BAYESIAN MODEL AVERAGING TO PREDICT INTEREST IN ELECTRIC VEHICLES IN GERMANY

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Overview

Electric vehicles (EVs) have noteworthy potential to reduce global and local emissions and are expected to become a relevant future market for vehicle sales. Both policy makers and car manufacturers have an interest to understand the future EV user groups, also those beyond the current 'early adopter'. However, there are only a few empirical results available about potential future EV users. Here, we use data from a representative survey on EV interest from Germany to analyse factors that are related to interest in EVs of private car buyers. Interest in EV implies a positive attitude towards this new technology and is thus a prerequisite for later adoption. Our results show that technology affinity and the feeling that an EV can serve the user's driving need are positively connected to interest in EVs. Furthermore, persons that connect a strong feeling of independence with conventional vehicles are less likely to be interested in EVs. Our results indicate that automakers promoting EVs should focus their marketing on the new yet ready technology in the next years.

Introduction

The diffusion of electric vehicles (EVs) is an important cornerstone in decarbonizing the mobility sector in Germany and elsewhere. In 2013 about 19 % of the energy related green house gas emissions in Germany came from the transport sector (Umweltbundesamt 2014). Since 1990 the primary energy consumption in the transport sector has risen from about 2,400 PJ to 2,600 PJ (Arbeitsgemeinschaft Energiebilanzen e.V.) despite high energy efficiency gains in the power train construction which are propelled by fossil fuels. Putting it in a nutshell, fossil fueled vehicles do not seem to have the ability to drastically scale down the emissions in the transport sector. Therefore, other technologies need to be in the focus by car manufacturers and policy makers. One possible alternative is the electrification of the power train shifting the focus towards electric vehicles (EV).

EVs were originally invented more than 150 years ago, but the passenger vehicle market has remained dominated by internal combustion engine vehicles (ICEVs). Several attempts to re-introduce EVs to major markets after the oil-price shocks in the 1970s failed (Chan, 2007). However, the situation today is a different one with rising fuel prices volatility, the increasing awareness of the anthropogenic causes of global warming and a growing acceptance of political greenhouse gas emission reduction targets.

The roll-out of EVs faces multiple challenges. One quite overarching challenge is to design future EVs according to future customer's expectations and needs. This is done more effectively if specific target groups are identified. Furthermore, government incentives will be more effective and efficient if they address the needs of these groups. Thus, reliable estimates of the characteristics of future customers are of great interest to policy makers and vehicle manufacturers alike. The characterization of future target groups for EVs is therefore one prerequisite for realizing a low carbon mobility sector.

One standard categorization utilized to divide future customers of a product or technology into subgroups was initially suggested but Rogers (2003). He introduced a classification into five groups. Innovators are those individuals who are the first to adopt a new product; analyses have shown that these people usually have above-average financial means and "are able to cope with a high degree of uncertainty" (Rogers 2003, p. 22). The next group that adopts a product is called Early Adopters followed by Early and Late Majority; within these groups financial means and willingness to cope with uncertainty degrade continuously (cf. Rogers 2003, p. 290). Laggards are characterized as the last group to adopt new technologies. Their point of reference is the past and their resources are limited. Thus, they have to be very certain about the functionality of an invention before they spend money on it.

The early adopter of EVs have received a considerable amount of attention in the literature (cf. Frenzel et al. 2015, Plötz et al. 2014, Peters and Dütschke 2014, Jarass et al. 2014, Egbue and Long 2012, Hidrue et al. 2011, Ozaki and Sevastyanova 2011, and Rezvani et al. (2015) for a review). For Germany, the early adopters of EVs have been characterized as middle aged men, with technical and environmental interest and higher socio-economic status, living in rural or suburban areas (Peters und Dütschke 2014, Plötz et al. 2014).

For the US, Curtin et al. (2009 P. 43f) found that potential buyers of Plug-In-Hybrid-Electric-Vehicles (PHEV) tend to be wealthy, are enthusiastic about the idea of being able to avoid gas stations, value the environmental benefits offered by PHEVs and want to demonstrate their personal convictions by their decision to purchase an environmentally-friendly car. No clear results were found with regard to the gender of early adopters or where they live (rural or urban). Hidrue et al. (2011) found that that early adopter of EVs in the US are young or middle-aged and have a bachelor degree or higher. Unlike Curtin et al. (2009), Hidrue et al. did not find any evidence that household income influences the likelihood of EV adoption.

