 1983, p.143)". Similar shortcomings are confirmed by Ketchen & Shook (1996). They state that "Ward's method tends to produce clusters with roughly the same number of observations and the solutions it provides tend to be heavily distorted by outliers (Ketchen & Shook, 1996, p.445)". The authors find that "using an iterative method to refine the solution derived using Ward's method would have enhanced validity (Ketchen & Shook, 1996, p.445)". Hence Punj & Stewart suggest a two-step clustering procedure to compensate for the caveats of Ward's method. In the first step they apply Ward's method to generate an approximation of the solution. The approximation is used to determine candidate clusters and a starting point for the ensuing iterative partitioning analysis. The best performing iterative solution in Punj & Stewart's work is the k-means method. Hallman & Wicker (2012) identically apply the combination of Ward's method and k-means.

5.3.1 Ward's Method: Creating Initial Clusters

We apply Ward's method for hierarchical clustering as the first step for the grouping operations in this study. We found this decision on the literature that we review above. Ward's error sum squares method is "a procedure for forming hierarchical groups of mutually exclusive subsets, each of which has members that are maximally similar with respect to specified characteristics…" (Ward, 1963). In his study Ward (1963) applies an "objective function" that minimizes the error sum of squares (ESS) in order to assess the similarity between two values. In our particular case we apply the "squared Euclidean distance" as the objective function. It is the standard objective function of the software package SPSS and formulates as:

Equation 1

$$d(p,q) = \sum_{i=1}^{n} (q_i - p_i)^2$$

Ward uses the objective function to group those values that show the smallest error terms between them. Hence the operation enables the researcher to group those values that are most similar according to the objective function. Ward applies a hierarchical method for the grouping of these values. Initially all values are separate and are considered to be a group for themselves. In Ward's methodology groups are called subsets. This means that at the beginning of the procedure there are as many subsets as there are values in the sample. In mathematical terms there are n values in the sample equalling n subsets. The method systematically reduces the number subsets while the number of values remains the same; they are clustered into groups. The procedure unifies the initial n subsets to n-1. We choose to pair those values that produce "the least impairment of the optimal value of the objective function (Ward, 1977)". Afterwards, the method examines the resulting n-1 subsets accordingly. It determines a third member that can be unified with the group of values. This is again the most optimal outcome of the objective function, reducing the subsets to n-2. The technique continues until a single subset remains containing all values. The hierarchical grouping cycle is formulated as follows:

First, the statistical software creates the n-1 subsets out of the initial n subsets. It applies the objective function, which reduces the amount of overall subsets to n-1 (Ward, 1963):

Equation 2

$$S(p_{n-1}, n-1) = [S(p_{n-1}, n)] \bigcup [S(q_{n-1}, n)]$$

The objective function analyses each union of the n*(n-1)/2 possibilities. The procedures record the results of the combinations and "the identity of the "best" union is maintained throughout the sequence (Ward, 1963)". Once the best solution is determined the subsets are reduced to n-1. Here

p_{n-1} denotes the smaller identifier of the original n subsets and q_{n-1} denotes the larger identifier of the original n subsets. The result for the objective function of these values is denoted in the same manner (Ward, 1963):

Equation 3

$$Z[p_{n-1}, q_{n-1}, n-1]$$

The subsequent union for the reduction to n-2 subsets is hence formulated as follows (Ward, 1963):

Equation 4

$$S(p_{n-2}, n-2) = [S(p_{n-2}, n-1)] \bigcup [S(q_{n-2}, n-1)]$$

and

Equation 5

$$Z[p_{n-2}, q_{n-2}, n-2] \qquad (p_{n-2} < q_{n-2})$$

We stop the continuation of the hierarchical grouping once large jumps in the squared Euclidean distance coefficients become evident. We can visualize this effect by plotting the coefficient on the y-axis and the number of groups on the x-axis of a graph. As soon as large jumps along the y-axis are visible, we stop the clustering procedure. Churchill (2005, p.593) describes similar methods for Euclidean distance measurements. The remaining groups are those that show the strongest similarities according to the measured factors. We apply this method throughout the whole sample of EV-owners. This procedure results in groups for each factor that share distinct opinions about the charging infrastructure.

We determine the weight of each factor in a regression analysis, which we explain in the following chapters. Initially however we describe the k-means method, which we use to design more accurate clusters.

5.3.2 K-Means to achieve accurate Clustering

According to Hallmann & Wicker (2012) and Ketchen & Shook (1996) the additional application of the k-means method refines the results that are obtained from Ward's method. K-means is an iterative approach to clustering that partitions the data according to a pre-defined number of groups. The data is partitioned to minimize the within cluster sum of squares (WCSS) (Steinley, 2006, p.10).

The results of the survey are assigned to a matrix N x P., N represents the number of respondents and P represents the number of variables prompted in the survey. The matrix quotes the scores of the respondents (N) to the respective question (P). Based on Ward's method we define k seed vectors. A seed vector is a data-set (a set of answers) of a respondent that we use as a "base" for a group of users. Each seed vector represents a different initial cluster. The k-means method subsequently fills these clusters with values (sets of answers of other respondents, also called objects) that are closest to the seed vector and the average values of each cluster. This method does not create groups of users, but assigns them to a pre-fixed group that they resemble the most.

"If $X_{NxP} = \{x_{ij}\}$ N x P denotes the N x P data matrix, the k-means method constructs these partitions so that the squared Euclidean distance between the row vector for any object and the centroid vector of its respective cluster is at least as small as the distances to the centroids of the remaining clusters (Steinley, 2006, p.2)". The k-means method calculates the centroid-value per column of the cluster using

Equation 6

$$\bar{x}_j^{(k)} = \frac{1}{n_k} \sum_{i \in C_k} x_{ij}$$

and it gives the complete centroid vector for a cluster C_k by

Equation 7

$$\bar{x}^{(k)} = \left(\bar{x}_1^{(k)}, \bar{x}_2^{(k)}, \dots., \bar{x}_p^{(k)}\right)'$$

Here x_{ij} describes the individual value of respondent i to question j. C_k describes the cluster of values that are closest to one another according the squared Euclidean distance between the seed vector and the objects. n_k is the number of values in a cluster's column and $\bar{x}_j^{(k)}$denotes the centroid value per column. This basically creates a mean value per column of a cluster. These means are collected in the row vector $\bar{x}^{(k)}$.

Steinley (2006) introduces four steps to derive clusters using the k-means method. These steps are conducted iteratively until the grouping process is complete. First we define the initial seed vectors, which are P-dimensional vectors, and we calculate the squared Euclidian distance between every object and the respective clusters. The formula used for this process is:

Equation 8

$$d^2(i,k) = \sum_{j=1}^{P} \left(x_{ij} - s_j^{(k)}\right)^2$$

Here, again, x_{ij} denotes the individual value per variable per respondent. $s_j^{(k)}$ denotes the respective value of the seed vector k or the value of the centroid vector. d^2 denotes the squared Euclidean distance. The index j describes the column number (question) of the cluster. The index i describes the rows (respondents). The process works in four steps:

(1) The procedure uses the smallest squared Euclidean distances to allocate each value x_{ij} to a seed vector. (2) Subsequently the procedure calculates the cluster centroids as described above. (3) It compares the squared Euclidean distances of the individual row vectors to the centroid values and reallocates the respective values to the clusters with the closest values. (4) Afterwards we recalculate the centroids per cluster and the procedure recommences without the initial allocation to the seed vectors. (Steinley, 2006)

5.3.3 Combining K-Means and Ward's Method

We combine Ward's method and k-means to arrive at a more accurate clustering result. Hallmann & Wicker (2012) use a similar methodological approach. We first use Ward's method to obtain an indication for the grouping of the data. This indication yields the seed-vectors, which are necessary for the start of the k-means procedure. This combination of method is a solid foundation for the creation of clusters. Ketchen & Shook (1996) note that "using an iterative method to refine the solution derived using Ward's method" enhances the "validity because the iterative methods do not share the biases of Ward's".

5.4 Regression Analysis

We substantiate the grouping of the respondents with a regression analysis of all factors involved. Before the actual calculation of the regression we conduct univariate- and bivariate-examinations of the data. For the bivariate analyses it is interesting to see if particular variables have a stronger influence on the frequency of use of the infrastructure. Depending on the results of these analyses, we omit factors from the regression analysis, if we cannot confirm the validity or expressiveness of the variable. Hallmann & Wicker (2012) equally apply regression analysis to estimate the impact of the consumer profile on the dependent variable.

The regression analysis permits us to make judgements about the factors in the survey, their significance and effect size. We use the effect sizes and significances to rank the groups of respondent that we obtain using the clustering methodology. We use the variable "frequency of usage" of public charging infrastructure (Q5) as the dependent variable in the regression formula. The other variables that we presented in paragraph 3.4 perform as independent variables. In the following we present a table with the respective variables and the regression formula.

Table 6: Variables, Abbreviations and Descriptions

Type of question	Variable name	Abbreviation	Description
1	EV-Type	Q1	An unstructured question to reveal the various car-types.
1	EV-Consumption	Q2	A nominal scale for the consumption of EVs.
1	EV-Usage	Q3	A nominal scale measuring the EV-Usage in km per week.
1	Comfortable range	Q4	A nominal variable for the average distance in km that an EV-owner drives between to charging instances
2	Frequency of usage	Q5	A nominal scale to measure the frequency of usage of public charging stations.
2	Station Density	Q10.2	A semantic scale to measure the experienced density of charging stations.
2	Frequently used stations	Q6	A nominal scale the measures the stations in the Cologne area that users most frequently make use of.
2	Average charging time at stations	Q7	Nominal scale for the value of the average charging-time indicated in hours.
2	Convenience	Q10.1	A scale for the perceived convenience of the charging stations.
2	Perception of density	Q10.2	The variable measures the perceived density of the charging stations in the Cologne area.
2	Perceived charging speed	Q10.3	The scale measures the perceived charging speed.
2	Perceived station reliability	Q10.4	The variable measures the "reliability" of the stations.
2	Importance of fast-charging	Q10.5	A semantic scale measuring the importance of fast-chargers.
2	Preferred charging location	Q11	A nominal variable indicating the preferred location for public charging infrastructure.
2	Subscription for public charging competitors	Q12	A nominal variable that measure if and what type of competitive charging service a EV-driver is using.
2	Usage of competitive services	Q13.1	A semantic scale measuring the frequency of usage of competitive services.
3	Range Anxiety	Q13.2	The scale measures if the respondents perceive range anxiety.
3	Intensity of Range Anxiety	Q13.3	A scale measuring the intensity of range anxiety.
3	City-scenario: High price option	Q14.1	The respondent is presented with a short term charging scenario in the city. This scale records the agreement with the high price charging option.
3	City-scenario: Medium price option	Q14.2	This scale records the agreement with the medium price charging option.
3	City-scenario: Low price option	Q14.3	This scale records the agreement with the low price charging option.
3	Type of dwelling	Q15	A nominal variable indicating the type of dwelling that a respondent lives in.
3	Preferred billing method	Q16	A nominal variable indicating the preferred billing method (kWh, h, kWh + h, or flat-rate).
3	Acceptance of Charging Speed Reduction	Q17.1	This scale measures the acceptance of charging speed reductions at peak-hours.
3	Privacy concerns	Q17.2	A semantic scale measuring the perceived privacy issues of EV-driver when they use charging stations.
3	Night-scenario: High price option	Q18.1	The respondent is presented with a long term charging scenario (overnight). This scale records the agreement with the high price charging option for this scenario.
3	Night scenario: Low price option	Q18.1	This scale records the agreement with the low price charging option for this scenario.
4	Education	Q22	A nominal variable for the type education of the respondent.
4	Marital Status	Q23	A dummy variable indicating whether the respondent is married.
4	Children	Q24	A dummy variable indicating whether the respondent has children.
4	Gender	Q25	Dummy variable for the gender of the respondent.
4	Age	Q26	Unstructured question for the age of the respondent.
4	Income	Q27	A nominal scale measuring the income of the respondents.

6 Results

6.1 Evaluation and Analysis of the Charging Data

The charging information is stored in two databases on RheinEnergie's servers. We analyze the charging data from January 2010 to July 2013 for EBG stations and from January 2013 to September 2013 for Mennekes charging stations. In this time window the server stored 8514 unique entries in the EBG database and 1531 in the Mennekes database. We analyze each database separately, because they hold different types of information.

6.1.1 EBG Database

The data in the EBG database is recorded at two locations. 5275 values emanate from the charging station in Cologne's city-center and 1300 values come from a station which is situated on firm's property (the company is called e-Wolf) In Frechen, just outside Cologne. Each charging event in this database consists of two entries. One entry is labeled "on" the other "off". Entries labeled "off" also record the amount of energy that is transferred to a car's battery during the charging process. Each entry quotes the respective user's unique ID number. We use the ID number per client to combine these two entries into a single entry. The charging station or the server transmits the ID with every charging request. The database stores the ID number in an SMS text for each charging request. The combination of the "on"- and "off"-entries reveals 3444 unique charging-occasions. These occasions allow for an exact match between "on" and "off" events and are definitely relatable. To refine the data, we add several other exclusion criteria (e.g. parking time must not be 0 and meter value must not be 0). These restrictions reduce the sample of charging instances to 2630. After an outlier analysis of the data, we decrease the sample to 2612 data points.

The charging data does not record the type of socket (charging type) that is used to charge a vehicle (Schuko or Type-2). Additionally the database does not record the amount of time that a vehicle was charged. Instead each charging pole measures the time period between a user's authentication on the system and the moment when the plug is disconnected from the car. However, the charging process of the vehicle can stop before the plug is disconnected. As a consequence the database solely measures the parking duration of a vehicle and the charged amount of energy. Therefore we need to estimate these values. To achieve the estimation we use the average charging speeds per plug-type. A car that charges with a Schuko plug connection replenishes its battery with about 2.2kW per hour. A Type-2 plug charges about 3.7kW per hour (Spitzlei et al., 2013).

These are approximate values (2.2kW and 3.7kW), because every battery-type has different charging characteristics (Hu & Jung, 2013). It is not in the scope of this study to estimate the charging dynamic of every vehicle that charges at the public stations. Hence, we are aware of this approximation.

Nevertheless, we want to classify the charging events without the respective information on charging duration and socket-type.

We create two new data columns and divide the energy amount charged per charging instance with the respective hourly average charge values. The first column depicts the value meter-value divided by 2.2kW; the second column depicts the result of the division of the meter-value and 3.7kW. We compare the newly created data columns with the actual parking time. This comparison yields two indications. First, if the calculated charging time of the Schuko plug is bigger than the parking time and the calculated charging time of the Type-2 plug is smaller than or equal to the parking time, the car must have been charged with a Type-2 plug. Second, if both values for the calculated charging time are smaller than the parking time, we can say that the charging type is irrelevant for the respective parking duration. We define these two indicators as “Type-2 charging processes” and “charging type irrelevant”. The indications contain several implications that allow us to analyze the charging behavior of EV-drivers in more detail. Table 5 lists the results of the analysis. The table splits up the data according to parking durations. We created five groups of different parking durations. For each one of them we indicate the average meter-value, start-time, end-time, parking duration, and number of occurrences (n). The meter-value is the amount of kilowatt hours that the users charge on average during the respective time-period. The start-time is the average time of the day when the users commence their charging procedure. The end-time is the time when the user leaves the parking space by unplugging the charging cable. This does not mean that it compulsively indicates the end of the charging procedure; the battery can be fully replenished long before the user unplugs the cable. The parking duration quotes the average parking duration per time-horizon in hours and minutes. The column ‘n’ shows the number of recorded charging instances that occur for each charging-duration. We also list the percentage of each group and sub-group. The column ‘% of Total’ shows the percentage value of the respective group-size according to the overall sample size of 2612. The column ‘% of Sub-group’ shows the respective percentage value for the ‘Type-2 charging processes’ and ‘charging type irrelevant’ in relation to the overall amount of charging instances in a group. Figure 3 and 4 visualize the results.

