CHALMERS
UNIVERSITY OF TECHNOLOGY

# Analysis on the determinants of EV purchase intention in Sweden

Master’s thesis in Master Program Infrastructure and Environmental Engineering

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**Depatment of Architecture and Civil Engineering**
**Master thesis ACEX30**

CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2025

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## ABSTRACT

This study uses a discrete choice experiment embedded in a survey to explore the determinants of Swedish consumers' choice between electric vehicles (EVs) and internal combustion engine (ICE) vehicles. A total of 373 respondents, resulting in 7,266 valid choice observations, were collected and analyzed using binary logistic regression models. Model specifications include both vehicle-specific attributes (e.g., price, range, maintenance costs, charging time, charging convenience, and emissions) and demographic characteristics (e.g., age, gender, education, income, and family structure).

The results show that economic and infrastructure considerations dominate consumers' decision-making process. Specifically, vehicle price, maintenance costs, and the availability of home charging infrastructure are significant attributes of EV adoption. The existence of a home charger is a particularly important driver, increasing the probability of choosing an EV by nearly 60 percentage points on average. In contrast, attributes such as range and charging time, while in the direction of theoretical expectations, are not statistically significant in the current sample. The probability analysis also highlights that in the absence of home charging facilities, the impact of price cuts is relatively limited, suggesting that policymakers should increase investment in EV charging facilities.

The study provides practical insights for policymakers aiming to accelerate the adoption of EVs in Sweden. In addition to targeted financial incentives, efforts should focus on improving private and public charging infrastructure. The findings also contribute to a broader understanding of how practical and infrastructure factors influence low-carbon transport choices in European markets.

Keywords: Electric Vehicle, Discrete Choice Modeling, Vehicle Attributes

**Acknowledgement**

The completion of this paper is inseparable from the support and help of many people. We would like to express our sincere gratitude to all the teachers, friends, and family who have given us care and guidance during our research and writing.

We would like to express our special thanks to my thesis supervisor, Xiaohan Liu, and examiner Kun Gao, for their careful guidance and rigorous academic training throughout the research process. From survey design to model construction, from data analysis to paper writing, your professionalism and patient guidance have benefited me a lot and provided a solid guarantee for the successful completion of this research. During the research process, we also received encouragement and help from many classmates and friends.

We would like to thank my family for their understanding and support. It is you who have given us the confidence and strength to focus on academic exploration and keep moving forward.

In the end, we would like to express our sincerest gratitude to all those who have helped us through this article!

# Notations

| | |
|---|---|
| $V_n$ | Deterministic utility of alternative n |
| $U_n$ | Total utility of alternative n, including stochastic component |
| $ASC_n$ | Specific constant of utility for alternative n |
| $\beta_i$ | Coefficient of attribute i |
| $B_i$ | Value of attribute i |
| $L$ | Likelihood function |
| $P(c_i\|C_i)$ | probability that individual i chooses $c_i$ from its alternative set $C_i$ |
| $\varepsilon_n$ | Unobserved part for attribute n |

# 1. Introduction

Transportation is one of the largest sources of greenhouse gas emissions worldwide. Road traffic is responsible for roughly 72% of all transportation-related carbon emissions (International Energy Agency, 2023). The European Union has set a goal to achieve climate neutrality by 2050. European countries are accelerating the shift from vehicles with internal combustion engines (ICE, e.g., gasoline and diesel cars) to cleaner alternatives like electric vehicles (EVs). Sweden is a leading example of this drive toward sustainability in Europe. The country has committed to ending fossil-fuel car sales by 2030 and aims to increase the share of EVs in new-car sales (Government Offices of Sweden, 2021).

Despite EVs' clear potential to cut fossil-fuel use and curb transportation emissions, EV adoption varies widely by region and buyer segment (Hardman, Shiu, & Steinberger-Wilckens, 2017). Even with government incentives and a growing network of charging stations, many drivers remain reluctant to make the switch from petrol-powered cars (Rezvani, Jansson, & Bodin, 2015). Their main concerns center on the high upfront cost of EVs, driving range anxiety, long recharging times, and uneven charger availability (Sovacool, Axsen, & Sorrell, 2018).

The existing studies have shown that factors such as environmental concern, social norms, technological comfort, and demographic characteristics can significantly influence decision-making (Gnann, Plötz, Funke, & Wietschel, 2018).

This thesis aims to examine the key factors influencing Swedish consumers' intention to purchase EVs. To achieve this aim, a stated preference survey is implemented to collect a wide range of comprehensive user profiles and purchasing preferences between EVs and ICE vehicle options, based on the designed scenarios. The user profiles include prior EV experience, income, education, and primary car-choice criteria. The designed scenarios involve varied economic, functional, and charging attributes of EVs and gasoline vehicles.