In contrast to these findings for the Early Adopter, later adopter groups have hitherto received little to no attention in the literature (Rezvani et al. 2015). However, the next adopter group is important for mass market adoption. So far, only few studies have quantitatively analyzed the potential early or late Majority of EV buyers, i.e. little research went beyond early adopter and innovators (Rezvani et al. 2015).[1]

Based on qualitative data from expert interviews Dütschke, Schneider and Peters (in press) propose four Majority groups. (1) Technology enthusiasts which are expected to predominantly include men who use the EV as an additional car and for which joy of driving and the image of an EV are important. (2) Environmentally aware individuals who regard driving a conventional vehicle in conflict with their personal values. (3) Urban individualists with a high need for mobility and a high emphasis on comfort and flexibility. (4) Well-off consumers motivated to choose an EV as an optimal combination of something new and innovative that is also useful in everyday life. These groups and their characteristics largely correspond to the findings of Truffer et al. (2000), who analysed the characteristics of early EV users in the 90s.

Axsen et al. surveyed 1754 'new vehicle buyers' in English-speaking Canada. In order to analyze the next EV-user group they first applied a design space approach (Lee-Gosselin, 1990; Kurani et al., 1994; Turrentine and Kurani, 1998) to filter the potentially battery electric vehicle (BEV)-interested customers. They found that 36% of their analysed group would potentially buy a PHEV or BEV and coined the members of this group "potential early mainstream EV market" (Axsen et al. 2015, p. 197). The group was clustered into six groups using the k-means clustering algorithm: A "Strong Pro-environmental" cluster (17%) "where respondents have higher than average engagement in environmental oriented lifestyles, higher environmental concern, and are highly liminal (open to change)", a "Tech-enviro" cluster (12%) which distinguishes itself with "high levels of engagement in both the technology- and environment-oriented lifestyles", a "Concerned" cluster (19%) which can be characterized only "to have a high level of environmental concern", a "Techie" cluster (17%) "that only have a high level of technology-oriented lifestyle", an "open" cluster (18%) "that have a relatively high degree of lifestyle openness" and an "Uninvolved" cluster (18%) that was characterized by having "lower than average on all four variables" that were named so far. These four clusters were a posteriori merged into two groups: The "Pro-environmental" group one the one hand contained the "Strong Pro-environmental", the "Tech-enviro" and the "Concerned" clusters. The "Non-environmental" group on the other side contained the "Techie", "Open" and "Uninvolved" clusters. In a second study, Kurani et al. (2015) conducted workshops in California where owners of EVs and owners of conventional vehicles met. From these meetings they derive that potential later EV customer groups will be more price sensitive than earlier customer groups (Kurani et al. 2014, S. 12).

The aim of the present study is enhancing the knowledge on the possible future large adopter group for EVs. The present work differs from previous studies in several aspects. First, it uses novel techniques to quantify the model selection uncertainty. Second, it is the first study to analyze the future early and late Majority of EV adopters in Germany based on quantitative data. Third, it discusses possible predictors of EV interest in order to characterize future EV buyers.

Data and Methods

Data

The data used for the analysis has been taken from a representative survey for Germany that amongst other topics analyzed different potential electricity tariffs for future EV-owners. It was conducted within the iZEUS-project (Zero Emission Urban System – iZEUS) and funded by the German Federal Ministry for Economic Affairs and Energy. It aimed at finding ways to efficiently integrate mobile electrical storage in vehicles utilizing innovative information and communication technologies (http://www.izeus.de/). For the survey 1,017 adult German citizens answered questions on attitudes towards EVs as well as the interest in EV and the intention to purchase an EV. The data was collected in April 2013 employing an online questionnaire taking advantage of a professionally managed online access panel. The sample is representative for the German population regarding gender, age, level of education, size of household and federal state.

4,017 German citizens were initially invited to participate out of which 1,107 individuals accessed the online questionnaire. 1,017 of these 1,107 people completed the questionnaire (overall response rate of 25 %). The questionnaire included several indicators in order to divide the respondents into four different groups connected

1 Since our focus is on private EV adopters, we do not discuss the interesting findings concerning EV adoption in fleets (cf. Rezvani et al. (2015) for a review and Globisch et al. (2016), Frenzel et al. (2016) as well as Ensslen et al. (2016) for case studies from Germany).

to Rogers' (2003) five adopter categories. Here we follow an approach introduced by Peters and colleagues (cf. Peters & Dütschke, 2014; Peters, Agosti, Popp & Ryf, 2011) in which early and late majority are aggregated into one group. Peters et al. (2011) demonstrated the validity of this approach with respect to the target variable "intention to purchase and use an EV". Participants who confirmed that they own or regularly drive an EV in everyday life were selected as Innovators. Two further items assessed the general interest in EVs on the one hand and the intention to buy a EV within the next 5 years on the other hand. If both items were answered positively, the participant was assigned to the purchase intention group (Early Adopters). If only the interest item was affirmed, participants were classified as interested (Majority). Participants affirming none of the above were classified as not interested (Laggards).