Table 7: Average Values for Charging Instances listed according to Parking Duration (EBG database)

	Meter-value kWh	Start time (hh:mm)	End time (hh:mm)	Parking duration (hh:mm)	n	% of Total	% of Sub-group
<u>0h - 3h</u>	2.51	15:09	16:00	0:59	1361	52.1%	100%
σ	2.76	03:45	3:54	0:47			
Type-2 charging-processes	2.96	15:11	16:06	1:02	588	22,5%	43,2%
σ	2.44	03:45	03:54	0:48			
Charging type irrelevant	1,53	15:02	15:55	1:00	678	26,0%	49,8%
σ	1.29	03:41	03:52	0:47			
<u>3h - 6h</u>	7,34	14:01	17:11	4:13	254	9,7%	100,0%
Σ	3.9	03:36	04:45	0:52			
Type-2 charging-processes	11.25	14:20	17:11	3:54	90	3,4%	35,4%
σ	2.3	03:25	04:38	0:48			
Charging type irrelevant	5.15	13:50	17:13	4:23	163	6,2%	64,2%
σ	2.74	03:46	04:51	0:53			
<u>6h - 12h</u>	10.08	14:21	11:31	9:04	258	9,9%	100,0%
	6.7	07:54	05:40	01:45			
Type-2 charging-processes	21.07	12:08	13:48	7:40	32	1,2%	12,4%
	6.5	07:57	06:14	01:35			
Charging type irrelevant	8.53	14:40	11:12	9:16	226	8,7%	87,6%
	5.04	07:52	05:30	01:41			
<u>12h -24h</u>	12.11	17:19	10:29	16:33	547	20,9%	100,0%
	10.8	03:51	03:13	02:43			
Type-2 charging-processes	44.87	16:25	11:23	16:29	29	1,1%	5,3%
	6.5	05:19	04:00	01:50			
Charging type irrelevant	10.27	17:22	10:26	16:33	518	19,8%	94,7%
	7.6	03:43	03:10	02:45			
<u>24h <</u>	16.10	15:32	12:22	52:40	196	7,5%	100,0%
	13.5	04:36	04:53	41:35			
Type-2 charging-processes	57.95	13:02	15:09	26:07	1	0,0%	0,5%
Charging type irrelevant	15.89	15:33	12:22	52:48	195	7,5%	99,5%
	13.2	04:34	04:54	41:44			
Overall Average	6.74	15:26	14:16	8:48	2612		

Figure 3: Distribution of Charging Processes according to Parking Duration and Charging Technology

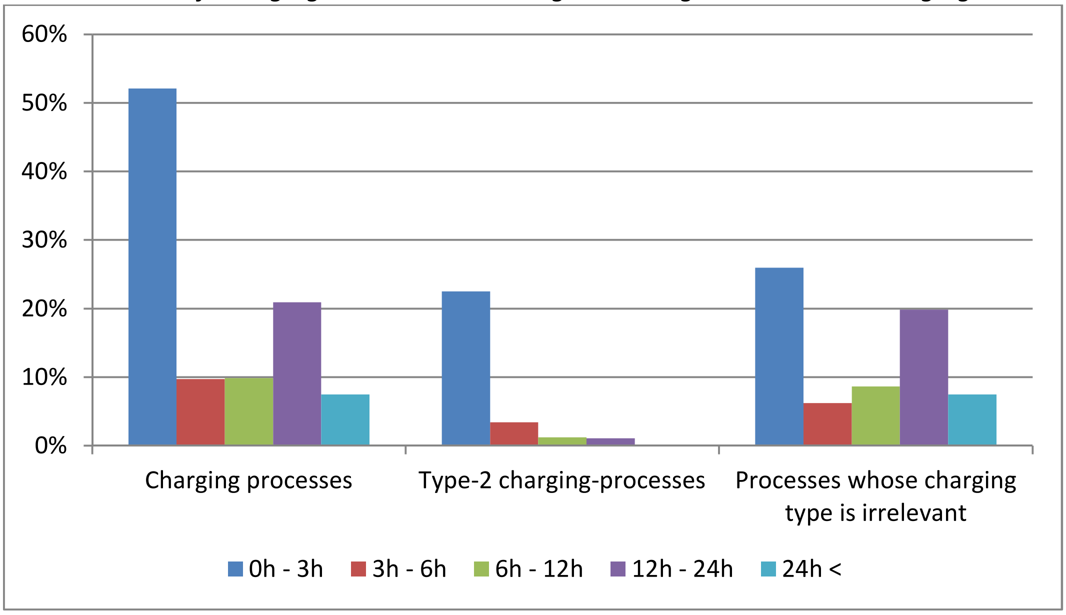
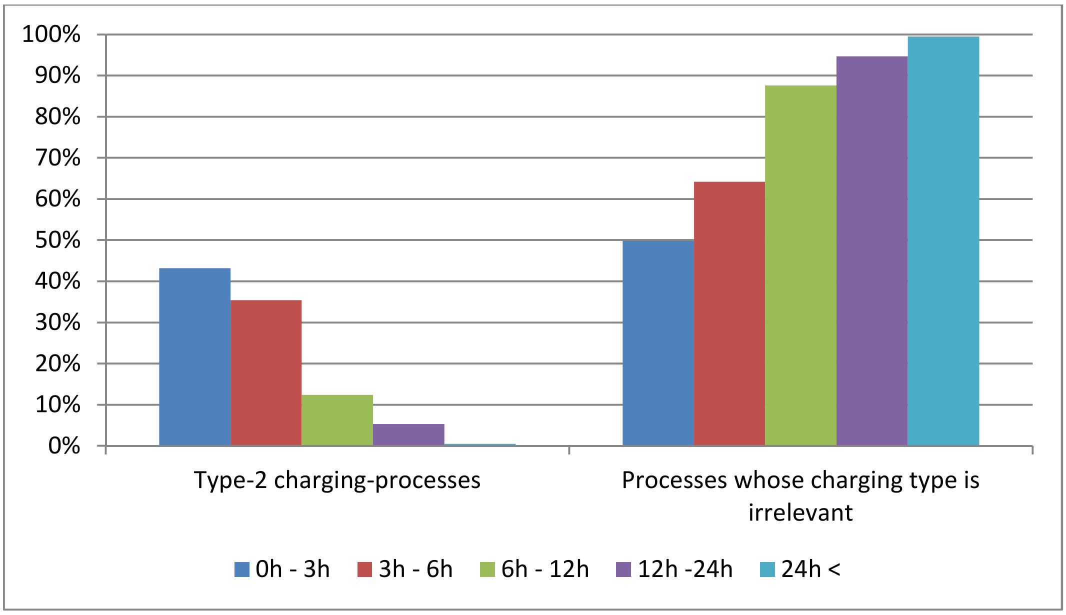


Figure 4: Distribution of Parking-Duration Sub-Groups according to Charging Type



We split the data according to parking duration and list the number of occasions for each time horizon. We observe most of the charging instances for parking durations between 0 to 3 hours and 12 to 24 hours. Additionally, we quote the average start and end time of the charging instances per duration period. Here we see that nearly all charging processes commence in the afternoon between 12 to 17 o'clock. For the parking durations of 12 to 24 hours and more than 24 hours we observe that the end time lies before the start time. We explain this with average parking durations of more than 16 hours. Once a car is parked for more than 12 hours starting in the afternoon, it is disconnected from the station the next day, which results in "smaller" time values for the end time. The distribution of the table also shows the amount of those charging processes that have to apply Type-2 charging. We observe a steady decline with increasing parking durations. This is a logical occurrence: The longer the parking duration, the higher the probability that the battery is fully charged. In the first time-slot (0h - 3h) we can classify 43.2% of the data as definite Type-2 charging processes. On the other hand, the charging-type (Schuko, 2.2kW or Type-2, 3.7kW) is irrelevant for 49.8% of the charging instances in this time-period. This figure underlines that drivers appear to consume only marginal amounts of their EV-batteries in daily commutes. Many batteries are replenished below three hours even if they use slow charging infrastructure. The percentage for the “irrelevance of the charging type” constantly increases with longer parking-durations.

We pair the “irrelevance of charging type” with the information that most of the charges take place for parking durations of 0h - 3h and 12h – 24h. Based on this we can derive three conclusions.

First, we find that already short-term urban parking durations do not require fast-charging stations, because 49.8% of the charges are achieved with slow charging infrastructure. This has important implications for the CSP as well as the EV drivers. According to these results, the CSP does not need to invest in a large scale roll-out of fast-charging infrastructure in urban environments. Instead the CSP can focus on preferable parking-locations to ensure a constant occupation of charging stations to recover the costs.

Second, we find that 20% of the sample park their EVs between twelve and 24 hours. Solely 5% of these parking occasions require a Type-2 charge of 3.7kW over the full parking-duration. The charging instances in this category mostly include overnight charges. These factors make them interesting for DSM integrations. 94% of the cars in this time-horizon can potentially contribute to DSM schemes, such as valley-filling and load-shifting (Attia, 2010).

Third, the results corroborate the potential for the application of V2G technologies. 49% of the EVs are fully charged below three hours and 94.7% of the vehicles have replenished batteries below parking durations of twelve to 24 hours. Both percentages do not depend on the applied charging type. This shows that there is potential to store energy in EVs, which a DSM system can feed back to the grid during load peaks (for example in the morning hours) (Kahlen et al., 2013). We have to keep in mind that RheinEnergie capped the charging energy of Type-2 plugs to 3.7kW, whereas transfers of 22kWh are actually attainable with the infrastructure (Mennekes Elektrotechnik GmbH & Co. KG[b], 2013, EBG-Group, 2013). This discrepancy underlines the capabilities that the system can still achieve. An increase of Type-2 charges up to 22kWh probably shifts the ratio between “Type-2 charges” and “charging type irrelevance” to the advantage of “charging type irrelevance”. Such a change in the charging speed can further corroborate the usage of V2G technologies.

However, we must mention some limitations that are connected to this analysis. Most of the cars that are in the analysis feature rather small batteries as compared to the most recent models of electric vehicles. We present a list of car-types in the subsequent paragraph. Bigger battery sizes equally increase the charging-time. This can skew the percentages in Table 7 towards the higher parking-durations and reduce the share of "processes whose charging type is irrelevant". The low discrepancy between slow and fast charging (2.2kW and 3.7kW) also distorts the picture. More efficient fast-charging will increase the effectiveness of the system and increase the number of "processes whose charging type is irrelevant". Lastly we also have to take into account that the users of RheinEnergie's charging station network currently do not have to pay neither for the charged amount of energy nor for the parking spaces. This has an effect on the data. Consumers tend to park longer hours, because they are not billed for the parking spaces in popular areas of the city (e.g. city center).

6.1.2 Distribution of Vehicles in the EBG Database

The EBG database shows client ID's per charging occasion. It also includes a reference list for the vehicle type per client ID. Based on this information we associate the type of vehicle to every charging occasion. This information adds guidance to the analysis of the previous chapter. Table 8 presents those vehicle types that have more than 50 charging instances.

Table 8: Average Charging Instances per Type of Vehicle

Vehcile type	Number of charging instances	Number of registered vehicles	Standard battery capacity of the vehicle (kWh)	Average parking time (hh:mm)	Average energy amount charged (kW)
Citroën Berlingo Electrique	1104	2	22.5[a]	12:49	7.5
Twike	391	2	9.7[b]	0:43	1.2
CityCom City EL	196	8	2.3 - 4.8[c]	1:41	2.7
Ford E-Transit	147	3	28[d]	31:07	16.9
Renault Twizy	119	15	6.1[e]	1:39	2.4
Tesla Roadster	83	4	53[f]	17:53	31.4
Smart Eletric Drive	58	11	17.6[g]	2:05	4.7

Source: a: EVWorld.com, 2013;b: FINE Mobile GmbH, 2013; c: CITYCOM GmbH, 2013; d: Ford Motor Company, 2013; e: Renault Deutschland AG, 2013; f: Berdichevsky et al., 2006; g: Daimler AG, 2013

We observe that those vehicles with larger batteries (Citroën, Ford, and Tesla) also have notably longer average parking times than cars with smaller batteries. We explain this not only with the size of the battery, but also with the reduced Type-2 charging capacity of 3.7kW. The effect of the reduction for Type-2 charging particularly affects cars with larger batteries. As an example, a full charge for a Tesla Roadster takes about 14 hours using the reduced charging-speed. With the full charging-speed of 22kWh this duration is reduced to circa 2.5 hours. For vehicles with smaller batteries this spread between the two charging-speeds is diminishes.

The Citroën Berlingo and the Ford E-Transit are utility vehicles, which can explain their longer parking durations. Utility vehicles are mostly unused during weekends and are driving on regular schedules during the week. The Twike and Citycom EL are small three-wheeled vehicles with aerodynamic chassis that consume little energy (FINE Mobile GmbH, 2013, CITYCOM GmbH, 2013). In the future it is likely that vehicles e.g. like the Smart electric drive will replace these three-wheeled cars. This means that larger batteries have to be charged at the charging stations.

Next to the charging information of the individual vehicle types, we analyse the vehicles' cities of origin. In the EBG database each vehicle is registered with its official number plate. Of all 138 registered vehicles, 48 are registered in Cologne or the city's periphery. The periphery includes the cities Leverkusen, Bergheim, Siegburg, and Bergisch Gladbach. The remaining 90 vehicles are registered in municipalities outside of Cologne and its periphery. Table 9 shows the distribution of the vehicle registrations according to municipality.

Table 9: Registered Vehicles and their Municipalities

Municipality	**Vehicles registered in RheinEnergie's system**
Cologne	33
Leverkusen	1
Bergisch Gladbach	3
Siegburg	5
Bergheim	6
Total Cologne and peripheral cities	48
Other municipalities	90

The charging-data underlines that most users of the infrastructure do not live in Cologne, but rather make occasional trips to the city. Once they are in Cologne they need a possibility to charge their vehicle in order to make the return trip. The fact that 65% of all users have cars that are not registered in Cologne or its periphery leaves two ultimate conclusions, which we test in the questionnaire. One, the drivers mostly charge their vehicles at home and only use public charging infrastructure on long-distance trips, which require a recharge to accomplish the return-trip. Or, two, the drivers are registered for multiple charging services and use a different provider when they are travelling in their local municipality. The above presented insights further corroborate the investigation of this subject in the survey.

6.1.3 Mennekes Database and Data Comparison

The database for Mennekes charging stations holds less values, but stems from a more divers set of charging stations. 17 values are from eWolf-Frechen, 107 values were recorded at the Airport, 23 values at the Kreissparkasse Cologne, 292 at the Cologne city center station (Lungengasse), 91 at RVK

Meckenheim, 15 values come from the park and ride location at Weiden-West, 192 values are from the station in front of RheinEnergie's headquarters, 19 values were recorded in front of the PSA Headquarters in Germberghoven and 238 data-points stem from the charging stations at TÜV Rheinland. A total of 994 values are in the Mennekes database at the time of analysis. After an outlier analysis and the removal of short charging durations (below one minute), we reduce the sample to 646 values. This divers set of locations helps to account for parking situations outside the city, as the EBG database mostly holds values from the charging station in the city center (Lungengasse).

The Mennekes database does not support any inferences about the charging types. This is because these charging stations are not generally reduced to 3.7kW. As a consequence the charging speeds differ for every vehicle and hence we cannot calculate any estimation for the usage of Type-2 and Schuko plugs. Additionally the database does not allow us to analyse the registered vehicles.

In Table 10 we observe that the charging patterns are essentially the same as for the EBG database, with two peaks between 0 – 3 hours and 12 – 24 hours of 50.2% and 19.7%, respectively. This corroborates the results revealed in Table 7. Table 11 shows an independent sample's t-test with unequal variances assumed that compares the data from the Mennekes database and the EBG database. We observe that the parameters duration, meter value and start time are significantly different in both samples. We interpret the result for end time as significant at the 10% level (α = 0.1). We explain the difference with the different locations of the charging stations. The values in the Mennekes database hold many data-points from locations outside the city center. In this respect the charging station at the airport Cologne/Bonn is a particular case in this respect, because drivers tend to park longer at airports than at the other locations. Charging stations that show particularly long average parking durations in this sample are: Airport (16h 06m on average and 65 charging instances) and the station at RheinEnergie's headquarter (21h 12m on average and 157 charging instances).

Table 10: Average Values for Charging Instances listed according to Parking Duration (Mennekes Database)

	Meter Value kWh	Start time (hh:mm)	End time (hh:mm)	Parking Duration (hh:mm)	n	% of Total
0h - 3h	2.89	13:47	14:49	01:11	324	50.2%
σ	2.79	03:46	03:57	00:49		
3h - 6h	5.91	12:31	15:36	04:06	94	14.6%
σ	4.55	03:30	04:23	00:49		
6h - 12h	10.34	10:32	14:43	08:33	33	5.1%
σ	6.43	04:59	06:08	01:43		
12h - 24h	8.30	14:22	10:34	18:18	127	19.7%
σ	6.12	03:27	03:47	03:05		
24h <	11.03	12:37	13:06	02:36	68	10.5%
σ	10.08	03:27	03:47	19:03		
Total	6.84	13:21	13:45	06:37	646	
Total σ	6.02	03:40	04:09	16:47		

Table 11: Independent Samples T-test comparing Data from the EBG and the Mennekes Databases

		N	Mean	F-Test	t-value	Significance
Duration	**Mennekes**	652	689.47	57.81	3.530	.000
	EBG	2610	521.81			
Meter value	**Mennekes**	652	5.63	35.65	-3.887	.000
	EBG	2610	6.74			
Start time	**Mennekes**	652	13.42	13.83	-11.487	.000
	EBG	2610	15.44			
End time	**Mennekes**	652	13.91	11.36	-1.777	.076
	EBG	2610	14.26			

The results confirm the tendency of users to mostly park between 0 - 3 hours and 12 – 24 hours. We can also infer that the two databases are significantly different from one another and hence show different patterns of consumer behavior. Particularly important is that the locations of the stations differ; the EBG database recorded predominantly values in the city-center, whereas the Mennekes database also holds information from locations outside the center. As a consequence we conclude that there is a difference between charging behaviors depending on the location.