The information gathered from the survey is analyzed using a discrete choice model, with a special focus on a binary logit model in our study. This approach quantifies the importance and significance of explored factors in Swedish consumers' purchase intention between EVs and gasoline vehicles. Our primary goal is to provide insights for automakers, urban planners, and policymakers seeking to accelerate EV adoption in Sweden. By getting a clear picture of the true drivers of car choice behavior, EV incentives and infrastructure strategies will closely align with consumers' real preferences and needs in Sweden.

## 1.1 Research Objective and Questions

The objective of this thesis is to identify and quantify the key determinants influencing Swedish consumers' decision to purchase EVs. Therefore, the study aims to answer the following research questions:

- What socioeconomic and behavioral characteristics are associated with higher willingness to purchase an EV?
- How do Swedish consumers trade off different vehicle attributes such as cost, range, emissions, and charging time?
- What are the implications for EV market design and public policy in Sweden?

By answering these questions, this study contributes to the growing literature on sustainable transport and supports Sweden's ambition toward carbon-neutral mobility.

# 2. Literature Review

This chapter first gives an overview of existing research on EV purchase behavior. We focus on factors that affect EV purchase behavior, like purchase and maintenance costs, driving range, environmental attitudes, and charging availability. We also summarize the case studies on EV adoption in different countries. Following that, the challenges of EV adoption in Sweden are discussed. Finally, this chapter reviews studies that used stated preference surveys and discrete choice models to understand consumer behavior. Particular attention is paid to comparing these methods with the approach used in this thesis, illustrating how our employed method aligns with our research.

## 2.1 EV Purchase Behavior

Deciding to purchase an EV involves multiple considerations. Consumers' choices are influenced by past driving experience, ownership costs (e.g., purchase price and maintenance), vehicle specifications, environmental attitudes, and personal attributes such as age, income, and lifestyle. This subsection reviews the literature on how these factors influence car-purchase preferences and how stated-preference surveys and discrete-choice models have been used to study them.

### 2.1.1 Vehicle Ownership Experience and Familiarity

Driving experience on EVs of consumers often plays an important role in shaping their EV purchase intentions. Individuals with direct EV experience, whether through ownership, test drives, or regular interaction with other EV users, tend to feel more confident in the technology. This kind of exposure helps remove doubts and builds trust (Axsen & Kurani, 2013). For example, a study by Hidrue et al. (2011) showed that people who had used EVs before were less worried about how the car would perform and were more accepting of unique features like how quiet they are or the way regenerative braking works (Hidrue, Parsons, Kempton, & Gardner, 2011). In addition, how far someone usually drives each day can influence how they view EVs. If their daily commute is short, they are less likely to be concerned about the car's driving range, which makes EVs seem like a better fit for their needs (Franke & Krems, 2013). In our study, these aspects were considered in the first part of the survey, which asked about EV ownership, driving experience, and how far participants typically travel in a day.

### 2.1.2 Economic Considerations and Upfront Cost

Cost is one of the biggest factors holding people back from choosing EVs. While EVs usually cost less than fossil-fuel vehicles due to cheaper electricity and fewer maintenance issues, their higher purchase prices still put off a lot of buyers (Egbue & Long, 2012). Research shows that people tend to focus more on what they must pay right now rather than considering the cost they could save over the long term (Greene, Park, & Liu, 2014). This kind of thinking, often called present bias, makes the initial price tag a major part of the decision. On top of that, other financial details like yearly maintenance costs and how much it costs to drive each kilometer also influence whether someone chooses an EV. These two factors were included in the choice scenarios used in this study, since earlier research has shown they matter a lot in people's decisions (Helveston et al., 2015). While government subsidies and tax breaks can help ease these concerns, their success often depends on whether buyers clearly understand the long-term financial benefits (Jenn, Springel, & Gopal, 2018). That is the reason why the survey used in this study includes questions designed to see how people balance short-term costs with longer-term savings.