Analyzing the data with respect the Rogers classification and the assignment via the Peters and colleagues' classification, it turns out that 0.4% of the survey participants can be considered as innovators as their interest is of such high level that they already own an EV. Even though this number seems to be quite low it is consistent with the sales share of EV in Germany of 8,522 units in 2014 or 0.3% of sales (Kraftfahrtbundesamt 2015). Furthermore about 1% of the participants show purchase intention and are therefore classified as Early Adopter. 46% of the participants state to be generally interested in EVs. They are classified as early and late Majority. 52.6% of the participants are not intrigued at all by EVs and are hence designated to be part of the Laggard group. Further questions outlined in the questionnaire are concerned with the participants' interest in technology, their willingness to pay for EVs, and their usage of other means of transport. Usually one-item-measures are used with the exception for the variable "technology affinity". This measure is the average of three items, which showed sufficient, albeit not very high internal consistency (Cronbach's alpha 0.59). Education was measured applying the following categories 1 = No school-leaving diploma, 2 = Basic schooling without apprenticeship, 3 = Basic schooling with finished apprenticeship certificate, 4 = Secondary school certificate, 5 = High school diploma, 6 = University diploma; although this variable is ordinal we treat it in the following as a quantitative indicator.

For the following analyses we employed overall 26 different variables from the online survey described above which encompass all socio-economic variables and others on attitudes towards EVs and electricity tariffs for EVs (see Appendix for a full overview). In the following tables only the labels of the variables will be displayed due to space reasons. The variables are laid out more thoroughly in the appendix.

Methods

We use logistic regression to predict interest in EV. Since many potential factors could play a role in EV interest, model selection plays an important role, however, many empirical studies do not take into account the uncertainty from the actual model selsction process. Instead, many studies show p-values from the final regression model suggesting over-confident findings. Here, we use Bayesian model averaging (BMA) to account for model uncertainty in a systematic fashion. BMA provides a coherent way to take model uncertainty into account (Hoeting et al. 1999). Based on Bayesian statistical reasoning it yields the posterior distribution for the coefficient β given data D as the average of K individual models M_K each weighted by its posterior model probability $\mathrm{pr}(\beta|D) = \Sigma_k \mathrm{pr}(\beta|M_k, D)\ \mathrm{pr}(M_k, D)$. The computational difficulty stems from the calculation of the many posterior model probabilities.

$$\mathrm{pr}(M_k|D) = \frac{\mathrm{pr}(D|M_k)\mathrm{pr}(M_k)}{\sum_{l=1}^{K} \mathrm{pr}(D|M_l)\mathrm{pr}(M_l)}$$

Since the denominator contains the integrated likelihood, a high-dimensional integral, and the large number of possible models 2^P if P is the number of variables (Hoeting et al. 1999).

The BMA requires running many individual models and we use the best of all models for further analysis. We use binary logistic regression to predict interest in EVs and k-means clustering to identify subgroups towards EV adoption. The binary logistic regression is used in a manual stepwise model selection approach commencing with all variables covering attitude and socio-economic factors enquired in the questionnaire. Information on the power and significance of effects are given by the odds ratio and the Wald statistic, indicating the contribution of individual predictors to model fit. After each fitting round, some variables that had initially been certified having an effect on interest in EV needed to be removed since their impact on the prediction had diminished under the significance threshold (5%). Encompassing this general effect, the amount of variables attested an impact had shrunk from 26 variables initially inserted into the model to six variables.

The cluster analysis of those interested in EV is performed by k-means clustering to identify subgroups with the Majority group. The k-means clustering is a rather explorative approach to analyze data since the number of clusters is fixed a priori. The k-means method has been chosen in contrast to hierarchical clustering methods since it is more likely to produce clusters of similar size. In order to choose the best number of clusters, we analyzed the solutions for two to five cluster groups and found that the presented version of four groups offers more insights and is easier interpretable than the others. We inserted all socio-economic variables, all variables that proved to have a significant impact predicting interest in EV in the regression model and two more variables which were the only ones which featured environmental interest (all in all 16 variables). Rescaling all variables to zero mean and unit standard deviation did not qualitatively alter the clusters. After the k-means algorithm had defined the final distribution, the variables were examined by ANOVAs on differences between clusters. Six of the 16 variables were found to differ significantly.

