Analysing the effect of heterogeneous preferences on electric vehicle adoption: The case of Denmark

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Short summary

For the next decade, car markets are expected to see a large increase in the adoption of battery-electric vehicles (BEVs) by many segments of the population. These segments have different preferences, making the design of transport policies more complicated. This research aims to identify groups of car buyers who could be expected to drive BEV adoption and those who are likely to be laggards. To do so, we estimate preferences related to car technology, charging facilities and car characteristics such as size and environmental impacts, using a discrete choice experiment with three fuel types and six car segments. Using a Latent Class (LC) modelling approach, we find four classes to capture the varying preferences across the population. Each class captures different preferences for attributes and effects of sociodemographic variables, providing insights for a detailed analysis of the car users' preferences and perceptions.

Keywords: Electric vehicles, Discrete choices modelling, Latent class choice models, preferences and perception.

1 Introduction

After a decade with a very low share of registered battery electric vehicles (BEVs) in most countries, the majority uptake will most likely happen in the coming decade. Worldwide, BEVs are seen as a key to reducing carbon emissions, and thus, several countries have introduced incentives to speed up the uptake. The current BEV market includes a wide range of prices, vehicle sizes and technological features that have made them more affordable and attractive for different types of users with different transport needs. Widely research literature has been studying how the adoption of BEV is influenced by policies and incentives, business models, attributes of vehicles, charging infrastructure and transport actors such as policymakers and civil society(Kumar & Alok, 2020; Corradi et al., 2023).

However, in the current discussion, it is not obvious how the next phase of adoption could be optimized from a societal perspective. In particular, how different user segments might have different preferences and expected behaviours when it comes to car attributes such as the pricing, car characteristics and charging infrastructure. This study seeks to investigate user segments and their preferences and behaviour in order to propose a more efficient policy-making to encourage the BEV uptake.

Segments for BEV users and expected demand have been studied by means of intention studies, stated preference methods and analyses of early adopter samples. These studies indicate different profiles for BEV pioneers, being more often male (Axsen et al., 2016; Johnson & Williams, 2017), but not for the early majority (Axsen et al., 2016; Johnson & Williams, 2017; Fevang et al., 2021). Furthermore, BEV buyers seem to have higher than average education and income, which might indicate higher price sensitivity among certain segments in the population as BEVs have a higher up-front cost (Jensen et al., 2021; Bansal et al., 2021). Moreover, BEV demand is affected by whether the customer has the possibility to install a charger (Jensen et al., 2021; Fevang et al., 2021; Johnson & Williams, 2017; Axsen et al., 2016) and finally, a higher preference for BEVs has been found for drivers of smaller sized cars (Jensen et al., 2013; Hackbarth & Madlener, 2013).

These findings show how the intention to adopt a BEV technology varies across the population and might be more focused on different sociodemographics profiles than others, making policy regulation, analysis and effectiveness more complex.

Most often, some of the preferences for BEVs have been studied using an interaction of socioeconomic variables and different car alternatives. Likewise, unobserved groups and discrete mixture techniques have been helping to identify heterogeneity in consumers' preference for different fuel types (Jia & Chen, 2023), such as internal combustion vehicles (ICV), plug-in hybrid electric (PHEV) and fully battery electric (BEV). In many cases, either the dataset or method used does not facilitate an in-depth analysis of a more general classification of these user segments and their preferences for car characteristics and charging infrastructure.

The aim of this study is to provide an overview of the main groups of user segments when it comes to car purchases. Utilizing a detailed stated choice dataset from Denmark, we apply a latent class model to identify the main groups of car buyers and what their preferences are when it comes to car technology, charging facilities and car characteristics such as size and environmental impacts. While previous models have also applied latent class models to stated choice data on BEV demand, our study highligts more details and preference heterogeneity since we rely on a fairly large study that includes attributes on charging facilities and car size which have not been fully covered in previous studies.