7 Survey-Results

We conduct the survey over a time period of seven days. We include it in a formal email that we send to 196 clients of RheinEnergie’s EV-charging project. Of these 196 recipients 131 had a look at the survey, 100 started it and 65 completed the full questionnaire. This yields a response ratio of 33.2%. There are three types of questions in the survey, semantic differential scales (Likert-like scales) (1-7), nominal scales (context specific, e.g.: frequency of usage) and ordinal scales. Table 12 presents a comparison of the demographic characteristics of the sample and the general German population. The table states clearly that the sample diverges from the average German population. The respondents are mostly male, well-educated and have a higher household-income than the average population. Large disparities are particularly visible in the difference of university degrees (64.2% of the sample, and 12.9% of the population) and the gender of the sample (92% male). The respondents in the sample also have a higher household income, about €20,000 more on average per year than the population. In the following we present the bivariate analyses of the individual scales in three tables. Table 13 presents the correlations coefficients of the differential (semantic) scales. Table 14 depicts the correlation of semantic and nominal scales and their respective ANOVA results. Table 15 shows the cross-table results and frequencies of nominal scales with one another and their Chi-square values. The subsequent figures illustrate the distribution of the data and allow for a brief comparison with the results that we obtain from the charging station database.

Table 12: Demographic Comparison of the Sample with the Average German Population

	Sample	**Population**
Education	None: 0.0% Secondary school: 1.9% O-Level: 7.5% A-Level: 17% University: 64.2% Doctorate: 9.4%	None: 3.8% Secondary school: 35.6% O-Level: 22.1% A-Level: 27.3% University: 12.9% Doctorate: 1.1%
Gender	Female: 8% Male: 92%	Female: 51% Male: 49%
Age	43.74	43.88
Yearly household income	€ 68,000	€ 44,400

Figure 5: Charging Durations as indicated by the Survey-Respondents

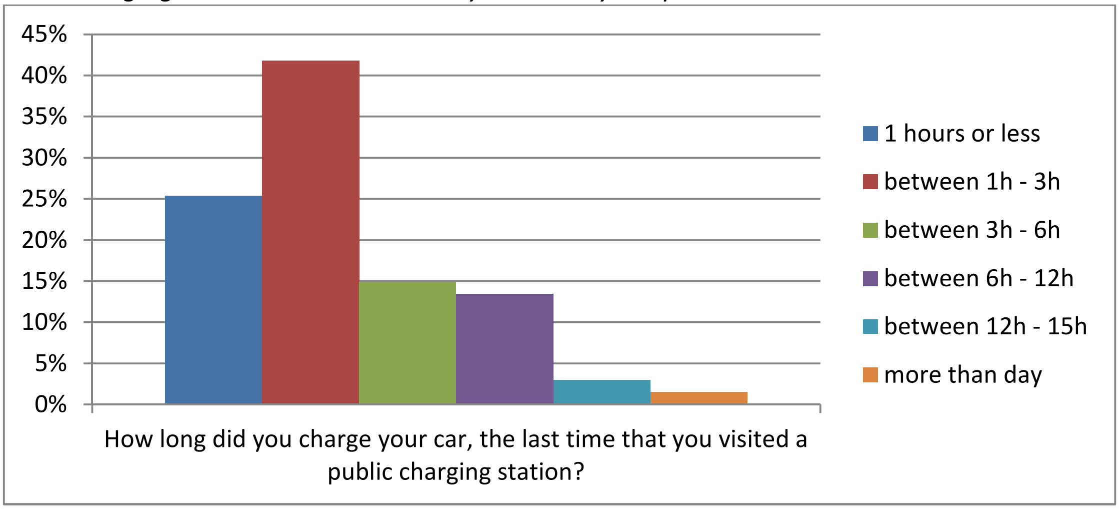


Figure 6: The Frequency of Usage as indicated by the Survey-Respondents

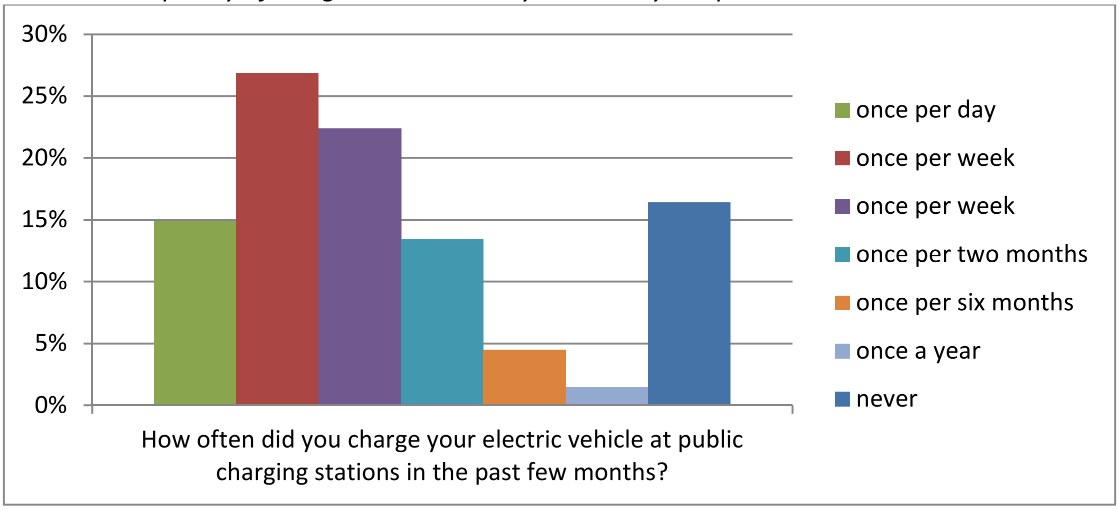


Table 13: Correlation Coefficients of Semantic Scale Questions, (n = 67)

	Q10.1 Convenience	Q10.2 Density perception	Q10.3 Charging speed perception	Q10.4 Reliability perception	Q10.5 Fast-charging importance	Q10 Reliability	Q12 (Sum) Subscriptions	Q13.1 Provider loyalty	Q13.2 Range anxiety	Q13.3 Range anxiety intensity	Q14.1 City-charging high price	Q14.2 City-charging medium price	Q14.3 City charging low price	Q17.1 Charge reduction	Q17.2 Privacy	Q18.1 Night charging high price
Q10.2 Density perception	.319**															
Q10.3 Charging-speed perception	.267**	.107														
Q10.4 Reliability perception	.549**	.191	.147													
Q10.5 Fast-charging importance	.033	.192	-.224	.019												
Q10 Reliability	-.892**	-.293*	-.238*	-.868**	-.030											
Q12 (Sum) Subscriptions	.140	.184	-.039	.237	-.098	-.211*										
Q13.1 Provider loyalty	.193	.118	.018	.102	.146	-.170	-.486**									
Q13.2 Range anxiety	.235*	.005	-.126	.220*	-.071	-.258*	.423**	-.218								
Q13.3 Range anxiety intensity	.056	-.103	-.115	.021	-.207*	-.044	.297*	-.263*	.618**							
Q14.1 City-charging high price	-.023	-.113	.027	.068	.261**	-.023	.031	.301**	-.062	-.125						
Q14.2 City-charging medium price	.127	.146	.043	.251*	.194	-.211*	.077	.103	.026	-.132	.399**					
Q14.3 City charging low price	.117	.078	.096	-.092	-.039	-.020	-.073	.088	.220	.196	-.139	-.106				
Q17.1 Charge reduction	.152	.295*	.040	.040	-.281*	-.112	.019	.124	-.054	.172	-.209*	.069	.292**			
Q17.2 Privacy	.297*	.326**	.396**	.134	-.205*	-.249*	.155	-.051	.084	.084	-.042	-.004	.346**	.250*		
Q18.1 Night charging high price	-.157	.013	-.190	.112	.186	.033	.218*	.051	.292*	.092	.559**	.219*	.013	-.034	-.112	
Q18.2 Night charging low price	.130	.171	.197	.202	.269**	-.186	-.162	.094	-.001	.006	.190	.352**	.338**	.062	.186	.112

* Correlation is significant at the 0.1 level (2-tailed)

** Correlation is significant at the 0.05 level (2 tailed)

Table 13 reveals the correlations of the most relevant semantic scale variables. In the following we describe the relevant and significant results of the correlation table.

The convenience (Q10.1) of the charging stations shows strong correlations at the 0.05 level with the variables for perceived station density (Q10.2), the perception of the charging speed (Q10.3) and the reliability of the charging stations (Q10.4). The positive linear relationship between the convenience and the perceived density of charging stations shows that users who are satisfied with the current charging station density also perceive charging stations as convenient. The analysis further corroborates this factor of satisfaction with the service. The additional positive correlation between the perceived charging speed and the convenience of the stations underlines that users who are satisfied with the service are content with multiple dimensions of it, not just a single one. The strong positive correlation between convenience and reliability indicates that these scales measure a similar concept. We summate and average the scores for these variables and derive the Q10-Reliability score. This score is again strongly negatively correlated with the perception of density and the perception of charging speed. Q10-Reliabilty is also negatively correlated (at the 0.1 level) with the Q12(Sum) score. This score summates the different subscriptions-types that users have, to generate a score between 0 and 3. 0 means that a user solely has a subscription for RheinEnergie's charging services. If a user has more subscriptions for different types of providers the score increases to maximum of 3. The negative correlations show that particularly drivers with less subscriptions, and possibly less experience, perceive the charging stations as having high reliability. The more subscriptions a user has, the lower he perceives the reliability of the charging stations. Variable Q13.1 measures the frequency of charging a vehicle at different service providers. Its negative correlation with Q12(Sum) underlines the validity of the scales. Variables Q13.2 and Q13.3 measure the existence and intensity of range anxiety, respectively. A correlation of 0.618 at the 0.05 level supports the validity of these two variables. Both range anxiety scores correlate with the Q12(Sum) variable with coefficients of 0.423 (Q13.2) and 0.297 (Q13.3). We interpret this as a relation between the number of public charging service-subscriptions and range anxiety. Drivers who perceive more range anxiety have less subscriptions for different charging providers. The intensity of range anxiety (Q13.3) is negatively correlated with the importance of fast charging (Q10.5). This is a counterintuitive result, because we rather expect that a higher range anxiety enhances the importance of fast-charging stations, the contrary seems to be the case. Variables Q14.1 to Q14.3 describe the first pricing scenario. Q14.1 shows significant correlations with the importance of fast charging and the frequency of charging at different service providers. This means that users who rather prefer to have their vehicle fully charged within two hours for a high price (in this case €20), also perceive fast charging infrastructure as more important. It also means that users who rather choose the high price also tend to have more subscriptions for different charging providers. A correlation coefficient of 0.399 for between Q14.1 and Q14.2 underlines the relationship between the two pricing variables. The option to pay €10 and to have the car's battery not fully charged, but only so far that one can drive home comfortably, is positively related to the reliability of charging stations (Q10.4). This shows that people who perceive the charging stations as reliable, and are consequently sure that their car will have the required charge to reach home, also rather prefer this pricing option. Variable Q17.1 measures the willingness to accept a reduction in charging speed, when high demand at the charging station occurs. It is positively correlated with the perceived density of charging stations. Drivers who perceive the density as sufficient find a charging speed reduction more acceptable than otherwise. This correlation possibly portrays "sharing"-users who do not mind the reduction instead of extending the charging station network (and creating additional charging spots). The willingness to accept a charging speed reduction (Q17.1) is also negatively correlated with the importance of fast-charging (Q10.5). This means that drivers, who do not mind the reduction, perceive a reduced importance of fast-charging infrastructure. The willingness to accept a charging speed reduction also shows a negative and a positive correlation with Q14.1 and Q14.3, respectively. Users who are willing to accept the reduction in charging speed rather dislike to paying a high price for a 2-hour recharge. They prefer to pay a low price for a longer recharge period. The variable that measures the acceptance of privacy revealing identifications methods (Q17.2) is positively correlated with several convenience scores (Q10.1, Q10.2, and Q10.3). This shows that the users who find it appropriate to identify themselves at the charging stations tend to perceive them as more convenient, faster and also perceive the density of stations as more satisfactory. The variable also depicts a strong relation with the low-price option of the short-term charging scenario (Q14.3). Users who find it acceptable to identify themselves rather prefer to pay less and wait longer in the respective scenario. Moreover Q17.2 positively correlates with Q17.1, which means that drivers who do not mind the reduction in charging speed, also rather do not mind to identify themselves at the charging station. The high price option of the second scenario (Q18.1), in which respondents are presented with an overnight charging situation, correlates with the intensity of range anxiety. This shows that users, who agree that range anxiety is an intensive feeling, have a tendency to choose the expensive price option. This relation can be interpreted as a compensation for range anxiety and a wish for flexibility during a night charging scenario. Q18.1 equally correlates with the high price (Q14.1) and the medium price (Q14.2) of the city (short-term) charging scenario. This suggests that drivers who score high/low on these two scales also tend to score the same direction for question Q18.1. We can deduce from this, that users who prefer the immediate charging option at a high price in the city scenario prefer the same type of charging option in the overnight scenario. We see similar tendencies for the low price options of both scenarios (Q14.3 and Q18.2). Furthermore, Q18.2 (€5 for an overnight recharge, with the vehicle being available fully charged at 6AM in the morning) positively correlates with Q10.5 (the importance of fast-charging). This interaction is counterintuitive and exerts that drivers who think that fast charging is important rather tend to choose the slow charging option for the overnight scenario. A possible interpretation is that fast charging is important for specific occasions, but not when the car is parked for extended time-periods.

Finally we evaluate the impact of the semantic scale questions on the attribute involvement of the charging stations. Attribute involvement includes the concepts according to Scherer & Lane (1997). The privacy scale of the survey shows correlations with the convenience, density and the charging speed (effectiveness) of the charging stations. Additionally we observe correlations between the concept of convenience and the variables station density, charging speed, and the reliability of the stations. We conclude from these significant correlations that the concept of attribute involvement applies to public charging infrastructure. Moreover, this means that the factors that make up the attribute involvement reinforce one another. So in order to increase the attribute involvement with public charging stations CSPs will have to work on all factors to achieve a maximum of involvement.

Table 14: ANOVA Results of Semantic Scales and Nominal Scale Questions

Question No.		**Q3 Mileage**	**Q4 Charging distance**	**Q5 Frequency of usage**	**Q7 Charging duration**	**Q9 Usage type**	**Q11.1R1 City preference**	**Q11.2R1 Country preference**	**Q11.3R1 Highway preference**	**Q15 Dwelling**
Q10.1 Convenience	F-Test	0.692	**2.523****	0.833	1.117	0.360	2.453	**3.725**	0.070	0.740
	p-value	0.648	**0.050**	0.532	0.357	0.699	0.122	**0.058**	0.792	0.481
	N	66	**64**	65	65	65	66	**66**	66	62
Q10.2 Density perception	F-Test	0.858	1.651	0.240	1.778	**3.088**	0.118	0.203	0.001	0.092
	p-value	0.531	0.173	0.943	0.145	**0.053**	0.732	0.654	0.973	0.912
	N	66	64	66	65	**65**	66	66	66	66
Q10.3 Charging-speed perception	F-Test	1.015	0.410	1.158	0.865	0.813	1.163	0.050	1.165	1.876
	p-value	0.424	0.800	0.341	0.490	0.448	0.285	0.823	0.284	0.162
	N	66	64	65	65	65	66	66	66	66
Q10.4 Reliability perception	F-Test	0.505	0.640	0.388	0.928	0.143	0.416	1.383	0.040	0.345
	p-value	0.802	0.636	0.855	0.454	0.867	0.521	0.244	0.842	0.710
	N	66	64	65	65	65	66	66	65	63
Q10.5 Fast-charging importance	F-Test	0.382	**4.302**	1.305	0.822	2.396	**8.717**	1.790	**5.076**	0.247
	p-value	0.888	**0.004**	0.274	0.516	0.099	**0.004**	0.186	**0.028**	0.782
	N	66	**64**	65	65	65	**66**	66	**66**	61
Q10 Reliability	F-Test	0.69	1.688	0.737	1.241	0.065	1.634	6.522	0.002	0.122
	p-value	0.659	0.165	0.599	0.303	0.937	0.206	0.013	0.961	0.886
	N	67	64	65	65	65	66	64	66	66
Q12 (Sum) Subscriptions	F-Test	2.59	0.354	**2.063**	0.322	2.817	.871	.113	0.666	2.163
	p-value	0.027	0.840	**0.083**	0.898	0.067	.354	.738	0.417	0.123
	N	67	64	**66**	66	65	66	66	66	66
Q13.1 Provider loyalty	F-Test	1.54	1.805	**3.989**	0.458	1.739	.021	.856	0.856	0.943
	p-value	0.181	0.140	**0.003**	0.766	0.184	.885	.358	0.356	0.395
	N	66	64	**65**	65	65	66	66	66	66