Results

Model Averaging and Model Uncertainty

Several factors positively impact the probability to be interest in EV. In our data, the interest in technology has the largest positive marginal effect on interest in EV. Other positive factors are the willingness to pay for this new technology, the feeling to be able to perform all driving with an EV and the usage of public transport. A strong feeling of freedom or independence associated with conventional vehicles reduces the likelihood of being interested in EVs. In total, 1988 models were selected. Table 1 shows the resulting posterior effect probabilities as well as mean and SD of the coefficient over the different models weighted by the model qualitty (variables not shown had zero posterior effect probability).

Table 1: Posterior effect probabilities as well as mean and SD of the coefficients.

Predictor	Posterior Effect Probability P(β≠0)	Posterior Mean	Posterior SD
Technology affinity	100.0	0.742	0.096
Willingness to pay more	100.0	0.063	0.010
Autonomy EV	100.0	0.337	0.059
Drivers license (yes)	99.3	1.161	0.317
Freedom ICE	85.2	-0.270	0.149
Education	64.7	0.123	0.106
Public Transport Available (yes)	30.1	0.118	0.203
Train Available	27.7	0.127	0.232
Availability ICE	18.3	0.033	0.079
sex (male)	16.7	0.052	0.132
Availability EV	14.9	0.016	0.044
Autonomy ICE	7.9	-0.016	0.070
Working	6.4	0.015	0.069
Children	5.1	-0.012	0.066
Independence ICE	4.7	-0.006	0.038
Independence EV	3.4	0.002	0.018
HH members	3.0	0.002	0.016
Climate	2.2	0.003	0.034
Age	1.7	0.000	0.001
Freedom EV	1.7	0.000	0.011

We observe that the top four variables show very posterior effect probability and are thus highly likely to impect the intention to purchase an EV. These are the technology affinity, the Willingness to pay more (WTPM) for an EV, the agreemtent to thte statement that one can be autonomous with an EV as well as the availability of a driver's license. The next two factors Freedom with an ICE and the level of education are more likely than that to influence the intention to adopt an EV when comparing many individual models. The other variables might appear in some of the analysed regresssion models but in comparison aomng all models, there impact seems limited. Please note that the posterior means of the coefficients have the expected signs. Furthermore, due to the model averaging the ratio between coefficient mean and SD is not as promosing as one would expect from a single model run. This is the inherent model selection uncertainty which is usually not quantified in most regression models but only discussed. Please compare the ratio of coefficient mean and SD also to the analysis of the best model as given in the next section leading to the typical over-confident estimates.

Models of different size can be used to predict the intention to purchase an EV. Figure 1 shows the posterior model size probabilities, i.e. models of which size are best to predict EV purchase intention. The average model size is 6.9 and the most probable models contain 6 to 8 variables.

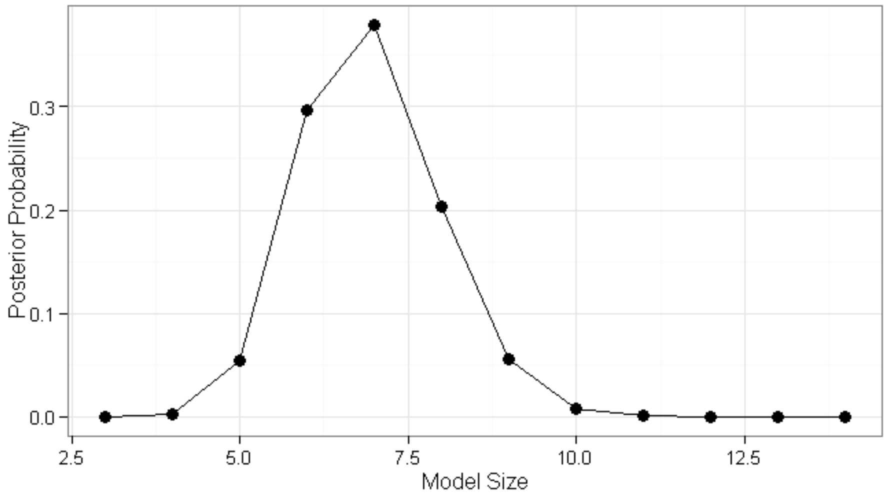

Figure 1: Posterior model size probabilities.

Additionally, Table 2 shows the ten best models including the model coefficients and the model's posterior probabilities. Note how the coefficient estimates and the number of variables change from model to model indicating model selection uncertainty. We omit symbols for coefficient significance for brevity.

Table 2: Best 10 models (cumulative posterior probability = 0.398) including posterior coefficient means.