2 Methodology

The data are stated choice data from Jensen et al. (2021) reflecting current technology states with respect to three cost attributes, four car characteristic attributes including carbon emissions, and four charging infrastructure attributes. The survey design allows a joint representation of six **car segments (Mini, Small, Medium, Large, Premium and Luxury/sports)** and three **fuel types (ICV, BEV, PHEV)**, i.e. eighteen alternatives. To reduce the complexity, an individual-specific subset of the two most likely car segments and three fuel types is chosen. Each respondent is asked to answer four choice tasks with these six alternatives.

We use a pivoted design with separate choice experiments set up for individuals with potential access to private charging (e.g. mainly those living in a detached house) and individuals without access to private charging (e.g. mainly those living in an apartment). Each one of the attributes used in the choice design and their levels are defined by Jensen et al. (2021). An overview of the model framework is presented in Figure 1.

The analysis applies the class of RUM-based mixed logit models known as Latent Class (LC) models. These models take into account heterogeneity by allowing preference parameters to differ across classes and each individual to be a discrete mixture of these classes; see Train (2009), Hensher and Greene (2003). As these models do not have closed-form probabilities, we apply maximum simulated likelihood (MSL) to estimate the models, see e.g. Train (2009).

The acceleration (ACC), carbon emissions (CO_2), the distance between fast charging stations (FChInfDist), fast charging speed (FChSpeed), operational cost (CostOp), purchase cost (CostPur), annual fixed cost (CostYr), trunk sizes (TrunkSize), the distance (HmChDist) and the probability of public charging stations available (HmChAv) near home were included as generic variables among the alternatives. The driving ranges for the three types of fuel technologies were transformed into non-linear logarithm specifications, and they were included as generic among their same technology alternatives. The alternative specific constant ASC_i and ASC_j represent the correlated generic constant among fuel types i and car segments j, respectively. The sociodemographic attributes were considered explanatory variables in the membership function of the latent classes. The proposed models were estimated in PandasBiogeme V.3.2.13 (Bierlaire, 2023)