Question No.		Q3 Mileage	Q4 Charging distance	Q5 Frequency of usage	Q7 Charging duration	Q9 Usage type	Q11.1R1 City preference	Q11.2R1 Country preference	Q11.3R1 Highway preference	Q15 Dwelling
Q13.2 Range anxiety	F-Test	1.329	5.581	0.773	1.152	2.566	2.606	2.614	0.312	1.620
	p-value	0.259	0.125	0.573	0.341	0.085	.111	.111	0.578	0.206
	N	66	64	65	65	65	66	66	66	66
Q13.3 Range anxiety intensity	F-Test	0.625	1.132	0.228	2.193	**3.046**	.467	.787	0.006	1.870
	p-value	0.709	0.350	0.949	0.080	**0.055**	.497	.378	0.940	0.162
	N	66	64	65	65	**65**	66	66	66	66
Q14.1 City-charging high price	F-Test	0.188	0.855	1.195	0.930	**4.016**	.056	.878	1.101	**4.038**
	p-value	0.979	0.496	0.322	0.452	**0.023**	.814	.352	0.298	**0.022**
	N	66	64	65	65	**65**	66	66	66	**66**
Q14.2 City-charging medium price	F-Test	0.64	1.143	0.496	1.684	2.075	.022	1..262	1.203	0.264
	p-value	0.698	0.345	0.778	0.165	0.134	.882	.265	0.277	0.769
	N	66	64	65	65	65	66	66	66	66
Q14.3 City-charging low price	F-Test	1.318	**4.454**	2.818	0.366	1.361	1.226	.102	1.067	2.000
	p-value	0.263	**0.003**	0.024	0.832	0.264	.272	.750	0.305	0.144
	N	66	**64**	65	65	65	66	66	66	66
Q17.1 Charge reduction	F-Test	0.585	0.390	0.499	**2.464**	**6.248**	1.342	.381	0.714	0.243
	p-value	0.741	0.815	0.776	**0.054**	**0.003**	.251	.539	0.401	0.785
	N	66	64	65	**65**	**65**	66	66	66	66
Q17.2 Privacy	F-Test	1.598	0.316	**2.732**	0.837	0.162	**5.495**	0.324	0.604	0.737
	p-value	0.163	0.866	**0.027**	0.507	0.851	**.022**	.571	0.440	0.482
	N	66	64	**65**	65	65	**66**	62	66	66
Q18.1 Night charging high price	F-Test	0.321	1.155	0.371	2.148	1.933	.716	2.031	0.027	0.498
	p-value	0.923	0.340	0.867	0.086	0.153	.401	.159	0.871	0.610
	N	66	64	65	65	65	66	66	66	66
Q18.2 Night charging low price	F-Test	0.709	**5.260**	**2.061**	0.238	2.098	.031	1.878	0.820	0.383
	p-value	0.643	**0.001**	**0.083**	0.916	0.131	.860	.175	0.369	0.683
	N	66	**64**	**65**	65	65	66	66	66	66

Table 14 presents the results of the statistically related nominal and semantic scales of the survey. We obtain these results from one-way ANOVA analyses of one nominal and one semantic scale respectively. A first significant difference between quantitative variables clustered along qualitative features occurs for Q3 (Mileage) and Q12 (sum) (Subscriptions). This relation shows that users who drive longer mileages have a tendency to own more subscriptions for public charging service providers. A second significant difference between user groups occurs for the variables Q4 and Q10.1. Q4 describes the distance between two charging instances and Q10.1 the convenience of charging stations. Particularly those users who drive shorter distances (25 to 50km) between two instances are more in favor of the convenience of charging stations (avg=2.46, std=1.59) than those who drive 50 to 75km per charge (avg=3.29, std=1.92). However drivers, who drive longer distances between charges, perceive charging stations even more convenient with means of 1.38 (std=0.52) and 2.15 (std=1.07), for distances of 75 to 100km and 100 to 150km per charge, respectively. We also find a significant connection for groups that are partitioned along the importance of fast charging (Q10.5) and the distance between two charging instances (Q4). Drivers who drive short distances value fast charging much less than those who drive longer distances between two charges. This rather obvious result becomes apparent by looking at the different means for these groups. For example, drivers who drive 25km or less on one charge have a mean of 6 (7 being "disagree completely") for the importance of fast charging. Drivers making 75km or more on a charge have a mean of 2 ("agree"). The groups that are in between show gradual tendencies of agreement / disagreement. The low-price option of the city-charging-scenario (Q14.3) also shows significant differences when we cluster it along the distance driven per charge (Q4). The group of drivers that make 75 to 100km per charge on average have the highest agreement with this question (avg=2.75, std=2.12). Particularly those who drive less than 25km strongly disagree with this price-option on average (avg=7, std=0.0). The biggest group of users drives 25 to 50km per charge. They are on average "neutral" with a tendency towards agreement concerning the low price of the sort-term charge with a mean of 3.58 (std=1.84). We observe similar behavior for the low-price option of the long-term scenario (Q18.2). Here again those with the shortest distances show the strongest disagreement (avg=5.68, std=2.31) and those driving longer distances show higher scores of agreement (avg=1.77, std=1.64). We deduce that these results are caused by the amounts of money that we chose in the two scenarios. €5 for a full charge still is expensive when one drives below 25km kilometer per week, because many users also have the option to charge the vehicle at home.

The main dependent variable in our model (Q5: frequency of usage) depicts marginal correlation and significances when we compare it to the semantic scale questions. This weakens the explanatory power of the variable. We observe two variables (Q13.1, Q17.2) with significant differences at the

0.05 level when they are clustered according to the frequency of usage. A third variable shows differences at the 0.10 level (Q18.2). The significant differences between the frequency of usage (Q5) and the frequency of charging at different providers (Q13.1) shows that those users who never charge their vehicles at RheinEnergie's charging station, also do not charge them at competitors' stations. We hence observe that users that frequently share at public charging stations, also have multiple subscriptions for different providers. The mean for the group of users who never charge and the group that charges the car once every six months at public charging stations is 6 ("disagree"; never std=1.183; once per six months std=1.732). For the other groups we see a gradual decline of the frequency of charging at different providers. The group that asserts that it charges the car once a day at public charging stations has the highest agreement with the frequency of charging at different providers (avg=2.60, std=2.01). This agreement gradually declines with the frequency of usage: once a week (avg=3.72, std=2.35), once a month (avg=3.87, std=2.33), once in two months (avg=5.11, std=1.83). The frequency of usage also creates a significant difference in groups for the variable Q17.2 (privacy concerns). Privacy concerns are particularly diminished for those users who frequently use the charging stations. Drivers who charge their car once a day or once a week at a public charging station "agree" with the acceptability of phones or RFID's to identify themselves at the stations (avg=1.70, std=1.06 and avg=2.11, std=1.18, respectively). Particularly those users who use public charging stations infrequently find the identification method less acceptable. The users who charge their cars once a month or once every two months "rather agree" or are "neutral" towards the identification method, with means of 3.67 (std=2.225) and 3.22 (std=1.986). The low price option of the overnight charging scenario (Q18.2) also shows a significant difference when we categorize it according to the frequency of usage (Q5). Here we observe that users who charge more frequently rather choose the low price option (once per day avg=1.6, std=1.075) than those users who charge less frequently at public charging stations (once per six months avg=4.33, std=2.517).

Moreover we notice a significant relation for the charging duration (Q7) and the willingness to accept a reduction in charging speed (Q17.1). The group that charges the car for 12 to 15 hours shows the highest acceptance for the reduction of charging speeds (avg=2, "agree", std=0.0). Drivers who normally charge their car less than one hour at a public charging station are "neutral" (avg=4.12, std=1.9) towards the reduction. Users who charge one to three and three to six hours perceive the reduction slightly more positive and score between "rather agree" and "neutral" with means of 3.79 (std=1.79) and 3.20 (std=1.93), respectively. Users who dislike the reduction the most charge between six to twelve hours (avg=5.33, std=1.5) on average. We interpret this result with the user's expectation. Drivers, who park their car for more than six hours, expect to return to a fully charged vehicle after such a prolonged period of time. For those time periods that are significantly longer than six hours, the probability that the vehicles is not charged on return decreases strongly and hence users are more willing to accept the reduction.

Significant differences are also apparent for user groups clustered along the usage of their car (Q9) (private, work and work & private) and the perceived density of charging stations (Q10.2). Drivers who use their car just for private purposes perceive the density as being better (avg=4.42, std=1.84) than those who use their car for work and private occasions (avg=5.59, std=1.47). Those users who just use the car for work are in the middle of these scores with a mean of 4.92 (std=1.94). Overall users perceive the density as rather insufficient. Furthermore we see that the usage of the car (Q9) also impacts the intensity of range anxiety (Q13.3). The intensity is weakest for drivers who use EVs for private and work purposes (avg=4.93, std=2.09) and strongest for drivers who use EVs just for work purposes (avg=3.31, std=1.70). We explain this with the stronger motivation of the users, who use the EV for both purposes, to integrate the technology in their lives. They have hence more experience and feel less range anxiety. Moreover, on the one hand we see that work & private drivers are more willing to accept the high price option (Q14.1) of the city scenario (avg=5.04, std=1.951) than private drivers (avg=6.27, std=1.04). On the other hand private drivers are more willing to accept a reduction in charging speeds (avg=3.12, std=1.68) than private & work drivers (avg=4.81, std=1.71). For both relations drivers who use the car just for work are in the middle of these scores.

The variables Q11.1R1 to Q11.3R1 describe whether the respondents rated the city, country roads, or highways as being their first locational choice for charging stations. Users who choose the city as their favorite location for charging stations perceive fast charging (Q10.5) as being less important (avg=3.07, std=1.88) than users whose favorite location is not the city (avg=1.76, std=1.09). Inversely, users who choose highways (Q11.3R1) as their favorite location prefer fast charging (avg=1.75, std=1.138). The users who prefer the city also find it more acceptable to identify themselves with a phone or an RFID (Q17.2). In general 68% of the sample prefers charging stations in the city, 12% along country roads, and 20% along highways.

We also observe a strong relationship between the type of dwelling (Q15) and the high-price option of the city charging scenario (Q14.1). Drivers who live in a flat without a private parking space are “neutral” (avg=4.33, std=2.24), whereas drivers with a flat and a parking space “disagree” (avg=6.24, std=1.03) with the option. Drivers living in an individual dwelling disagree less with this pricing option (avg=5.61, std=1.67).

Finally we evaluate the influence of variables that compose the attribute involvement of public charging stations with the frequency of usage (Q5) and other nominal scale questions. With respect to this bundle of factors we observe the privacy variable (Q17.2) as the sole factor that shows a correlation with the frequency of usage. There is hence not enough evidence to conclude that the attribute involvement variables have significant influence on the frequency of usage. Based on the results from the previous section we can however say that most factors comprising the concept of attribute involvement show a high consistency.

Table 15: Results for the χ^2 Frequency-Tables of Nominal Questions

		Q3 Mileage	**Q4 Charging distance**	**Q5 Frequency of usage**	**Q7 Charging duration**	**Q9 Usage type**
Q5 Frequency of usage	Pearson χ2	**5.662**	0.287			
	p-value	**0.059**	0.592			
	N	**67**	56			
Q7 Charging duration	Pearson χ2		**3.376**	0.000		
	p-value		**0.066**	1.000		
	N		**56**	56		
Q8.3 Activity appointments	Pearson χ2		0.020	**4.139**		
	p-value		0.887	**0.042**		
	N		67	**56**		
Q9 Usage type	Pearson χ2	0.254	0.035	0.181	0.155	
	p-value	0.614	0.852	0.671	0.694	
	N	66	66	55	66	
Q11.1R1 City preference	Pearson χ2		0.617	0.084		
	p-value		0.432	0.771		
	N		67	56		
Q11.2R1 Country preference	Pearson χ2		0.884	0		
	p-value		0.347	0.639		
	N		67	56		
Q11.3R1 Highway preference	Pearson χ2		0.023	0.424		
	p-value		0.880	0.515		
	N		67	56		
Q15 Dwelling	Pearson χ2		0.605	2.695	0.061	4.331
	p-value		0.436	.101	0.805	0.115
	N		67	56	67	66
Q16 Billing Method	Pearson χ2			1.948		
	p-value			0.163		
	N			56		
Q24 Children	Pearson χ2			3.837		
	p-value			0.147		
	N			65		
Q25 Gender	Pearson χ2			2.550		
	p-value			0.110		
	N			52		

Table 13 presents the statistically relevant relationship of nominal questions in the survey. Due to the extent of the analyses we focus solely on the most pertinent connections. Only one pair of variables in this table has a relationship that is significant at the 0.05 level, the remaining significant relationships reach the 0.10 level. The variables for frequency of usage (Q5) and kilometers driven per week (Q3) have an interdependence at the 0.10 level. We see that 25.4% of the sample drives less than 200 kilometers per week and use public charging stations at least once a month. 28.4% of the sample use public charging less than once per month, but drive more than 200km per week. 10.4% never use public charging stations and drive less than 200km per week. Circa 6% drive more than 200km and never use any public charging stations. In this context we like to mention that there are many active EV communities in Germany, which guarantee each member of the community a free charge at the other member’s residence. The frequency of usage also shows a relationship with a side-variable, that we included in the model for classification purposes. Q8.3 and Q8.4 are part of the nominal question Q8, which asks respondents to choose from a list of activities that they engage in, when they charge their car at a public charging station. Response Q8.3 stands for “pursuing appointments (e.g. Sports, meeting friends)”, Q8.4 describes situations in which users solely park at charging stations to recharge their cars, without any other purpose in mind.

Table 13 also reveals a significant relationship between the variables for the distance driven between two charging instances (Q4) and the duration of a regular charge at a public charging station (Q7). We observe that 35.7% drive less than 50km between two instances and charge the vehicle shorter than three hours. 28.6% drive more than 50km and charge their vehicle shorter than three hours. Merely 10.7% charge their vehicle longer than three hours and drive less than 50km per charge. However, 25% of the sample drive their car longer than 50km on a charge and charge it longer than 3 hours. These results underpin that users who drive longer between two charges also charge longer. Nevertheless the granularity of these scales leaves much leeway for interpretations. In general we can ascertain that a charge of maximum three hours suffices for most of the drivers (64.3%) in the sample.

Despite the just mentioned relationships Table 13 reveals that there is a somewhat strong relationship (p-value .101) between the type of dwelling and the frequency of usage. The analysis shows that 60% of the sample lives in individual houses and 40% in apartments with or without parking spaces. Of those users, who live in an individual house, solely 41.2%, regularly visit (once per month) public charging stations. However, 63.6% of the drivers who live in apartment-buildings use a public charging at least once a month. These results underline the tendency that drivers who live in attached multi-unit houses have a higher frequency for the usage of public charging stations.

We conclude this section with the assertion that the dependent variable shows weak interaction with most of the independent variables. We observe five significant relationships with the dependent variable of 31 overall connections. As a consequence we strongly reduce the independent variables in the regression model. The following chapter presents the regression model in more detail.

7.1 Regression Results

Due to the limited amount of variables that show a correlation with the dependent variable in the bivariate analyses, we reduce the amount of independent variables in the regression model. In the following we present two regression models. One model is based on a logistic regression; the other model refers to a linear regression. We expect that the logistic regression model performs better, due to nominal and dichotomous nature of the dependent variable (O'Halloran, 2013). We transform the dependent variable frequency of usage into a dummy variable, which equals 1 in case a user charges his or her vehicle at least once a month at a public charging station. The variable equals 0 when a user charges less than once a month or never at public stations.

The regression models are formulated as follows:

Equation 9

$$\begin{aligned} Q5Frequency\ Use &= \beta_0 + \beta_1 Q10Reliability + \beta_2 Q10.3PerceptionSpeed \\ &+ \beta_3 Q13.1ProviderLoyalty + \beta_4 Q14.1CityChargeHigh \\ &+ \beta_5 Q14.2CityChargeMed + \beta_6 Q17.1Reduction + \beta_7 Q17.2Privacy \\ &+ \beta_8 Q18.2NightChargeLow + \beta_9 Q3D1Mileage + \beta_{10} Q15D2MultiUnitWith \\ &+ \beta_{11} Q15D3MultiUnitWithout \end{aligned}$$

The variable Q10-Reliability describes the above mentioned summated and averaged scales of convenience (Q10.1) and reliability (Q10.4). We use this variable in the regression, because it is an essential part of the research-model. However it does not appear to have a relationship with the frequency of usage in the bivariate analysis. We include variable Q10.3 ("perception of charging speed"), because the variable depicts a strong correlation with variable Q17.2 ("privacy"), which in turn displays a correlation with the frequency of usage. The variables Q3 (Kilometers driven per week), Q13.1 (Provider loyalty), Q17.2 (Privacy), and Q18.2 (Low-price option of night charging scenario) are part of the regression model, because they all show a significant relationship with the dependent variable in the bivariate analyses. The variable "Kilometers driven per week" (Q3D1) is included as a dummy in the model. It describes distances below 200km per week; it is equal to 1 when a user drives distances below that threshold; it equals 0 when a user drives above it. We also add the high-price variable Q14.1 to the model, because it correlates with Q13.1 (Provider loyalty). For reasons of consistency we equally include the medium-price counterpart (Q14.2) of this scenario in the regression. Moreover we add the willingness to accept a reduction in charging-speed (Q17.1) in the regression, because the variable depicts correlations with the charging duration (Q7) and the usage of the vehicle (Q9). Correspondingly the reduction in charging speed (Q17.1) has a negative relationship with the high-price variable (14.1). Next to these variables we include Q15 (Type of dwelling). This variable is part of the model, because it almost depicts a significant relationship with the dependent variable in the bivariate analysis (p-value = 0.101). We incorporate the type of dwelling as dummy variables in the formula. We apply two dummy variables, which discern detached or semi-detached house with a parking space, attached multi-unit housing with a parking space (Q15D2), and attached multi-unit housing without a parking space (Q15D3). Q15D2 equals 1, if the respondent lives in an attached multi-unit housing with a parking space. The variable it equals 0, if the respondent does not live in such a type of dwelling. The same logic applies to the dummy variable for attached multi-unit housing without a parking space (Q15D3.) We use the set of variables in a logistic regression and a linear regression model, in order to refine the results. Table 14 presents the results of the two analyses.