Predictor	**M_1**	**M_2**	**M_3**	**M_4**	**M_5**	**M_6**	**M_7**	**M_8**	**M_9**	**M_{10}**
Posterior Probability	13.1%	5.0%	3.8%	3.2%	3.0%	3.0%	2.5%	2.2%	2.1%	1.8%
Intercept	-5.16	-5.49	-5.39	-4.52	-4.89	-4.97	-5.18	-5.19	-5.20	-5.55
Tech. affinity	0.75	0.75	0.75	0.77	0.76	0.76	0.74	0.72	0.75	0.73
WTPM	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
Autonomy EV	0.35	0.35	0.35	0.35	0.34	0.34	0.36	0.36	0.30	0.35
Drivers license (yes)	1.10	1.26	1.19	1.23	1.32	1.39	0.99	1.08	1.08	1.14
Freedom ICE	-0.31	-0.28	-0.27	-0.31	-0.27	-0.28	-0.43	-0.30	-0.31	-0.42
Education	0.20	0.18	0.18	.	.	.	0.20	0.20	0.19	0.18
Public Transp. (yes)	.	0.36	.	.	.	0.41	.	.	.	0.41
Train available	.	.	0.40	.	0.48	.	.	.	.	.
Availability ICE	.	.	.	.	.	.	0.16	.	.	0.19
Sex (male)	.	.	.	.	.	.	.	0.28	.	.
Availability EV	.	.	.	.	.	.	.	.	0.10	.

Analysis of best model

Despite existing model uncertainty, several variables have been found to influence the interest in EV. In the present section, we further analyse the best model. In particular, the marginal effect of the different predictors will be analysed.

Table 3: Best model regression results.

Predictor	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**
(Intercept)	-5.16	0.63	-8.2	< 2e-16 ***
Technology affinity	0.75	0.09	8.0	9.2e-16 ***
WTPM	0.06	0.01	6.7	2.5e-11 ***
Education	0.20	0.07	3.1	0.0020 **
Autonomy EV	0.35	0.05	6.7	1.4e-11 ***
Freedom ICE	-0.31	0.08	-3.7	2.4e-4 ***
Drivers license	1.10	0.28	4.2	6.8e-5 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Interpreting the coefficients of the final equation from this best model (see Table 3) we find that technology affinity, the possession of a driver's license, a high WTPM, and the utilization of public long distance transport predict interest in EVs. Furthermore, people who approve of the statement "An ICEV takes me everywhere" are less likely to be interested in EVs. All together, these six factors explain about a quarter of the observed variance

(Cox & Snell R-Squared: 0.226 and Nagelkerke's R-Squared 0.302). Note how all coefficient estimates are signficantly different from zero despite the general model selection uncertainty.

Even though all socio-economic variables were analysed as well, none of them was found to have a significant impact on interest in EVs. The variables used for the logistic regression included only one variable covering the environmental issue (climate protection as the driving principle when choosing an EV-tariff) but was not significant in predicting EV-interest.

In a second step, we calculate marginal effects (at the variables mean vaules) for the predictors. The marginal effects for all variables of the best model (Technology affinity, willingness to pay more, Education, Autonomy with an EV, Freedom with a conventinal car, and Drivers license ownership) are highly significant (cf. Table 4).

Table 4: Marginal effects at mean (MEM) for best regression model.

Predictor	**dF/dx**	**Std. Error**	**z value**	**Pr(>|z|)**
Technology affinity	0.188	0.023	8.0	9.0e-16 ***
WTPM	0.016	0.002	6.7	2.6e-11 ***
Education	0.051	0.016	3.1	0.0021 **
Autonomy EV	0.088	0.013	6.8	1.4e-11 ***
Freedom ICE	-0.076	0.021	-3.7	2.4e-4 ***
Drivers license	0.256	0.056	4.6	4.3e-6 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

The average marginal effects are similar and probit regression lead to similar marginal effects.

Cluster analysis of the majority

As the Majority is quite a large group and includes a high share of consumers, we further analyze this group by applying cluster analysis in order to identify sub-groups. In order to reach this goal we utilized the standard k-means algorithm with four clusters. Initially the size of the (Majority) group who had declared to be interested in EVs consisted of 468 individuals. Out of these 468 individuals, 343 persons had completed all variables used in the clustering process. All variables which comprised a significant impact on interest in EV from the regression analysis, all available socio-economic variables and two more variables which were the only ones which featured environmental interest were used within the clustering process (all in all 16 variables). They are marked in the appendix with a "C". From the sixteen variables seven proved to significantly explain variance ($p < .05$) within the four clusters: Age, education, employment status, WTPM, household size, car availability in household and frequency of car use.