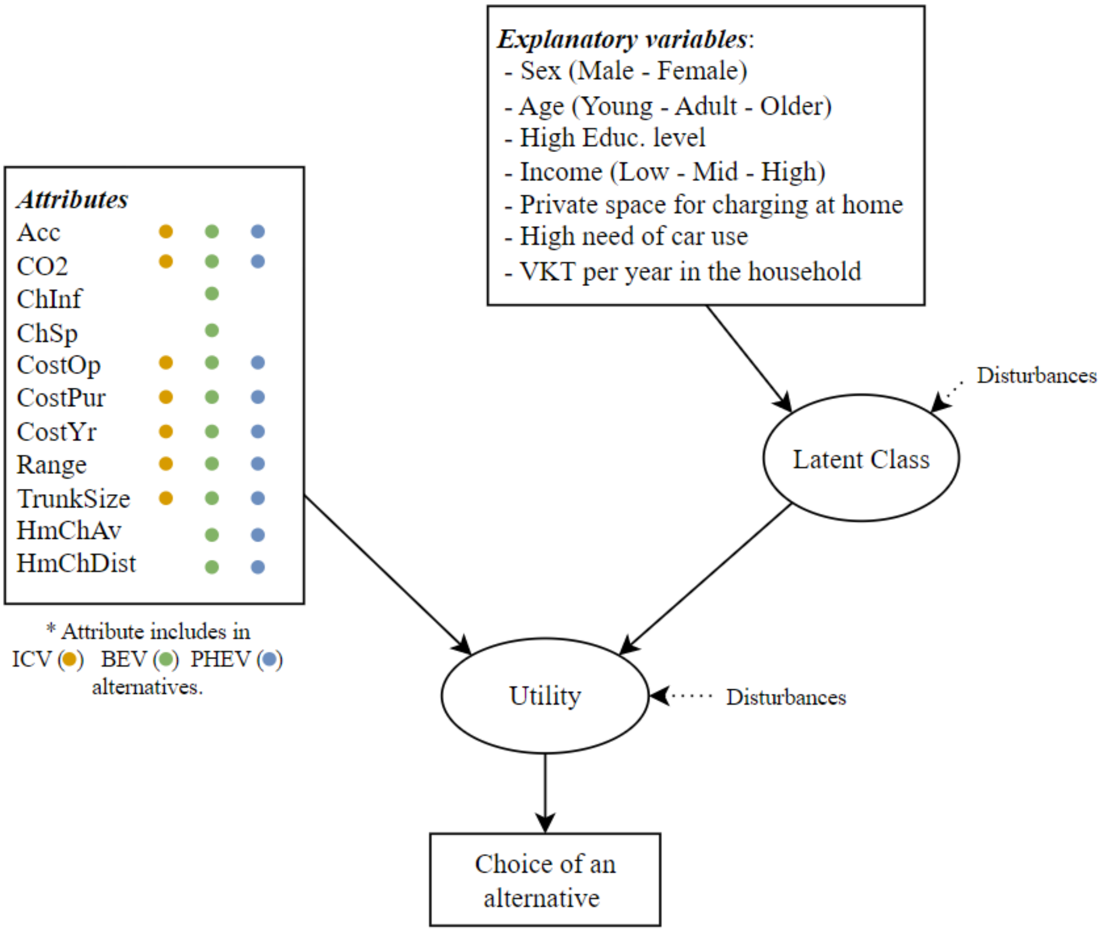

Figure 1: Modelling approach

3 Results and discussion

Invitations to participate in the choice experiment were sent out to a representative sample of 25,209 individuals of the Danish population in June 2020. After cleaning and considering individuals who completed the questionnaire and the four choice sets, the sample size was 2956 participants and 11824 choice observations.

The number of classes was selected considering the AIC and BIC criteria as well as the interpretation of classes in the estimated models. Table 1 shows the results for the models with two, three, four and five classes. The lower AIC and BIC suggest a better fit, in this case, a model with five classes. However, the model results with five classes show identification issues in the estimation of some parameters. The specification with four classes was selected for the analysis.

Table 1: Godness of FIT and number of classes tested

Classes	Parameters	Null LL	Final LL	AIC	BIC
2	62	-21185.8	-17536.3	35196.6	35568.1
3	98	-21185.8	-16159.4	32514.9	33102.0
4	**134**	**-21185.8**	**-14813.5**	**29895.1**	**30697.9**
5	170	-21185.8	-14286.87	28913.7	29932.3

Considering the model with four latent classes, parameters with the wrong sign were omitted, and those whose statistical values of estimated parameters were similar (range between one standard deviation) were considered the same across their classes. Table **??** shows the results for the significance parameters estimated for the attributes included in the proposed utility functions. After the inclusion of generic parameters across some classes, this model estimated 99 parameters. Given the individual probabilities to belong to each class, some class composition stats were calculated for the covariates and other sociodemographics attributes. Furthermore, considering the probability of belonging to the class membership functions, the class size predictions were estimated within simulation mode with confidence intervals settled up to 90% for sensitive analysis.

Figure 2 presents the class choices according to the fuel type technologies and car segments. The most frequent choice among class 3 was the ICV fuel type, and for classes 1 and 2, the fuel types with an electric option (BEV or PHEV) were highly chosen.