Table 16: Results of the Linear and Logistic Regression Model

Dependent Variable: 0 = less than once per month; 1 = at least once per month

	Linear Regression Model				Logistic Regression Model		
Variables	Pred. Sign	Coeff.	t	Variance Inflation Factor	Pred. Sign	Coeff.	Wald Chi-squared
(Constant)	+	1.489	4.869		+	7.974	8.234
Q10 Reliability	+	0.032	7.772	1.234	+	0.208	0.708
Q10.3 Charging-speed perception	-	0.065*	-1.748	1.285	-	0.458*	3.231
Q13.1 Provider loyalty	-	0.081**	-3.3115	1.305	-	0.549**	8.563
Q14.1 City-charging high price	-	0.064	-1.646	1.610	-	0.618*	3.298
Q14.2 City-charging medium price	+	0.029	1.061	1.484	+	0.205	1.071
Q17.1 Charge reduction	-	0.021	-0.679	1.222	-	-0.177	0.795
Q17.2 Privacy	+	0.2	0.555	1.403	+	0.149	0.387
Q18.2 Night charging low price	-	0.049	-1.31	1.249	-	-0.283	1.072
Q3D1 Mileage (below 200km)	+	0.02	0.17	1.273	+	0.274	0.137
Q15D2 Dwelling (attached multi-unit, with parking space)	+	0.280**	2.135	1.225	+	1.582*	3.525
Q15D3 Dwelling (attached multi-unit, without parking space)	+	0.002	0.009	1.248	+	0.080	0.004
R^2	0.364				Nagelkerke R-squared		0.500
n	66				Cox & Snell R-Squared		0.365
					Correctness		0.791

** Correlation is significant at the 0.05 level

* Correlation is significant at the 0.10 level

The regression formulas show similar results for the influence of the independent varaibles on the dependent one. The linear regression model has an explanatory power of about 36.4%. Three independent variables in this model show a significant influence on the dependent variable. The binary logistic regression has a correctness of 79.1% between the predicted and observed results. The Nagelkerke R-squared reaches 0.500, the Cox & Snell R-squared 0.365. The results of the model show a total of four significant independent variables. We set the levels for significance at the 0.05 and the 0.10 level. The variables do not show a strong multicollinearity. Most of the VIF scores are between 1 and 1.5, only the City-charging high price variable (short-term charging: Q14.1) shows a level of above 1.6. We attribute Q14.1's larger VIF to the fact that we also include the City-charging medium price variable (Q14.2) in the model. The variables show a significant positive correlation-coefficient in Table 13. However, the VIF values are below the threshold of 2 and we consequently do not see substantial evidence to revise the model due to multicollinearity.

Both models reveal the significant impact of the perception of the charging speed (Q10.3). The variable has a beta coefficient of -0.065 and -0.458 in the linear and the logistic regression, respectively. The negativity of the coefficient shows that the perception of charging speed is an important factor to explain the frequency of usage of public charging stations. The scale for this question ranges from 1 "fully agree" to 7 "fully disagree". The more negative a user perceives the charging speed, the less frequent will she/he make use of the services. The coefficient for the charging at different providers (Q13.2) is -0.081 in the linear model and -0.549 in the logistic model. The significant negative coefficient allows drawing the conclusion that users who charge more frequently at charging stations of different suppliers also have a higher frequency of usage of public charging infrastructure. Both models also expose a positive significant impact for the attached multi-unit housing with a parking space (Q15D2) on the frequency of usage. This result suggests that drivers who live in apartments or flats with parking spaces are more likely to frequently visit public charging stations. We expected a similar result for drivers who live in these types of buildings without a parking. This expectation however does not materialize. As an explanation for this result we put forward the circumstance that a mere 11% (7 respondents) of the sample live under such conditions. The low quantity of respondents can consequently lead to the insignificance of the variable in the model. Finally we constitute a significant influence of the high price city-charging variable. Its significance is however limited to the logistic regression at the 0.1 level. The variable has a coefficient of -0.618, which illustrates that respondents who disagree with this pricing option tend to use public charging stations less often.

In conclusion we find that the research model as presented in chapter 2.5 does not function as we hypothesize in the methodological section. A limited number of variables have a significant influence on the frequency of usage of public charging infrastructure. This result leads to the circumstance that we cannot support some hypotheses. We "partly confirm" several hypotheses, which means that the respective variables either show a significant impact in the regression- or the bivariate-analysis. Subsequently we present the results for the hypothesis-tests.

Table 17: Hypothesis Test Results

Hypotheses	Tests (Q5 as dependent variable)	Result
H1: Range anxiety has a positive relationship with the frequency of usage of public charging infrastructure.	Q13.2: F = 0.773; p = 0.573 Q13.3: F = 0.228; p = 0.949	not supported
H2: Station-density has a positive relationship with the frequency of usage of public charging infrastructure.	Q10.2: F= 0.240; p = 0.943 Q6(sum): F = 1.385; p = 0.243	not supported
H3: EV-consumption has a positive relationship with the frequency of usage of public charging infrastructure.	Q2: F = 0.297 ; p = 0.586	not supported
H4: The distance between two charging instances has a negative relationship with the frequency of usage of public charging infrastructure.	Q4: F = 0.287; p = 0.592	not supported
H5: The average weekly mileage has a positive relationship with the frequency of usage of public charging infrastructure.	Q3: F = 5.662; p = 0.059 Linear Regression: β = 0.020; p = 0.866 Logistic Regression: β = 0.274; p = 0.711	The variable has a significant effect in the individual F-Test, but does not show significant impact in the statistical models. The hypothesis is partly supported.
H6: Fast-charging has a positive relationship with the convenience of public charging infrastructure.	Q10.3 -> Q10-Reliability: r = -0.238; p = 0.052 Q10.5 -> Q10-Reliability: r = -0.030; p = 0.811 Q10.3 -> Q10.1: r = 0.267; p = 0.029 Q10.5 -> Q10.1: r = 0.033; p = 0.792 Q10.3 -> Q10.4: r = 0.147; p = 0.236 Q10.5 -> Q10.4: r = 0.019; p = 0.879	Perceiving the charging stations as fast has a positive effect on the perception of the convenience of the stations. Perceiving fast charging as important does not have an effect on the perception of the convenience. The hypothesis is partly supported.
H7: Living in detached- and semi-detached houses has a negative relationship with the frequency of usage of public charging infrastructure.	Q15: χ2 = 2.695; p= 0.101 Linear Regression Q15D2: β = 0.280; p = 0.037 Linear Regression Q15D3: β = 0.002; p = 0.993 Logistic Regression Q15D2: β = 1.582; p = 0.060 Logistic Regression Q15D3: β = 0.080; p = 0.947	Living in detached- and semi-detached houses does not have a negative effect on the frequency of usage. However, living in attached multi-unit housing with a parking space does have a positive relationship with frequency of usage. Hypothesis is partly supported.
H8: The possession of subscriptions has a positive relationship with the frequency of usage of public charging infrastructure.	Q12(sum): F = 2.063; p = 0.083	Hypothesis confirmed. The more subscriptions a user has the higher is the frequency of usage.
H9: The use of different charging services has a positive relationship with the frequency of usage of public charging infrastructure.	Q13.1: F = 3.989; p = 0.003 Linear Regression: β = -0.081; p = 0.003 Logistic Regression: β = -0.549; p = 0.003	Hypothesis confirmed. The more often user charges the EV at different charging station the higher is the frequency of usage.

Hypotheses	Tests (Q5 as dependent variable)	Result
H10: Privacy concerns have a negative relationship with the frequency of usage of public charging infrastructure.	Q17.2: F = 2.732; p = 0.027 Linear Regression: β = 0.020; p = 0.581 Logistic Regression: β = 0.149; p = 0.534	The variable has a significant effect in the individual F-Test, but does not show significant impact in the statistical models. Privacy appears to have significant effect on the frequency of usage. The hypothesis is partly supported.
H11: The satisfaction with the charging speed has a positive relationship with the frequency of usage.	Q10.3: F = 1.158; p = 0.341; Linear Regression: β = -0.065; p = 0.086 Logistic Regression: β = -0.458; p = 0.072 Q10.5: F = 1.305; p = 0.274	The perception of charging speed (Q10.3) has no significant effect in the bivariate analysis. However it shows a significant (0.10 level) negative effect in the regression models. The importance of charging speed (10.5) has no significant impact in the bivariate correlation. The hypothesis is partly supported.
H12: The reliability of the charging stations has a positive relationship with the frequency of usage.	Q10-Reliability: F = 0.737; p = 0.599 Linear Regression: β = 0.032; p = 0.444 Logistic Regression: β = 0.208; p = 0.400	not supported

Table 17 displays the explanatory capabilities of the research- and methodological models that we establish in previous chapters. We learn that the vehicle and driver characteristics, such as consumption, station-density, distance between two charging instances and range anxiety have no significant impact on the frequency of usage of public charging infrastructure in our model.

It is surprising that range anxiety does not show any significant relationship with the frequency of usage. A possible cause for this result is the fact that the sample mostly comprises lead-users of the electric vehicles market. They show a strong motivation to integrate the technology in their lives and consequently suppress or show fewer tendencies for the development of range anxieties. Another reason why we see no result for this correlation can be that users only use their cars for very short distances and use other modes of transport or ICE cars for longer trips. This behavior can be a way to overcome range anxiety in EVs. We are unable to make any statements about this association, because we did not include a question in the survey asking whether EV drivers also own an ICE vehicle and how often they use it,.

Station density does not appear to have a relationship with the frequency of usage. We presume that this can have two reasons. The first reason is that the density hasn't reached such a level of development, yet, that it can actually influence the frequency of usage. Secondly we are unable to compare two regions of differing densities in the survey. If we can compare the density and frequency of usage in one city with the same parameter in another place, we receive a more meaningful outcome.

The variable for the consumption of EVs has no significant impact on the frequency of usage. A possible explanation for this is that consumers have distinctly different motivations than the actual necessity to recharge their vehicle when they visit a public charging station. EV drivers currently park for free at RheinEnergie's charging stations, a circumstance which potentially causes part of the insignificance of the consumption data on the frequency of usage. Due to this situation the charging stations become an interesting option as city parking spaces. This can create different motives to charge a vehicle at a charging station despite the plain requirement or desire to recharge its battery.

The distance driven between two charges has no significant influence on the frequency of usage in our model. We try to explain this result by pointing out the short distances that most EV drivers drive between charging instances. Around 36% of the sample drives between 25km to 50km between charges. This is a very short distance, which certainly does not deplete the battery of most EVs. We consequently conclude that most users make use of public charging stations, because they have the option to do so, but they do not have the ultimate need. The fact that range anxiety does equally not have a significant effect supports this assumption. It appears as if most of the EV lead users use the charging stations for convenience and not because their batteries are empty and they are forced to recharge at a public station.

Additionally we obtain the result that reliability, measured as the summated and averaged value of convenience and reliability does not have a significant effect on the frequency of usage of the charging stations. We explain this missing effect with the low availability of charging stations. At the moment EV-drivers generally do not have a real choice when they want to charge their vehicles. There is currently very little competition between the CSPs and therefore the EV drivers simple have to "take it or leave it". That is why they are inclined to use the charging infrastructure even though they are not satisfied with its reliability. Another factor for this effect is possibly the influence of fast-charging. Drivers who are satisfied with the reliability of the stations might avoid them, because they do not offer appropriate charging speeds.

In turn we see three significant, confirmed and four partly supported variables. Their relationships partially explain the dependent variable. The results confirm the hypotheses that users who frequently shift their charging service provider and who own multiple subscriptions for charging services also charge more frequently at public charging stations. This shows that users need multiple subscriptions and have to charge at different charging providers, if they want to actively use charging stations and integrate them in their lives. We interpret this as an indication for the small-sized charging networks of the individual providers.

Additionally we deduce from the analyses that the perception of fast-charging has a positive effect on the perception of the convenience of the charging stations. We base this result solely on the bivariate analysis and do not corroborate it in a regression. Therefore we are able to partly support the hypothesis. We see that the perception of fast-charging has a relationship with the reliability-score and the convenience of the stations. We conclude that users, who perceive the stations as fast, also find them more convenient and reliable.

The results further indicate that there is a connection between the variables mileage, type of dwelling, privacy concerns, the importance of fast-charging, and the perception of charging speeds on the frequency of usage. However we are unable to confirm these relations to a larger extent. This is also due to the reduced scope and possibilities of this research. An additional survey that probes more deeply into these concepts would offer the potential to investigate these relationships in more detail. Unfortunately we were unable to widen the range of our analysis with respect to these significance issues.

We partly support the effect of mileage on the usage of public charging infrastructure. Users who drive longer distances seem to charge less frequently at public charging stations. The regression analysis also sustains the influence of the type of dwelling on the dependent variable. We did not record significant results for this effect in the bivariate analysis. Hence we partly support the hypothesis. It appears that users who live in multi-unit housings with a parking space tend to use charging stations more frequently than those who live in different types of dwelling.

The importance as well as the perception of fast-charging show partly supported relations with the frequency of usage. These effects underline the significance of fast-charging infrastructure to the EV drivers.

Lastly we partly support the influence of privacy on the frequency of usage. We prove the effect in the bivariate analysis, but are unable to verify it in the regression models. We conclude that the privacy of the identification method appears to have an effect on the frequency of usage. User find it more acceptable to identify themselves at a charging station also use charging station more often.

In the subsequent section we cluster the users into groups in order to verify. if the significant results are salient to specific groups.

7.2 Clustering Users of Public Charging Infrastructure

We analyze the survey-sample in two methodological steps, which we present in chapter 4, in order to create comprehensive consumers groups. We apply Ward's clustering method to a set of variables that we choose according to managerial objectives. The regression analyses as well as the bivariate results do not highlight specific variables that allow for effective clustering outcomes. Mooi & Sarstedt (2011) state for these cases that "it is important to select those (variables) that provide a clear-cut differentiation between the segments regarding a specific managerial objective (Mooi & Sarstedt, 2011, p.241)". The authors also suggest using variables in the clustering methodology that are not highly correlated, because "specific aspects covered by these variables will be overrepresented in the clustering solution (Mooi & Sarstedt, 2011, p.242)". We also avoid using "an abundance of clustering variables, as this increases the odds that the variables are no longer dissimilar (Mooi & Sarstedt, 2011, p.242)". We apply seven weakly correlated variables in the Ward filtering approach. We use Q3 the kilometers driven per week, Q9 the type of usage of the car, Q13.3 the intensity of range anxiety, the two pricing variables of the overnight charging scenario Q18.1 and Q18.2, and the Q10-Reliability score. We transform the values for Ward's method and standardize them on a scale between +1 and -1. Figure 7 shows a representation of the differences between the clustering-coefficients.