We coin the first identified group "Cost conscious families". It consists of about 35% of participants with interest in EVs. Representatives from this group live with their family, they are on average 40 years old and are (self-) employed. They use their car on a daily basis and are only willing to pay a small premium for EVs (< 2%).

The second group is called "Young families with high income" and includes 18 % of the analyzed participants. Members of this group also live in a small family setting (with an average of three persons per household), but they are on average about 11 years younger than the member of the "Cost conscious families" (29 years). They are willing to pay a higher premium of about 19% for a EV (WTPM). The average group member is (self-) employed and uses his or her car very every day.

14% of all participants interested in EVs fall into the third group. This group is called "Well-off elder couples" and is characterized by a relatively high additional willingness to pay for EVs (22%) and an average age of 63 years. Participants from this group typically live together with their partners. They still work, are likely to keep on earning money but use their car less frequently than members from group one and two.

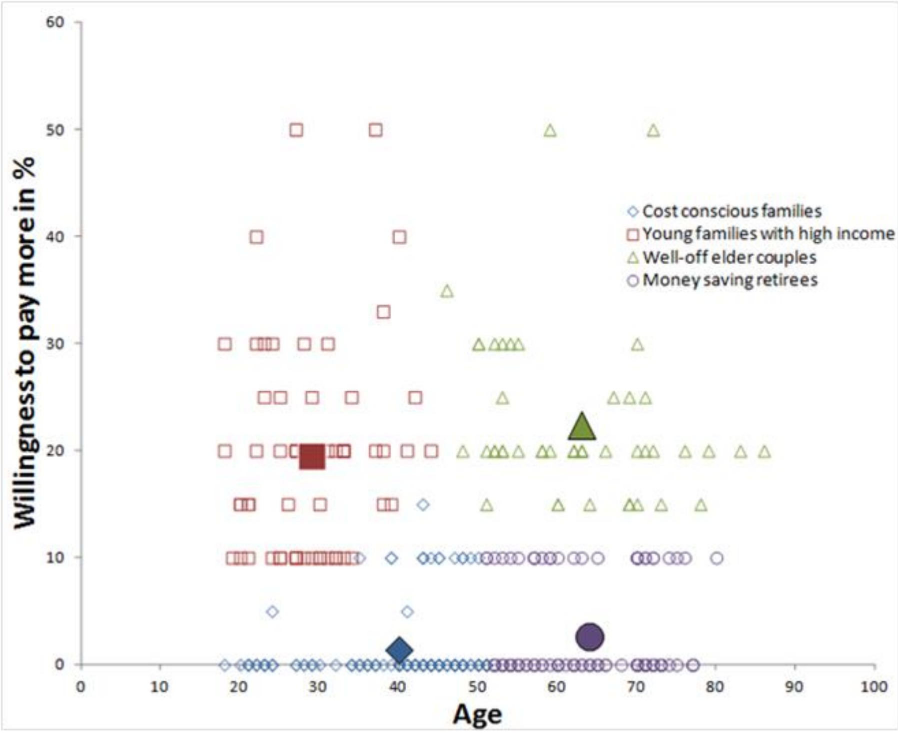

Figure 2: k-means clustering of 343 representatives of the “Majority” group; depiction in regard to WTPM (in %) and age; the enlarged pictograms indicate the cluster centres.

The fourth group contains 33% of the overall group and is called “Money-saving retirees”. They represent the oldest group (average age of 64 year). If they have children, these seem to have left by now, thus letting the parents live by themselves again. “Money-saving retirees” share a similar additional willingness to pay for EVs as the “Cost conscious families” which reaches only an average of 3%. They seem to use their car frequently but not as often as members of group one and two.

Table 5: Results of the k-means clustering according to each of the four clusters

	Clusters			
	Cost conscious families	Young families with decent income	Well-off elder couples	Money saving retirees
Size	119	62	48	114
Size in %	35%	18%	14%	33%
Age mean (SE)	40 (0.85)	29 (0.81)	63 (1.41)	64 (0.74)
Education	4	4	4	4
(Self-) Employment (1=yes/0=no)	1	1	1	2
Willingness to pay more in % mean (SE)	1,4 (M), 0.32 (SE)	19,5 (M), 1.21(SE)	22,4 (M) 1.11(SE)	2,6 (M) 0.41(SE)
Number of people in household	3	3	2	2
Frequency of car use (1=daily, 2= 1-3 times a week)	1	1	2	2
Car availability in household	1	1	1	1