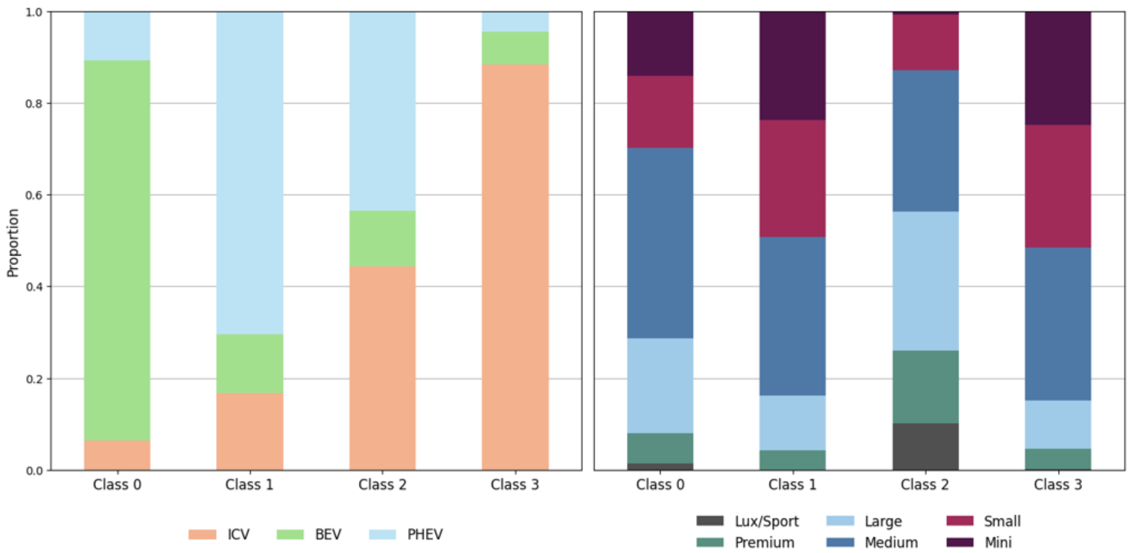

Figure 2: Composition of class choices for fuel types and car segments

Class 0, a **typical BEV first mover**, is the segment of the population mostly described in the literature so far based on revealed preference data. In this class we can identify the highest share of people interested in BEV alternatives. As found in the literature and compared with the other classes, there are more often males, young, higher income, and have access to private parking. However, no education level effect is found. While these individuals more often drive longer trips, the annual mileage for the cars in the household is lower compared to the other classes. 2. Even though BEVs often have good performance, the individuals in class 0 value acceleration less than individuals in the other classes, but there are significant preferences for fast charging speed in class 0. They also seem to put a higher value on the other charging attributes.

Class 1, the **utilitarian environmentalist**, can be described as a segment of the population that sees their car as a utility tool for everyday mobility. It is seen that class 1 mainly prefer PHEV fuel types, and more than half of their choices are for a car in the Mini and Small car segments. In this class, the purchase price and annual costs are highly valued, and they prefer cars with bigger trunk sizes. They seem to have intentions to buy more environmentally friendly cars, but maybe due to utilitarian needs, they overall prefer PHEV instead of BEV. Driving range of the BEV is not important for this class, maybe because they less often drive longer trips than class 0.

Class 2, **car lovers**, is a segment where they have a preference for larger and more expensive cars. In this segment, they show a lower household annual millage and focus more on operational costs than class 0 and class 1. They less often belong to the low-income group than the other classes. Furthermore, this segment drives significantly more than all other segments. The choice model indicates that this group has a significant preference for BEV-specific characteristics, including a driving range for BEVs and PHEVs and home charging facilities (private and public).

Finally, class 3, **car dependents without private parking**, within this group, they have less often the opportunity to charge a BEV or PHEV at home, and they show a higher preference for ICV cars. The choice behaviour of class 3 indicates that this group prefers smaller cars and that they have the highest price sensitivity when it comes to operation costs and purchase costs. They focus more on car characteristics such as acceleration and boot size than the other classes. Surprisingly, the driving range for BEVs is not significant, which might reflect their need to drive daily at a limited distance. This group is sensitive to charging facilities near their home but not charging speed, which is more related to longer trips. They are more often middle-aged women and less often high-income.