Figure 7: Coefficients of the Distances between the Values and the Stages of Ward's Method

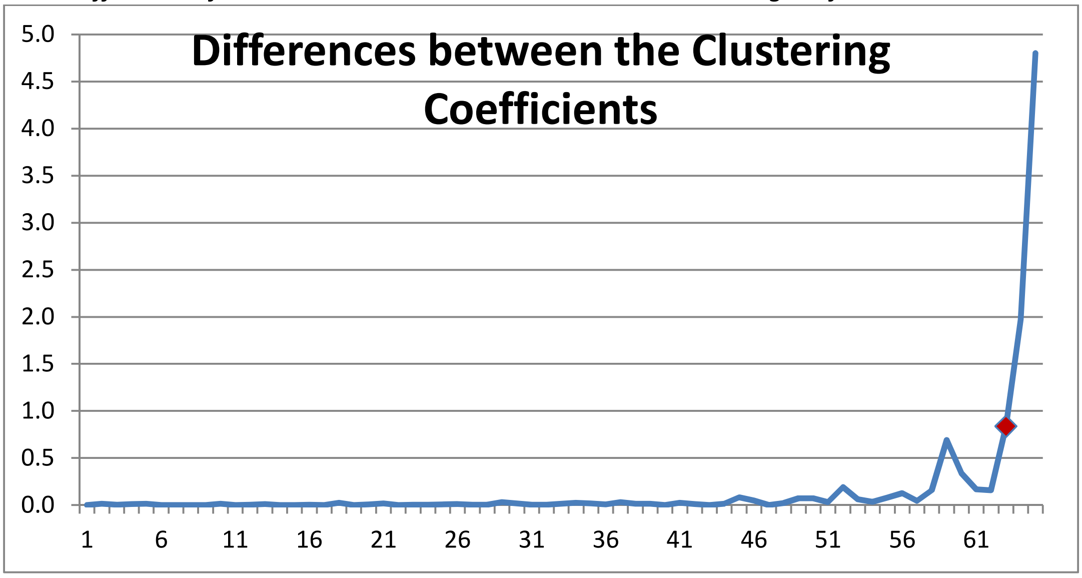
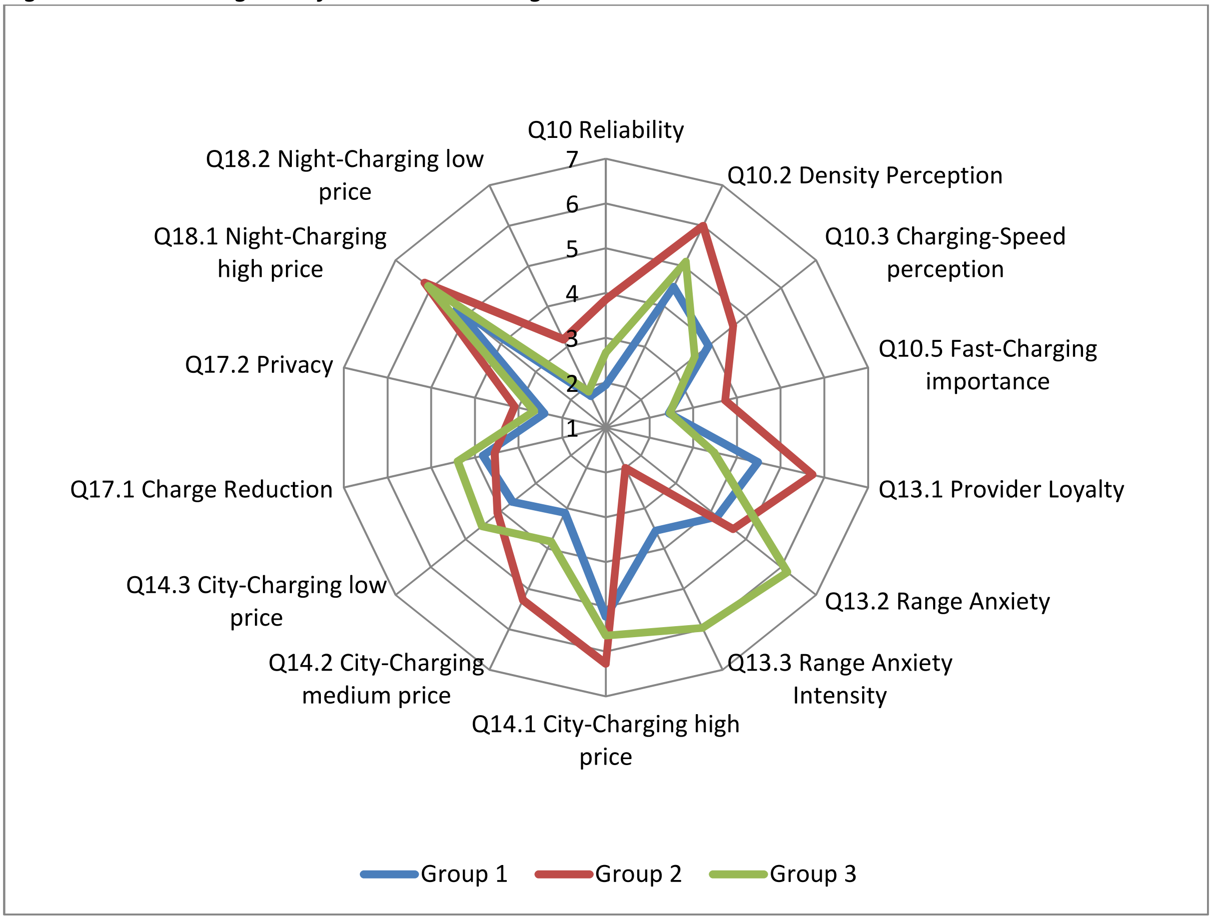


Figure 8: Radar-Diagram of the Clusters using K-means



Stage 63 Figure 7 shows a mark in the data. At that point the coefficient makes a jump from 29.418 to 33.057, a difference of 3.639. The previous coefficients in that series exhibit maximum differences between the coefficients of around 2.8. In total there are 66 values in the clustering analysis. As a consequence we cluster the sample into three distinctive groups.

Another reason for our decision to cut the clustering method at this point is the small sample size. The spike at stage 59 also points to a relevant formation of seven clusters. We dismiss the creation of seven clusters, because each cluster would have a sample-size of around nine respondents. This low number of respondents does not allow us to draw significant results from the groups. We consequently choose to take the second larger jump in the coefficients at stage 63.

We subsequently apply the k-means cluster and preset the cluster-number to three. The k-means iteration process maintains three groups and reassigns values to them. The final split cuts the sample into clusters of 27 (Group 1), 11 (Group 2), and 28 (Group 3) respondents. We consequently conduct independent sample t-tests between the variables of each group. The following table displays these groups and the differences between them. We assume unequal variances for F-tests that are significant at the 0.05 level.

Table 18: The Means of Groups 1, 2, and 3 and their independent Sample T-tests

Variables and Group numbers		N	Means	Std Deviation	Comparison 1 and 2		Comparison 1 and 3		Comparison 2 and 3	
					F-Test p-value	t-test p-value	F-Test p-value	t-test p-value	F-Test p-value	t-test p-value
	1	27	2.06	0.82	11.78	**3.411**	3.884	**2.454**	1.95	**-2.256**
Q10-Reliability	**2**	11	0.14	1.79	0.002	**0.005**	0.054	**0.018**	0.171	**0.03**
	3	28	1.32	1.34						
	1	27	4.48	1.81	1.501	**-2.489**	0.011	-1.313	1.576	1.521
Q10.2 Density perception	**2**	11	6	1.41	0.229	**0.018**	0.916	0.195	0.217	0.137
	3	28	5.11	1.73						
	1	27	3.93	1.59	1.347	-1.363	0.536	0.869	3.313	**1.967**
Q10.3 Charging-speed perception	**2**	11	4.64	1.03	0.253	0.181	0.467	0.389	0.077	**0.057**
	3	28	3.54	1.73						
	1	27	2.44	1.42	3.619	**-2.143**	2.581	-0.045	0.458	**1.83**
Q10.5 Fast-charging importance	**2**	11	3.73	2.20	0.065	**0.039**	0.114	0.965	0.503	**0.075**
	3	28	2.46	1.84						
	1	27	4.48	2.23	1.65	-1.637	0.004	1.704	2.026	**3.01**
Q13.1 Provider loyalty	**2**	11	5.73	1.85	0.207	0.11	0.95	0.094	0.163	**0.005**
	3	28	3.46	2.20						
	1	27	4.19	1.78	0.281	-0.713	15.705	**-5.078**	5.414	**-2.748**
Q13.2 Range anxiety	**2**	11	4.64	1.75	0.599	0.48	0	**0**	0.026	**0.017**
	3	28	6.18	1.02						
	1	27	3.56	1.65	5.204	**3.554**	4.095	**-6.228**	1.264	**-9.888**
Q13.3 Range Anxiety intensity	**2**	11	2	1.00	0.029	**0.001**	0.048	**0**	0.268	**0**
	3	28	5.96	1.17						
	1	27	5.22	1.74	2.537	**-1.869**	0.166	-0.873	3.802	1.073
Q14.1 City-charging high price	**2**	11	6.27	1.01	0.12	**0.07**	0.686	0.387	0.059	0.29
	3	28	5.64	1.83						
	1	27	3.11	2.03	0.16	**-3.1**	3.56	-1.152	3.937	**1.753**
Q14.2 City-charging medium price	**2**	11	5.27	1.74	0.692	**0.004**	0.065	0.254	0.055	**0.088**
	3	28	3.82	2.51						
	1	27	3.67	1.88	0.162	-0.599	1.345	-1.557	0.178	-0.561
Q14.3 City-charging low price	**2**	11	4.09	2.21	0.69	0.553	0.251	0.125	0.675	0.578
	3	28	4.54	2.24						
	1	27	3.81	1.84	0.409	-1.138	0.245	-1.112	0.899	-1.236
Q17.1 City-charging low price	**2**	11	3.55	1.70	0.526	0.262	0.623	0.271	0.349	0.224
	3	28	4.39	2.00						
	1	27	2.41	1.47	1.659	-1.138	1.421	-0.547	0.255	0.69
Q17.2 Privacy	**2**	11	3.09	2.12	0.206	0.262	0.239	0.587	0.617	0.495
	3	28	2.64	1.70						
	1	27	5.26	1.79	0.927	-1.589	0.001	**-1.772**	1.397	0.209
Q18.1 Night-charging high price	**2**	11	6.18	1.08	0.342	0.121	0.981	**0.082**	0.245	0.836
	3	28	6.07	1.61						
	1	27	1.78	0.93	11.284	**-2.1**	2.56	-0.315	1.622	**2.009**
Q18.2 Night-charging low price	**2**	11	3.18	2.14	0.002	**0.058**	0.116	0.754	0.211	**0.052**
	3	28	1.89	1.66						
	1	27	0.96	0.94	0.007	-0.393	0.288	**-2.943**	0.156	**-1.933**
Q12 (sum) Subscriptions	**2**	11	1.09	0.83	0.932	0.697	0.594	**0.005**	0.695	**0.061**
	3	28	1.68	0.86						

The t-tests between the groups reveal their distinctive properties. Group 1 perceives reliability the lowest while Group 2 perceives the stations as very reliable. Group 3 is in the middle of the two; all differences are of a significant nature. Group 1 perceives the density of stations (Q10.2) significantly better than Group 2. Between groups 1 and 3, and 2 and 3 there are no significant differences. Group 3 perceives the charging stations significantly faster (Q10.3) than Group 2. Group 1 identifies fast-charging as very important (Q10.5); significantly more important than Group 2. Group 3 also finds fast-charging more important than Group 2 and is approximately on the same level as Group 1. Group 3 charges significantly more often at different charging service providers (Q13.1) than Group 2 and has the highest score of all the groups. Especially the variables for range anxiety (Q13.2 and Q13.3) show differences between the groups. Group 3 perceives the least range anxiety of all the groups, significantly less than Group 1 and Group 2. A similar pattern is visible for the intensity of range anxiety (Q13.3). Group 3 also perceives the feeling the least intensive. However we also see that Group 2 has the strongest intensity of the feeling, it is significantly stronger than in Group 1 and in Group 3. The pricing variables Q14.1 and Q14.2 reveal that Group 2 dislikes the high-price (Q14.1) and medium price (Q14.2) scenario the most, while Group 1 prefers the higher priced options, especially option Q14.2. The low price option of the short-term charging scenario (Q14.3) shows no significant differences, the groups are unanimously “neutral” on this question. The variables for the acceptance of a reduction in charging speeds (Q17.1) and the perception of privacy (Q17.2) do not depict any differences between the groups. For the variables of the overnight charging scenario, we observe again that Group 2 dislikes the high price option (Q18.1) the most, significantly more than Group 1. Q18.2 is the scale for the low price of the long-term charging scenario. Groups 1 and 3 show a strong sympathy for this pricing option. Again Group 2 dislikes this option the most. Variable Q12 (sum) describes the amount of the subscriptions per user. Here we observe significant differences between Group 1 and 3, and Group 2 and 3. Group 3 holds the most subscriptions, on average more than one, while Group 1 and Group 2 hold only one subscription on average.

In the subsequent table we present the distribution of the groups for the qualitative variables. We excluded Group 2 from the statistical comparison for the variables Q4 to Q27. For these variables the Chi-squared value solely shows the differences between Group 1 and Group 3. We choose this solution, because of the same sample size of n=67 and the reduced size of Group 2 (n=11). The small size has the effect that the contingency tables indicated cells with an expected count of less than five variables. This effect leads us to combine the variables' answer options and to omit Group 2 in the analysis. Nevertheless we show the quantities and distribution of Group 2 in Table 17 in the marked rectangle.

Table 19: Frequency Table and χ^2 Tests of Groups 1, 2, and 3 (Quantities in the Box are excluded from the statistical Analyses)

Variable and option name		Cluster number			Total	Chi-Squared p-value
		1	2	3		
Q3	200km per week or less	23	4	6	33	**23.331**
	more than 200km per week	4	7	22	33	**0.000**
Q4	Less than 50km per charge	13	*3*	11	24	0.439
	More than 50km per charge	14	*8*	17	31	0.508
Q5	At least once per month	15	*2*	11	26	**3.494**
	Less than once per month	6	*7*	14	20	**0.062**
Q7	Less than 3h	20	*6*	19	39	0.258
	More than 3h	7	*5*	9	16	0.612
Q9	Private	8	*6*	12	20	1.039
	Work or Private & Work	19	*5*	16	35	0.308
Q15	detached or semi-detached house with a parking space	15	*5*	20	35	1.497
	attached multi-unit housing with or without a parking space	12	*6*	8	20	0.221
Q16	Per kWh	23	*10*	21	44	0.891
	Per kWh and parking duration, or parking duration	4	*1*	7	11	0.345
Q27	Below 50.000 per year	10.0	*5*	8.0	18	1.097
	above 50.000 per year	12	*4*	18	30	0.295

We observe that only one qualitative variable (Q3) has significant differences between all three groups. Cluster 1 is a group of drivers that mostly drive below 200km per week, whereas cluster 2 has a tendency to drive longer distances. Drivers in cluster three use their cars to drive longer than 200km per week. Q5 (frequency of usage) also shows a significance difference between the groups, with the aforementioned exclusion of Group 2. The variable shows that more drivers in Group 1 use public charging infrastructure at least once per month than drivers who are in Cluster 3. Group 2 is not included in the statistical analysis, but it shows that most users (7 out of 9) charge less than once per month at a public charging station.

To conclude the clustering method, we collect the attributes of each group and assign overarching names to each one of them.

Table 20: Group Characteristics and Classification

Group number	Group name	Characteristics
Group 1	Short city-commuters	- Drive short distances, - Charge more frequently at public charging stations, - Find charging stations rather unreliable, - Are most satisfied with the density of charging stations, - Perceive fast-charging as important, - Have a stronger range anxiety and perceive it moderately intense, - Prefer the flexible charging option, - Prefer the cheap night charging option, - Own one subscription on average.
Group 2	Long commuters	- Drive medium distances, - Charge mostly less than once per month at public charging stations, - Find the stations very reliable, - Dislike the density of charging stations, - Experience strong and intensive range anxiety, - Perceive fast-charging as least important of all groups, - Charge rarely at different charging providers, - Prefer the low price scenarios, - Own one subscription on average.
Group 3	Long haul drivers	- Drive mostly above 200km per week, - Charge infrequently at public charging stations, - Perceive public charging stations reliable, - Dislike the station density, - Prefer fast-charging the most, - Perceive charging stations as fast compared to other groups, - Frequently charge at different charging providers, - Have the least range anxiety and intensity of all groups, - Prefer the flexible charging option for the city scenario, - Prefer the cheap option for the night scenario, - Have more than one subscription.

Table 20 visualizes the differences between the groups along the average distances that the drivers drive per week. We see that the more a driver uses the car in term of driven mileage, the less range anxiety he/she seems to feel. However we are unable to say which variable influences the other. It is possible that the more experience a drive has with driving long distances, the less range anxiety he/she perceives. But, it is also imaginable that drivers who perceive a stronger range anxiety drive shorter distances on average. We equally observe that drivers who drive longer distances have a stronger preference for fast-charging infrastructure and have the most subscriptions of all groups. Interestingly we see that the more drivers go long distances, the less often they use public charging infrastructure. We try to explain this finding with the current unavailability of fast-charging infrastructure and assume that long haul drivers rather prefer to fully recharge their EVs at the destination and not a public stations in-between. Their reduced feeling of range anxiety is indicative that this is a viable explanation for the behavior. Additionally long haul drivers also prefer the low-price charging option of the overnight scenario. In the city charging scenario we see that particularly the short commuters and long haul drivers prefer the flexible charging-speed option at a medium price, whereas long commuters prefer the low-price option that includes an extended charging duration. We try to explain this with the acceptance of extended charging period. For long haul drivers and short city-commuters it is inefficient to wait an additional hour for the recharge, because the distance they have to go is either too long or too short to afford the prolonged waiting period. For long commuters the balance between the way they have to go and the additional charge that they receive with an extra hour of waiting, might just be right to accept the longer charging period and pay a lower price. We also take into account the different car-types that the different groups of users drive. Appendix 1.2 shows a frequency-table of the vehicle-types per group. However we cannot detect a pattern of vehicle distribution per group.