Discussion

We find that the Majority group, defined by the participants who are interested in EVs but do not own or plan to own an EV so far, can be characterized similar to Early Adopter. However, we saw that the average characteristics are less pronounced than those of the Innovators and Early Adopter group. Comparing socio-economic and attitude variables between the Majority and the Laggard group suggest that the Majority group is significantly higher educated, more technology affine, consists of more men and its representatives are more often working than the Laggard representatives. Furthermore, members of the Majority adopter group feature a significantly higher willingness to pay more for an EV and have more often a car available at their homes. Concerning their attitudes in regard to EVs or ICEVs the data suggests that members of the Majority perceive the availability, the independence, freedom and autonomy related to EVs significantly higher than the members of the Laggard group. In addition to that they also assess the general availability of ICEVs as being higher in comparison to the members of the Laggards representatives. This points out that they are possibly more focused on car use in their daily mobility than Laggards.

The results on the socio-economic characteristics blend in well with the results proposed by Plötz et al. (2014). Using their propositions concerning the Early Adopter as a starting point, our results show that the Majority may be characterized as a hybrid between the Early Adopters and the Laggard group. However, this also implies that this group cannot be characterized very specifically.

From the binary logistic regression, we learn on the one side that six of the tested variables significantly predict interest in electric vehicles: technology affinity, the possession of a drivers' license, a high WTPM, and the utilization of public long distance transport. On the other side the data tells us that people who approve of the statement „An internal combustion engine vehicle takes me everywhere" are less likely to be interested in EVs. To foster diffusion of EVs, the main focus group for EVs in the next years are very likely to be car drivers with higher than average technology interest who are able to cope with the disadvantages of the EV (by taking the train and paying more). Therefore, it is advisable that carmaker's marketing campaigns continue to emphasize the novelty value of the advertised product. We further recommend to increase efforts to work on technical solutions to reduce the customers range anxiety, as the freedom that car drivers attribute to ICEVs is not yet developed to same degree ascribed to EVs. Only later, when customer groups are about to shift towards initially less interested customer groups it seems to be advisable to shift the core of marketing strategies towards the suitability for daily use including more affordable prices.

The aim of conducting a k-means clustering analysis to the Majority group was to analyze subsets of this large group. However, the k-means clustering is an explorative approach to analyze data since the number of clusters is fixed a priori. In order to choose the best number of clusters, we analyzed the solutions from two, three and five cluster groups and found that the presented version offers more insight and is easier interpretable. Rescaling all variables to zero mean and unit standard deviation did not qualitatively alter the clusters. As seen above the two biggest clusters (total of 67%) represent a big share of the Majority that are generally interested in EVs but only willing to pay a small or no premium for EVs. This matches very well with the overall picture of relatively low willingness to pay more in general.

Axsen et al. (2015) suggested a subdivision of his "Potential early mainstream buyers" group into two sub groups: "Pro environmental" and "Non-environmental". As the survey used here did not contain environmental-lifestyle oriented variables we can neither reject nor confirm this part of the study by Axsen et al. (2015). However, our division of those interested in EVs seems similar to the "potential early mainstream" of Axsen et al. (2015).

Several limitations apply to our analysis. First, following Peters and co-workers (cf. Peters & Dütschke, 2014; Peters, Agosti, Popp & Ryf, 2011), we use interest and purchase intention to define the adopter groups. However, other socio-economic variables and other definitions for the Rogers Group could yield additional insight. Second, as in every self-stated survey, the results of our analysis are likely to be influenced by social desirability and the real behavior may differ from the stated. This is especially true for future behavioural intentions as they are assumed in this kind of adoption study. Third, we chose four clusters as the outcomes where best interpretable; however, other numbers of clusters may have offered other insights as well and the optimal number of clusters could be analyzed in future studies, e.g. by maximizing the Bayesian Information Criterion or the gap statistics. Fourth, the variables used for the clustering included only one variable covering environmental issues (Climate protection as the driving principle when choosing an EV-tariff) which did not have significant impact. Nonetheless, from the finding from Axsen et al. (2015) environmental issues can play role when grouping future customers. Thus, it is likely, that a different measurement of environmental attitudes could have led to different results.

Mass market adoption of EVs requires large groups of consumers to seriously consider purchasing a EV. Here we analyzed the next large group of potential buyers as those interested in EVs and factors predicting interest. Our results show that technological affinity and no or low association of freedom with conventional vehicles are main factors in predicting EV interest. Accordingly, automakers and policy makers should highlight the technological advancement in order to accelerate market diffusion of EVs.