Table 2: Estimated parameters* for LC model

Variable	**Class 0**		**Class 1**		**Class 2**		**Class 3**	
ASC_{ICV}				*as reference*				
ASC_{BEV}	-2.51 (0.56)	***	2.06 (1.83)		-3.58 (1.60)	**	2.25 (2.42)	
ASC_{PHEV}	-1.27 (0.54)	**	3.26 (1.54)	**	2.07 (1.58)		2.38 (2.21)	
ASC_{Mini}	0.19 (0.35)		5.23 (0.92)	***	-8.50 (0.74)	***	5.45 (0.71)	***
ASC_{Small}	-0.38 (0.26)		2.51 (0.56)	***	-5.45 (0.49)	***	3.36 (0.59)	***
ASC_{Medium}	0.47 (0.15)	***	0.98 (0.27)	***	-1.95 (0.24)	***	1.85 (0.37)	***
ASC_{Large}				*as reference*				
$ASC_{Premium}$	0.48 (0.20)	***	-0.13 (0.35)		1.88 (0.35)	***	-1.31 (0.33)	***
$ASC_{Lux/Sport}$	1.20 (0.43)	***	0.41 (1.18)		5.40 (0.64)	***	0.14 (0.82)	
CostOp	-0.16 (0.17)		-0.16 (0.17)		-0.52 (0.20)	***	-0.89 (0.31)	***
CostPur	-0.43 (0.06)	***	-1.08 (0.09)	***	-0.30 (0.05)	***	-0.76 (0.14)	***
CostYr			-17.25 (5.29)	***	-6.53 (3.09)	**	-6.53 (3.09)	**
ACC	-0.02 (0.01)	**	-0.05 (0.01)	***	-0.05 (0.01)	***	-0.05 (0.01)	***
CO_2	-3.31 (0.73)	***	-3.31 (0.73)	***	-3.31 (0.73)	***	-0.51 (1.44)	
RangeICV			0.45 (0.22)	**	0.45 (0.22)	**	0.85 (0.33)	***
RangBEV	0.67 (0.09)	***	0.00 (0.17)		0.67 (0.09)	***	0.00 (0.17)	
RangPHEV	0.37 (0.12)	***	0.26 (0.08)	***	0.13 (0.08)	*		
TrSize3	0.11 (0.11)		0.51 (0.17)	***	0.11 (0.11)		0.51 (0.17)	***
TrSize4	0.19 (0.16)		0.75 (0.26)	***	0.19 (0.16)		0.75 (0.26)	***
TrSize5	0.25 (0.16)	*	1.04 (0.27)	***	0.25 (0.16)	*	1.04 (0.17)	***
ChInf	-0.14 (0.12)				-0.14 (0.12)			
ChSp	0.03 (0.01)	***						
HmChAv2	0.41 (0.19)	**	0.02 (0.13)		0.02 (0.13)		0.41 (0.19)	**
HmChAv3	0.52 (0.20)	***	0.34 (0.14)	**	0.34 (0.14)	**	0.52 (0.20)	***
HmChAv4	0.92 (0.31)	***	0.43 (0.16)	***	0.43 (0.16)	***	1.29 (0.22)	***
HmChDist	-0.70 (0.34)	**	-0.26 (0.28)		-0.26 (0.28)		-0.70 (0.34)	**
$HmChPos_{BEV}$	0.80 (0.19)	***	0.32 (0.20)		0.80 (0.19)	***	0.32 (0.20)	
$HmChPos_{PHEV}$	0.45 (0.15)	***	0.45 (0.15)	***	0.45 (0.15)	***		
Covariates in membership model								
Variable	**Class 0**		**Class 1**		**Class 2**		**Class 3**	
ASC_{Class}	*ref.*		0.50 (0.23)	**	0.03 (0.22)		0.98 (0.21)	***
Male			-0.43 (0.11)	***	-0.05 (0.12)		-0.36 (0.12)	***
Young			-0.40 (0.22)	*	-0.66 (0.22)	***	-0.66 (0.22)	***
Old			-0.04 (0.16)		-0.17 (0.17)		-0.34 (0.16)	**
HighEduc			-0.32 (0.12)	***	-0.57 (0.12)	***	-0.82 (0.13)	***
IncomeLow			-0.33 (0.20)	*	-0.55 (0.22)	**	-0.12 (0.18)	
IncomeHigh			-0.47 (0.15)	***	-0.19 (0.14)		-0.50 (0.16)	***
HmChPrivSp			-0.36 (0.15)	**	-0.39 (0.14)	***	-0.92 (0.14)	***
HighCarNeed			0.02 (0.13)		0.16 (0.13)		-0.05 (0.13)	
HhVKTYear			0.09 (0.04)	**	0.19 (0.04)	***	0.13 (0.05)	***
Class Size	30.7 %		26.1 %		21.1 %		22.0 %	
C.I. [90 %]	[25.8 % to 35.6 %]		[21.2 % to 31.4 %]		[17.3 % to 25.6 %]		[18.0 % to 26.5 %]	