8 Linking the Charging Data with the Survey Results

In this study we aim to give an enveloping view of the use of public charging infrastructure in the area of Cologne. The combination of the perspectives that we obtain from the charging station database and the survey among EV drivers allows us to judge in more detail whether public charging infrastructure is a suitable insertion point for DSM systems and the related technologies. In this context it is particularly relevant that the actual users are willing and capable of supporting the measures that accompany the implementation of such systems.

First and foremost we see in both data streams that the users of public charging infrastructure mostly charge and park below three hours at the stations. We also obtain the knowledge from the charging database that 50% of the people who charge their cars in this time-frame completely replenish their battery during this period. This means that the average parking duration of one hour for this time-timeframe (0h – 3h) is longer than the average recharging time of the battery. We complement this insight with the results from the survey. It demonstrates that most EV drivers charge their vehicles after a driving-distance of 25km to 50km. These two sources explain the short charging duration of the vehicles that park below three hours. At regular charging speeds the energy to drive up to 50km does not take longer than two hours in order to be transferred to the EV's battery. This assumes a car with an average consumption of 15kWh / 100km and the reduced Type-2 charging speed of 3.7kW. Once the charging stations are set to their full potential of 22kW, the possibilities for the implementation of DSM-mechanisms increase even further.

The second biggest user-group in the charging data (20%) parks the car between twelve and 24 hours, which means that they are mostly overnight parkers. According to the survey at least 13% of the sample belongs to this group. For this parking duration we also observe a stronger approval of the low-price charging option as compared to the short-term parking option. This is a significant benefit for DSM systems. Nevertheless the clustering procedure also reveals that those users who need the overnight charge the most, namely long haul drivers, visit public charging station the least often. Energy-suppliers that offer public charging infrastructure and that want to effectively integrate their infrastructure need to think of solutions to counterbalance this impairment. We suggest, for example, particular overnight charging offers for users who frequently visit the area of a certain CSP.

An additional user group that can gain importance in the following years is the group of EV drivers that live in apartments or flats (9 respondents in the survey, 13.4%). This group is underrepresented in the survey, which is mostly due to the immaturity of the EV market. However, this group shows in the bivariate table and the regression interesting tendencies towards the frequency of usage, and we presume that it can become a vital part of public charging service offerings.

In current economic terms the dilemma of public charging stations becomes evident in both streams of the data. The present charging stations are not part of any DSM system and charging speeds are not regulated. In this situation the service provider is only interested in those vehicles that actively charge their batteries at the stations. After the battery is replenished a vehicle becomes a financial dead weight for the service provider. The survey reveals that drivers strongly prefer to pay per kWh (81%) rather than per parking duration (8%) or a combination of both billing methods (12%). The situation for the service providers that do not apply DSM systems is, however, that they won’t get around a fee for parking duration, if they want to conduct their charging systems with a high degree of efficiency. A possible solution for this is to notify users when the charge of the vehicle is finished and to give them a grace period to return to their cars, before the CSP starts charging parking fees.

Overall we see potential for DSM systems in the realm of public charging infrastructure. Such implementations are particularly interesting for overnight charges, but we also see potential for the parking durations of below 3hours, which occur most frequently. This work does not take into account the acceptance of V2G systems by the users, but corroborates the effective potential of smart charging solutions as they are brought forward by scholars, such as Clement-Nyns et al. (2010) or Lyon et al. (2011). These systems would not discharge the vehicles battery, but would rather reduce the charging speed at given times. The results of the survey show that the overall sample of EV drivers is neutral (avg=3.99, std=1.9) when it comes to the reduction of charging speeds at times of high demand. As a consequence we have positive prospects for simple DSM implementations that are based on charging speed reductions and pricing options. These systems integrate particularly well, if users pre-define their charging horizon. We are unable to make assertions about the effectiveness of V2G systems, because of the users' lack of knowledge and experience in this area.

9 Discussion and Implications for Future Research

9.1 Main Findings

The analytical results that we achieve in this work stem from two sources: The usage data of the charging stations and the survey that we conducted among EV drivers. In this section we summarize the most pertinent results. First we focus on the results of the usage data analysis; afterwards we summate the results of the survey.

The charging station data reveals that drivers most frequently park for durations of 0h - 3h and 12h - 24h. The data also shows that 50% of the people who charge their car between 0h-3h do not require a fast-charging connection. Their cars are fully recharged after one hour of average parking time. This occurs even though the charging stations in the sample reduce the energy-output to 3.7kW. These results are very favorable for smart charging solutions and other DSM related procedures. Even for short durations an optimization of the charging process is attainable without disturbing the consumer's charging-experience.

The survey-results and the clustering procedure reveal a connection between the frequency of usage and the kilometers that an EV drives on average. However the result stands inverse to the general intuition, it indicates that the more kilometers the respondents drive per week the less often they use public charging infrastructure. Fast-charging becomes particularly important for users who drive longer distances. Hence we connect this result with the enhancing effect of fast-charging stations on the perception of convenience of charging infrastructure. Additionally we see that the satisfaction with the charging speed also increases the frequency of usage. Another important consequence that we draw form the survey is the influence of the type of dwelling on the frequency of charging. Especially those respondents who do not live in detached houses with parking spaces have a tendency to use charging stations more frequently. Their living situation is particular in line with the services that public charging stations offer. Furthermore we observe that users who have multiple subscriptions for public charging services and charge at different CSPs also use public charging stations more frequently. This means that these people either travel frequently between regions of different suppliers, or that the density of the network of charging station is not sufficient. The low average-score for the satisfaction of station density supports this assumption. In addition to this, the inquiry of EV drivers depicts that the identification method at the charging station has an effect on the frequency of usage.

Despite the above mentioned relations with the dependent variable, several relevant relations among independent variables appear in the correlation results. They display a divide between users who use their car for private purposes only and those who use them for work or work & private purposes. Especially in terms of price-perception these groups differ. Private users rather prefer a charging speed reduction and lower prices, whereas work and work & private users appreciate full charging speeds at higher prices.

Following the clustering procedure we are able to evaluate several intricacies of the three groups of EV drivers. A main indicator that divides the groups is the average weekly driven distance. Short city commuters show the highest frequency of usage, more than half of them charge at least once a month at public charging stations. Users in the other groups charge mostly less than once a month at public stations. The clusters reveal the different needs of the consumer-groups related to public charging infrastructure. This gives us the opportunity to conclude that the right balance between fast- and slow-charging, identification methods and pricing-options is the best way to cater to these different user groups.

The findings we present above underline the different situations of EV drivers and give indications on how CSPs can improve the client's perception of public charging infrastructure. We conclude that this first comprehensive analysis of consumer profiles related to this infrastructure has the potential to find an application in DSM systems, academia, as well as in the strategic orientation of CSPs.

9.2 Discussion

The results that we combine in section 7 reveal several attributes of the public charging market, that have been assumed in previous literature. The governmental schemes in the Netherlands (chapter 2.2) which focus on the creation of infrastructure rather than the purchase of electric cars, are a good way to combat factors such as range anxiety and the perception of the charging services. The survey shows that the perception of station-density influences the perception of reliability, a vital hint for the conductors of charging infrastructure that network-size influences user-satisfaction. Additionally we see that the reliability of the stations has a negative effect on the intensity of range anxiety. Combating the feeling of range anxiety allows a wider distribution of EVs in the population, because fewer drivers will have to fear the change from an ICE vehicle to an electric one. The positive influence of station density on reliability and the negative effect of reliability on range anxiety are clear signs that charging networks need to be extended in order to achieve a more pronounced use of EVs.

Our work equally confirms the importance of fast-charging. However instead of generalizing the charging speeds and assuming equal electricity prices like Schroeder (2011), we are able to say that charging networks require a balance between fast- and slow-charging infrastructures as well as high and low prices. Depending on the user, it is more appropriate to offer faster charges at a higher price or slower charges at a lower price. We cannot exactly calculate the ratio for this balance, but we see that short-city commuters and long haul drivers prefer fast-charging as an intraday method of recharging their vehicles. We combine this information with the fact the about 50% of the charges have a maximum duration of three hours. These occupancy rates lead us to estimate that about 20% - 40% of a charging station network should consist of fast charging infrastructure. Hence we question the results and assumptions publishes by Schroder (2011) and Li (2011) that unify the systems (in terms of price and speed) to calculate their profitability. We show that one should neither assume a fixed rate of users, nor fixed prices, or fixed charging speeds throughout the system.

This leads us to discuss our results with the DSM literature that we review for our work. Finn et al. (2012) and Attia (2010) either assume the consumers' willingness to accept the modification of electrical consumption or rely on unified consumers-types. In comparison to their work, we show that different types of consumers can integrate differently in DSM networks and hence need different kinds of incentives to do so. There is not only the price of the energy that needs to be considered for the systems, but factors such as the range anxiety of the users, the density and reliability of the network and the willingness to pay higher prices in the respective charging-scenarios. If public charging infrastructure does not bridge the objectives of a DSM system with the expectations of the users, a wider ecosystem of e-mobility is unattainable. This is because the possibilities of home-charging and e.g. charging stations at work do not suffice to reach a significant amount of users. We show that particularly those users without a charging-possibility at home (70% of the European urban population) require a well distributed and well-priced public network. If a DSM system of public charging stations demands too much of its users in terms of adaptability and pricing, it becomes unattractive and redundant for a large part of the population. We therefore suggest, on the basis of our research, that cheaper and slow overnight charges and well balanced fast- and slow-charging options (at differing prices) are a possibility to harmonize user-demand with DSM objectives. In general we see users being very skeptical about higher prices for charging services than for the regular energy price, but in combination with an advantageous parking location and/or fast-charging opportunities this dilemma can be overcome. Our work supports the results of

Lyon et al. (2011), as we conform that simple overnight smart-charging solutions are not only substantial for DSM systems, but also find are supported by many drivers (consumers).

We furthermore confirm Franke et al. (2012) results related to range anxiety. The authors identified it as one of the major issues for EV drivers. Nevertheless we also see that drivers who are either more experienced or more used to driving long distances also perceive less range anxiety. This is an indication that range anxiety is related to the experience with the car and possibly the properties of the car. We conclude that the issue of range anxiety can be combatted with a mixture of an extended charging station network and the growing experience of the drivers themselves. Long haul drivers seem to have reached the point where they can actively control the range anxiety by adjusting their comfortable range to the actual range of the car. Additionally we see that on average the distances between two charging instances are very small. This supports the extension of charging infrastructure to make the drivers feel safer when driving longer stretches. Another vital point to be mentioned here is that EV drivers are not yet part of the mainstream. The demographic results confirm this. So the results for range anxiety might possibly worsen once the larger (less motivated) population adopts EVs.

We also observe a significant correlation between the acceptance of identification methods and the frequency of usage, which is an analog result to Flaherty (1992). For the integration of DSM networks and pricing methods this effect needs to be taken into account. Especially DSM systems, relying on a more intensive data-exchange and convenient digital pricing systems can prevent some consumers from using the infrastructure. This also accounts for the involvement of the users with the infrastructure. The acceptance of the identification method shows a similar effect on the involvement with the infrastructure. This suggests that the identification method not only affects the usage of the stations, but also their perception as a product or brand. We can therefore support the assertion by Scherer & Lane (1997) that “attribute involvement is a consumer’s perceived importance of interest toward the product due to product attributes that are salient to an individual's inherent interests, preferences”. In our case these preferences are privacy, reliability, and station density.

In sum the results of this study detail that overly simplistic assumptions for consumer behavior and demand cannot reveal accurate models for charging station profitability and usage. A larger array of preference and attribute factors influence drivers when using public charging stations. The industry and scholars need to consider a deeper inclusion of the consumer as a vital part of their business models.

9.3 Managerial Implications

This study has several effects on managerial decision making related to the marketing, strategy and operations of public charging stations. In this section we deduce the managerial implications from the results of the survey and charging data analyses.

The databases reveal that even with reduced charging speeds there is a potential for the implementation of DSM methods. The results are also positive for parking durations below three hours. Increasing parking durations yield steadily growing percentages for DSM eligible users. Managers of CSP should be aware of this hidden potential to optimize their networks. The implementation of smart charging solutions can reduce the operation cost of a charging network without affecting customer satisfaction. On the contrary, the system becomes more efficient and saves natural resources, a message that is also considerable for marketing campaigns. A larger amount of users (20%) charges the vehicles overnight at the stations, offering a large potential for smart charging operations. We expect this percentage to rise as the urban population starts to purchase more EVs. We see the overnight charges as the second most important source of business for CSPs and as the most important possibility for a significant DSM application. As a consequence we suggest creating specific offers for drivers who charge their cars longer than six hours, especially overnight. These offers need to stand in relation to the local parking fees and the optimization potential for DSM methods in this time-frame. Managers can use these offers to attract urban clients and achieve a higher occupation-rate of the stations.

The positive effects of fast-charging that we find in this study, should be taken seriously by managers in this industry. The implementations of such facilities can boost the perception of the convenience of the infrastructure and hence have positive effects on a brand's image. However the management must also realize that fast-charging must be balanced with regular chargers to achieve equilibrium in prices for the different groups of consumers.

A strategic result that follows our research is the special situation of drivers living in attached multi-unit housing. These users appear to be one of the main usage groups of public charging infrastructure, as they fit into the group of short city commuters. This group of users is rather willing to pay higher prices for optimized charges that fit into their schedules.

Additionally the charging station providers need to realize that the registration of long distance drivers is essential for growing the network. Once these users can easily register on a network and receive faster charging services, they will have significantly less reasons to shirk public charging stations. Additionally it appears useful in this respect that CSPs create networks that have the same registration-database, to prevent users from having to make multiple registrations at different providers.

Our study also finds results for the importance of privacy and identification methods related to the charging stations. We observe that particularly those users who are willing to “give up” part of their privacy use the charging stations more often. For managers this means that privacy is a vital part of the product that can influence the decision making of the consumers. We therefore suggest implementing the opportunity of granting privacy-conscious consumers charging services without a registration in the database. We see opportunities for cash and credit-or debit-card systems.

We define three main groups of public charging station customers. The short city commuters are, as we already describe above, especially associated with multi-unit housing. CSPs should approach this group of consumers with two types of offerings. An intra-day charging offer that caters to their rather fast-charging and schedule related desires. In this category the consumers are also willing to purchase the charging-energy at a higher price. Therefore this group offers the potential to present fast-charging services as a different product. The second offering should focus on the night charging habits of these users. They prefer lower prices for less flexible charging procedures. Moreover these users require a more extensive charging network to alleviate their range anxiety. The reduction of range anxiety of these users has a positive relation with their perception of the convenience and reliability of the charging stations. So by increasing the network CSPs can increase the users’ satisfaction with the service.

Long commuters are rather price-sensitive and should hence be targeted with low-price options. For targeting this group managers should focus on the extension of charging networks with regular charging speeds. This strategic orientation addresses the users’ range anxiety, as well as their desire to charge at reasonable prices.

Long haul drivers are an interesting group for managers of CSPs. The users drive long distance and hence need to charge frequently. However this group charges the least often at public charging stations. We see this group as an important main aim for CSPs, because it contains drivers that push the envelope in terms e-mobility and are hence good advocates for a functioning charging network. Long haul drivers charge more frequently in general and are more willing to accept higher prices for charging processes that fit into their schedule. Mangers can target this group in a similar way as the city commuters. Like the city commuters long haul drivers require a healthy balance of fast- and slow-charging infrastructure.

The managerial implications that we present above are condensed in Table 21. We base all of the implications on our research and consider this approach as a type of evidence based management. Mangers who implement these recommendations should continue to monitor consumer behavior according to these factors in order to measure changes in the customers' perception of public charging infrastructure.

Table 21: Managerial Implications

Result	Implication
The distribution of charging and parking durations according to the EBG and Mennekes database.	- Both databases reveal the potential for DSM implementations, - The rising ration of fully charged cars measured by their parking duration is interesting for CSPs, it reveals the potential for smart-charging solutions, - A large share of the sample charges longer than 6hrs, CSPs should consider to make special offers to users who charge longer overnight periods - Special offers can ensure the attractiveness of the service and a smooth integration with DSM systems.
Fast-charging has a positive relationship with the convenience of public charging infrastructure. The satisfaction with the charging speed has a positive relationship with the frequency of usage.	- This is a signal that fast charging has a strong influence on the convenience of the service and hence on the brand image. - It can have a positive effect on a firm's clientele, if a firm shows commitment to fast-charging infrastructure. - It needs to be balanced with regular charging stations, as they are cheaper and better to integrate into DSM systems.
Living in detached- and semi-detached houses has a negative relationship with the frequency of usage of public charging infrastructure.	- CSPs should strategically also focus on drivers living in attached multi-unit houses - Managers should create charging networks in cities that particularly keep the need of this group in mind
The possession of subscriptions has a positive relationship with the frequency of usage of public charging infrastructure. The use of different charging services has a positive relationship with the frequency of usage of public charging infrastructure.	- Like in many industries frequent users are particularly interesting, - CSP's should make it particularly easy for travelers to register themselves with the services, - A network of cooperating CSPs is interesting for these types of users. Such cooperation could share the user database and increase the station density.
Privacy concerns have a negative relationship with the frequency of usage of public charging infrastructure.	- Managers need to retain a fine balance between privacy and service offerings, - CSPs should offer some charging stations that work without a registration system.