Following Rogers (2003) and Axsen et al. (2015), the next big groups of EV buyers are likely to be dividable into subgroups. Our findings suggest a division by age and willingness to pay a price premium for this new technology. In particular, the latter is in line with Rogers (2003) and has not been analyzed by Axsen (2015). According to our cluster results the early Majority would amount to a size of 15% of the overall population ($0.48 * (0.18 + 0.14) = 0.15$); the late Majority in contrast would represent about 32% of the overall population ($0.48 * (0.35 + 0.33) = 0.33$). Additionally, potential EV car buyers can by expected in all age groups, yet the biggest group of car buyers is probably to be found in the elder group, due to higher affluence in this group. In conclusion, car and policy makers can expect higher willingness to pay for a few more years but it should decline noteworthy when ten or more percent of vehicle sales will be EVs.

Conclusion

Mass market adoption of EVs requires large groups of consumers to seriously consider purchasing an EV. Here we analyzed the next large group of potential buyers as those interested in EVs and factors predicting interest. Our results show that technological affinity and no or low association of freedom with conventional vehicles are main factors in predicting EV interest. Accordingly, automakers and policy makers should highlight the technological advancement in order to accelerate market diffusion of EVs.

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Appendix

The characters used in the column "V-USE" display in which part of the analysis the respective variable has been used: A = adopter groups; L = logistic regression; C = cluster analysis

Variables	Labels & Values	V-USE
Age	years	(A, L, C)
Size of household	number of persons in household	(A, L, C)
Willingness to pay more for an EV (WTPM)	Share in %	(A,L,C)
Technology affinity	Scale - Cronbach's alpha 0.59; outcome between 1(low) up until 6 (high)	(A, L,C)
Education	1 = No school-leaving diploma, 2 = Basic schooling without apprenticeship, 3 = Basic schooling with finished apprenticeship certificate, 4 = Secondary school certificate, 5 = High school diploma, 6 = University diploma	(A,L,C)
Availability ICEV ("Ein Auto ist immer verfügbar." -"A car is always available")	„Does not apply" (1) to „does fully apply" (6)	(A, L)
Independence ICEV („Mit einem Auto bin ich nicht von anderen abhängig." – „With a car I am not dependent on others")	„Does not apply" (1) to „does fully apply" (6)	(A, L)
Freedom ICEV („Ein Auto bringt mich überall hin." - „A car takes me anywhere")	„Does not apply" (1) to „does fully apply" (6)	(A, L,C)
Autonomy ICEV („Mit einem Auto kann ich meine Route selbst bestimmen." - „Using a car I can determine my route by myself ")	„Does not apply" (1) to „does fully apply" (6)	(A, L, C)
Availability EV („Ein Elektroauto ist immer verfügbar." - "An EV is always available")	„Does not apply" (1) to „does fully apply" (6)	(A,L)
Independence EV („Mit einem Elektroauto bin ich nicht von anderen abhängig" - „With an EV I am not dependent on others")	„Does not apply" (1) to „does fully apply" (6)	(A,L)
Freedom EV („Ein Elektroauto bringt mich überall hin, wo ich möchte" - „An EV takes me anywhere")	„Does not apply" (1) to „does fully apply" (6)	(A,L)
Autonomy EV („Mit einem Elektroauto kann ich meine Route selbst bestimmen" - „ With an EV I can determine my route by myself ".)	„Does not apply" (1) up to „does fully apply" (6)	(A,L)

The characters used in the column "V-USE" display in which part of the analysis the variable has been used: A = adopter groups; L = logistic regression; C = cluster analysis).

Variables	Labels & Values	V-USE
Gender	share of females	(A, L, C)
(Self-) Employment status	(self-) employed / unemployed	(A, L, C)
Children in household	yes / no	(A,L)
Possession of driver's license	yes / no	(A,L,C)
Utilization of public long distance transport	yes / no	(L,C)
Car availability in household	yes / no	(A, L, C)
Frequency of car use	daily (1)/1-3 days a week (2)/ 1-3 days per month (3)/ less frequent (4)	(A, C)
Area of residence	rural region (1) / in a suburb (2) / urban but not in the city center (3)/ in the city center (4)	(L,C)
Climate protection as the driving principle when choosing an EV-tariff	yes / no	(A, L,C)
Full automation as the driving principle when choosing an EV-tariff	yes / no	(A, L, C)
Compensation as the driving principle when choosing an EV-tariff	yes / no	(A, L, C)
Easiness to use as the driving principle when choosing an EV-tariff	yes / no	(A, L, C)
First choice selector when assessing an EV tariff	climate protection / full automation / compensation / easiness to use (this variable is a merged variable of the former four variables; it was utilized for analyzing the group differences, but was not explicitly cited in table as the data would have been redundant as the results were are already shown by the former four variables)	(A, L,C)