*p<0.1, **p<0.05, ***p<0.01

With these results and considering a group of attitudinal indicators measured in the same data collection, we are able to assess how the variation of perception varies in attitudinal statements within each of the classes. As an example, we selected two indicators measured using a Likert agreement scale of 5 points (Strongly disagree to strongly agree). Figure 3 presents how the majority of classes 0 and 1 show positive perceptions about BEV and how classes 2 and 3 don't find it suitable for their lifestyles, which is aligned with our findings.

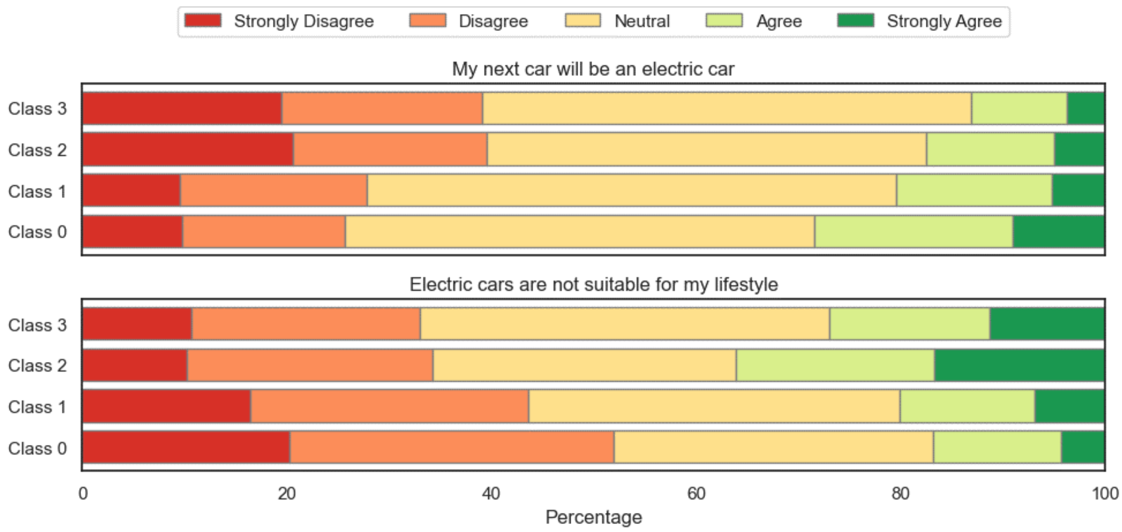

Figure 3: Perception about the electric cars across the classes

4 Conclusions

This study analysed preferences and perceptions among the main population segments relevant to car purchases in Denmark. Both the discrete model choice framework and a large dataset with a significant number of attributes and alternatives allow us to be confident in our findings and compare them with previous studies. With the upcoming rise in electric technology in the car market share, this study helps to understand the triggers of the adoption of BEV by identifying the most relevant population segments and their preferences. In particular, the proposed LC modelling approach allowed identify how three types of fuel (ICV, BEV or PHEV) and six types of car segments (Mini, small, medium, large, premium, luxury/sport) alternatives are valued from the identified latent classes. A high number of attributes related to the car (such as cost, performance, and size) and charging facilities were included, and the results showed how and which attributes are relevant for each class. Our findings show the preferences of those who see the car as a utility tool for everyday mobility (class 0), less driving and needs in urban areas (class 1), larger cars with more needs of driving (class 2), and expensive car to longer distances needs (class 3). This profile segmentation allows for more efficient policy-making, encouraging a socially efficient adoption of BEV. The assessment of attitudinal perception indicators varies across each latent class. Therefore, the next steps of this research include the study of how these indicators influence the membership class model, incorporating them as latent constructs in the specification of each latent class.

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