Result	Implication

Short city-commuters	- Associated with multi-unit housing
	- Catering towards these customer is twofold:
	    o Intra-day fast-charging stations that do not interfere with their schedule,
	    o Night charging stations with reduced charging speeds and low prices
	- To counteract their range anxiety, these users need a more extensive network of stations,
	- The group is rather profitable as they do not shirk higher prices to get on-time charging,
	- For this group fast-charging can be regarded as a different product with differing prices.

Long commuters	- To counteract their range anxiety, these users need a more extensive network of stations, - User prefer to charge at lower prices, so low speed infrastructure is more important here, - This is a very prices sensitive group that also charges at home, - Must be targeted with a low-priced widely dispersed charging network.

Long haul drivers	- Frequent chargers but infrequent users of public stations,
	- Should become an aim for CSPs,
	- Charge often and are willing to pay a higher price,
	- Like City-Commuter the catering towards these customer is twofold:
	    o Intra-day fast-charging stations that do not interfere with their schedule,
	    o Night charging stations with reduced charging speeds and low prices
	- CSP's should target these users with a good balance of fast-charging and normal infrastructure to balance their needs.

9.4 Future research

We see large potential in this field of research for future ameliorations and extensions of consumer behavior and its relation with the broader energy market and DSM systems. A first starting point for future research is the extension and specification of our survey. It is certainly helpful to conduct similar surveys with bigger sample-sizes. This helps to verify the results of this study and reveals if the sample is a fair representation of the EV consumer market. Additionally we suggest surveys in differing places to obtain more information in how far geographical and socio-economic factors influence the behavior and decision making processes of EV drivers. A bigger sample-size will permit the extension of the concepts that comprise our survey and a research on a more detailed scale. With a sample-size of 67 EV drivers, it is not possible for to us to have multiple survey designs that include control groups and different formulations of the research concepts to underpin their validity. In future research we see potential for large scale studies that focus on the concepts of our work more deeply. We suggest an exploration of each concept separately to ensure a higher reliability. The increased reliability can affect the scales, stem questions and should include test-retest methods or alternative forms to reduce measurement errors (Malhotra & Birks, 2007, p.357). Additionally we expect interesting outcomes from further research in the field of TOU-pricing and the consumer perception of charging speed reductions. Future research can help to accurately define the balance between fast-charging and regular-charging offers and their respective pricing approaches. Eventually we consider the measurement of the price elasticity of demand for fast-charging and slow charging stations as a vital future stream of economic research.

An additional extension of our study is an analysis of the charging behavior for charging stations that charge cars at higher kW rates (e.g. Mennekes and EBG charging stations' maximum rate is 22kW). Our study mostly comprises reduced charging speeds of 3.7kW. The influence of this change on the parking duration can turn out to be quite significant. Furthermore we think it is important to verify the consumer-clusters that we construct and to apply them in practice in order to validate their expected behavior. This leads to our final recommendation for future research possibilities, which we see in the analysis of the interface between behavioral- and preference-profiles of consumers and the objectives and mechanisms of DSM systems.

9.5 Conclusion

We conclude this paper with a compact presentation of the results in order to answer the overall research questions. The results show that we are able to explain the behavior and motivations of EV drivers to use public charging infrastructure to a certain degree. We are able to define relevant factors for the success of public charging infrastructure and especially identify three main areas of importance. The first area is the amount of subscriptions per user and the usage of various CSPs, which show the strongest impact in our model. The variable demonstrates that users who integrate public charging in their driving patterns have multiple subscriptions to ensure their access to wider network of charging stations. Once they have this access they also use charging stations more frequently. The second area is the integration of fast-charging. Consumers perceive it as very beneficial, if public charging stations offer a fast-charging possibility. The integration of this technology does not only augment the consumer's perception of the reliability and convenience of the stations, it is equally linked to the frequency of usage. Based on these results and the classification of additional variables we are able to construct three groups of consumers of public charging infrastructure.

These insights allow answering the research questions, formulated in the beginning of this study. We are able to show the consumer-patterns of using the public charging infrastructure. We analyse these patterns with the aid of the charging data of an urban public charging network. Moreover we show that it is possible to cluster the different behavioral aspects and perceptions of users into comprehensive groups. We create three consumer groups clustered along their average mileage and various additional factors for dealing with public charging infrastructure. Particularly significant are their differences in behavior related to prices, range anxiety, amount of subscriptions, perception of reliability, and the frequency of usage. Our study is able to statistically proof these disparities.

Our work helps to explain the industry that begins to evolve around electric vehicle transportation. We add to assess its clients and find important factors that influence satisfaction and profitability from a consumer's point of view. Governments that support the development of such technologies can apply our results to define the focus of their campaigns more precisely. We reinforce the importance of more extensive charging station networks and a balance of fast- and slow charging infrastructure that is based on consumers' needs. These aspects negatively influence the perception of range anxiety and positively affect the perception of reliability among users. Once the extension of the network and the integration of fast-charging become the main strategic focus for CSPs, a wide application of EVs can be drastically enhanced.

As soon as a higher percentage of EVs is on the market, the charging behavior of their drivers becomes an essential part for the efficient working of DSM systems. We show that, already today, the behavior of EV-drivers is in line with several DSM mechanisms. We see a strong support for smart charging solutions for overnight charges. We are also able to show that for parking durations of three or less hours the implementation for V1G (smart charging) systems is attainable. At the measured charging speeds the utilization capacity for short-duration smart charging systems lies at around 50% of all charges. In the future this ratio will increase due to faster average charging-speeds. Additionally we observe consumer-groups with different pricing preferences, who can add to achieve a sustainable pricing-portfolio for CSPs. Especially short city commuters and long haul drivers are interested in faster charges that they can flexibly integrate into their schedules at higher prices. This information can help future applications of DSM systems to integrate this kind of consumers into smart grid operations.

We add to the academic discussion around charging infrastructure, e-mobility and smart grids by giving a first comprehensive analysis of EV drivers and their public charging habits in a major European urban region. We hope that our study can help to refine academic work in this field of research. We show that consumers have the final say when it comes to these technologies, and are able to pinpoint situations in which consumers are more or less susceptible to the usage of public charging stations.

Electric vehicles are part of the solution to achieve a more sustainable way of transportation for mankind. To achieve this enormous task we do not only have to overcome the technological obstacles, but we also have to tackle to human impediments to achieve these changes. Our work is a first step to understand the lead-group of consumers and their way to integrate more environmentally friendly vehicles into their lives by using public infrastructure. The research is a small addition to the large space of more sustainable transport solutions. Nevertheless we hope to add knowledge to the discussion around these technologies and to the creation of more environmentally sustainable business-models.

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1 Appendix

1.1 Sample Questionnaire

Below you find an English version of the survey that we hand out to RheinEnergie clients. The original language of this survey is German.

Question No.	Sub-No.	Question	Answer No.	Answer
1		Please indicate what type of electric vehicle you drive?		
2		Think about the last time that you looked on the statistics display of the dashboard of your car, or the last time that you estimated the cars consumption. Now give an estimation on how much your electric vehicle consumes on a typical day:	1	less than 10 kWh / 100 km
			2	10 – 20 kWh / 100 km
			3	20 – 30 kWh / 100 km
			4	more than 30kWh / 100 km
			0	I don't know
3		Think about your daily trips with your electric vehicle last week, going to work, grocery shopping or picking up the kids from school. How many kilometers did you drive with your electric vehicle last week?	1	Less than 50km
			2	Between 50 – 100km
			3	Between 100 – 150km
			4	Between 150 – 200km
			5	Between 250 – 300km
			6	Between 300 – 350km
			7	More than 350km
4		Now think about your charging habits and how much you drive for example between going to work and back home. Try to estimate how many kilometers you drove between your last two charging instances?	1	Less than 25km
			2	Between 25 – 50km
			3	Between 50 – 75km
			4	Between 75 – 100km
			5	Between 100 – 150km
			6	Between 150 – 200km
			7	More than 200km
5		There are public services for charging electric vehicles. Maybe these recently played a role in your life and how you charged your car. How often did you use public charging infrastructure during the past months?	1	Once a day
			2	Once a week
			3	Once a month
			4	Once every two months
			5	Once every six months
			6	Once a year
			0	Never
6		Think about the times that you used public charging stations, where you traveled and what you did there. Maybe on a regular basis. Please mark the charging stations that you frequently used in the area of Cologne during the last months:	1	Lungengasse
			2	Kreissparkasse
			3	Airport
			4	TÜV
			5	P+R Weiden-West
			6	RheinEnergie Headquarters
			7	Procter & Gamble

				headquarters
			8	PSA headquarters
			9	None
			10	Other:
7		Take yourself back to last time that you used a public charging station and what you did while the car was parked, maybe shopping or other activities. During the last visit of a public charging station, I charged my car for about:	1	An hour or less
			2	Between 1 – 3h
			3	Between 3 – 6h
			4	Between 6 – 12h
			5	Between 12 – 15h
			6	Between 15 – 24h
			7	More than a day
8		What activities do you frequently persue, while you park and charge your car at a public charging station?	1	Shopping, Eating, and others
			2	Work
			3	Dates (meeting friends, sports etc)
			4	I park the car solely to charge it
			5	I don't have my own Parking space and park the car at a station close to my home
			6	Other:
9		For what type of purposes do you use your electric vehicle?	1	Private
			2	Work
			3	Privat and Work

Question No.	**Sub-No.**	**Question**	fully agree	agree	rather agree	Neutral	rather disagree	disagree	fully disagree
10	**10.1**	Take yourself back to the moment that you last parked at a charging stations to go for example shopping with a friend or for a walk with your dog. During my last visit of a charging station, I perceived the usage of the station as convenient.	1	2	3	4	5	6	7
	10.2	Think about the last time that you wanted to integrate a public charging station into your daily life, because you maybe wanted to go somewhere and park and charge your car at the same time. When I use my electric vehicle in my daily life, I perceive the density of charging stations in the Cologne area as satisfactory.	1	2	3	4	5	6	7

	10.3	Think about the moment that you returned from your activity back to the public charging station where your car was parked and how much the car's battery was charged during the time that you were gone. During the last charge of my electric vehicle at a public charging station, I perceived the charging speed as quick.	1	2	3	4	5	6	7
	10.4	Think about how you felt when you last used a public charging station and about the process to connect the cable to your car and start the energy flow. During the last usage at a public charging stations, I perceived it as reliable.	1	2	3	4	5	6	7
	10.5	Think about the last time that you actively searched for a public station and the criteria that were important to you during the search, maybe the location or the supplier that runs the station. When I charge my electric vehicle at a public charging station, fast charging is important to me.	1	2	3	4	5	6	7

Question No.	**Sub-No.**	**Question**	**Answer No.**	**Answer**
11	**11.1** **11.2** **11.3**	Think again about your daily trips to work, to go grocery shopping or to go to your favorite fitness training. When I drive with my electric vehicle in my daily life, charging stations along these roads are particularly useful to me:	Ranking 1 -3	In the city along country roads on highways
12		Think about your charging and traveling habits. Maybe there are different regions you go to, where different suppliers of public charging stations offer their services. Please mark the following services, if you use them.	1 2 3 4	RWE ePower basic A charging offer of my location energy distribution system operator (e.g.: RheinEnergie, N-Ergie, Mainova, SWM, etc.) A third-party supplier (local company, or corporation, e.g.: Tesla, shopping-malls, or restaurants etc.) Other:

Question No.	Sub-No.	Question	fully agree	agree	rather agree	Neutral	rather disagree	disagree	fully disagree
13	13.1	When you travel with your electric vehcile in your daily life you encounter public charging stations of different providers. During the last months I charged my vehicle at public charging stations of different providers.	1	2	3	4	5	6	7
	13.2	Imaging yourself driving your electric vehicle and how you feel when you make your daily trips and commutes. When I drive my electric vehicle, I am afraid that I might strand with an empty battery.	1	2	3	4	5	6	7
	13.3	Think about the last time when you checked thefuel gauge of your electric vehicle. When I am afraid that I might strand with an empty battery, the feeling is:	1	2	3	4	5	6	7

14		An Electric vehicle driver drives with a friend in the city to do some shopping. She parks her car at a public charging station in the city centre. She plans to stay for 2 hours in the city. The display of her car shows her the development of prices at the charging station. The following possibilities are presented to her: A: The car will be fully charged within the first 2 hours. This costs €20. B: The car will be charged within 2 hours, just that far that the two will be able to safely make their trip back home. This costs €10 C: The Charging process will only beginn by the end of the second hour, for a fully charged battery 3 hours are necessary. This costs €5.							
			fully agree	agree	rather agree	Neutral	rather disagree	disagree	fully disagree
	14.1	When I am in this situation, I choose possiblity A	1	2	3	4	5	6	7
	14.2	When I am in this situation, I choose possiblity B	1	2	3	4	5	6	7
	14.3	When I am in this situation, I choose possiblity C	1	2	3	4	5	6	7

Question No.	Sub-No.	Question	Answer No.	Answer
15		In what type of dwelling do you live in?	1	Detached or semidetached home with own parking space
			2	Attached multi-unit housing with own parking space
			3	Attached Multi-unit housing without own parking space
16		Imagine you drive with your electric vehcile to visit some friends in an area where you do not regularly travel. You find several public charging stations that all charge different amounts of money for the charge and the parking-time. If I have to pay for public charging infrastructure, I prefer to pay:	1	per kWh
			2	per parking duration
			3	per kWh and parking duration

Question No.	Sub-No.	Question	fully agree	agree	rather agree	Neutral	rather disagree	disagree	fully disagree
17	17.1	You park your car at a charging station that you regularly visit and see that there is an information display. The display shows that the charging speeds are reduced because of the high demand at the charging station. When I charge my electric vehicle at a public station, I can accept that charging speed is reduced when many other electric vehicles are charged at the same time.	1	2	3	4	5	6	7
	17.2	Take yourself back to your last visit of a public charging station. Please remember the way that you connected the cable and started the charging process. It is acceptable, when I have to identify myself at a public charging station (phone, RFID, etc.) to start a charging process.	1	2	3	4	5	6	7

18		An Electric vehicle driver comes back form work and parks his car at a public charging station that is close to his home. A Display in his car shows him the development of prices at the charging station. He can choose between the following possibilities: B: The car will be fully charged after 2 hours and is then with a 100% charge at the disposal of the driver . This costs €20 C: The car will eb caharged slowly and will be fully charged and available for the driver at 6 o'clock in the morning. This costs €5.							
			fully agree	agree	rather agree	Neutral	rather disagree	disagree	fully disagree
	18.1	When I am in this situation, I choose possiblity A	1	2	3	4	5	6	7
	18.2	When I am in this situation, I choose possiblity B	1	2	3	4	5	6	7

Question No.	Sub-No.	Question	Answer No.	Answer
22		Please indicate the highest level of education that you have completed	1	None
			2	Secondary school
			3	O-level
			4	A-level
			5	Bachelor degree or apprenticeship
			6	Master degree or Diploma
			7	Doctorate or professorship
23		Are you married?	1	Yes
			2	No
24		Do you have children?	1	Yes
			2	No
25		Please indicate your gender	2	Female
			1	Male
26		What’s your age?		
27		Please indicate your average income	1	Below 20,000
			2	Between 20,000 – 30,000
			3	Between 30,000 – 50,000
			4	Between 50,000 – 70,000
			5	Between 70,000 - 100,000
			6	Above 100,000

1.2 Table of Frequencies for Car-Types per Cluster

Rank	Group 1 Car-type	Group 1 Frequency	Group 1 Percentage	Group 2 Car-type	Group 2 Frequency	Group 2 Percentage	Group 3 Car-type	Group 3 Frequency	Group 3 Percentage
1	Ford Focus	6	22.2%	Nissan Leaf	2	18.2%	Renault Zoe	3	10.7%
2	Smart ED	5	18.5%	Opel Ampera	1	9.1%	Tesla Model S and Roadster	3	10.7%
3	Opel Ampera	4	14.8%	Smart ED	1	9.1%	Smart ED	2	7.1%
4	Renault Twizzy	4	14.8%	Renault Twizzy	1	9.1%	Nissan Leaf	2	7.1%
5	Peugeot 106 electric	2	7.4%	BMW active	1	9.1%	Opel Ampera	2	7.1%
6	Nissan Leaf	1	3.7%	Ford Focus	1	9.1%	Twike	2	7.1%
7	Mitsubishi i-MiEV	1	3.7%	Clio electrique	1	9.1%	Mercedes A-Klasse E-Cell	1	3.6%
8	Volvo v60 plug in hybrid	1	3.7%	Mega e-city	1	9.1%	Prius Plug-in hybrid		3.6%
9	City EL	1	3.7%				City EL	1	3.6%
10	Citroen Saxo electrique	1	3.7%				Renault Fluence	1	3.6%