### 2.1.3 Functional Attributes: Range, Charging Time, and Infrastructure

While individuals are deciding whether to buy an EV, technical features like how far the car can go on a single charge, how long it takes to charge, and how easy it is to find charging stations play a huge role (Rezvani et al., 2015). One of the most common concerns is known as "range anxiety"—the worry that the battery might run out before reaching your destination (Li, Long, Chen, & Geng, 2017). This issue is especially noticeable in colder countries like Sweden, where low temperatures can reduce battery efficiency and make the car's range even shorter (Yang & Yao, 2019). Another concern is how long it takes to charge an EV, which feels much slower compared to the quick fill-up times of regular gas cars. This can be a real issue for people with tight schedules who cannot afford long waits. To explore how much these worries affect people's choices, this study included three practical features in the vehicle choice tasks: driving range, charging time, and whether the person could charge the car at home. These factors were selected based on existing research showing they are key to understanding EV preferences (Train, 2009). Including them helps reveal whether improving these features could make more people consider switching to EVs.

### 2.1.4 Environmental Attitudes and Green Lifestyle

A growing number of studies show that a person's attitude toward the environment influences how they choose to buy a car. People who consider themselves environmentally friendly or regularly recycle things (Barbarossa et al., 2015), cut down on plastic use, or try to save energy are generally more willing to go for EVs, even if those cars cost more or have some performance trade-offs (Jansson, Nordlund, & Westin, 2017). This link between someone's values and their vehicle choice is often explained through the idea of "moral self-congruity," meaning people tend to pick things that match their personal beliefs and sense of what is right (Whitmarsh & O'Neill, 2010). In this research, Part IV of the survey was designed to measure how much participants care about the environment. It used a five-point scale to rate different everyday behaviors related to sustainability. The goal was to see whether people who reported more green habits also showed a stronger preference for low-emission vehicles in the choice tasks. Earlier studies, like the one by Degirmenci and Breitner (2017), found that environmental concern had a meaningful impact on people's interest in buying EVs, even after considering things like price and how far the car could go (Degirmenci & Breitner, 2017).

### 2.1.5 Socio-demographic and Psychographic Moderators

In EV research, personal background details like age, gender, income, education, and family setup are often used to understand how different groups make purchase decisions. For example, younger people usually feel more comfortable with new technology, and households with higher incomes are more likely to afford the initial cost of an EV (Wang, Tang, & Pan, 2017). Education level also plays a role, as people with more schooling tend to be more aware of both the environmental benefits and the technical features of electric cars (Potoglou & Kanaroglou, 2007). On top of these basic demographics, personality traits (like how open someone is to new ideas or how much risk they're willing to take) can also shape how attractive EVs seem to them (Bobeth & Kastner, 2020). In this study, all these details were gathered in Part III of the survey. They will be used as control variables when analyzing the results using the discrete choice model. Including this information helps identify differences in preferences between different types of users, which can be useful for policymakers and car manufacturers trying to design better strategies for specific customer groups.

## 2.2 Case Studies on EV Adoption

The pace of EV adoption varies widely across countries, driven by a combination of government policies, market structures, and cultural attitudes toward technology and the environment. This sub-section presents international case studies to illuminate the Swedish context and offer comparative insights into which strategies might succeed or fail locally.

### 2.2.1 Sweden

Over the past few years, Sweden has seen a big jump in EV sales. By the end of 2023, more than 60% of all new cars registered were either battery EVs or plug-in hybrids (PHEVs) (European Alternative Fuels Observatory, 2024). This rapid growth has been helped by national policies like the Bonus–Malus tax system, which rewards low-emission vehicles and penalizes high-emission ones, along with tax perks for company cars. However, when the government ended the EV purchase subsidy in late 2022, it raised concerns about the stability of such policies and whether unpredictable changes might affect consumer confidence in making the long-term switch to EVs (Reuters, 2022).

### 2.2.2 Norway

Norway is often seen as the world's front-runner when it comes to EV adoption. In 2023, fully electric cars made up over 80% of all new car sales in the country (Norwegian EV Association, 2023). This success did not happen overnight, it was the result of long-term, consistent government support. Incentives like exemptions from value-added tax, free access to toll roads, and the ability to use bus lanes all helped make EVs a much more attractive option. What is also interesting is that research shows social influence played a key role. As more people started driving EVs, it created a ripple effect where seeing others make the switch encouraged even more adoption. Early, visible policies helped start this trend before EVs were widely accepted, building a strong culture of electric driving over time (Figenbaum, 2017).

### 2.2.3 Germany

Germany's EV market grew quickly after the government rolled out the Umwelt bonus subsidy program and the EU introduced tougher emissions targets for car manufacturers. These policies gave a strong push to EV sales. However, many German buyers still tend to be quite price-conscious, which means that higher upfront costs can slow down adoption. Another noticeable trend is that EV uptake is not spread evenly across the country. It is much more common in cities, where charging stations are easier to find, while rural areas have seen slower growth due to limited infrastructure (Plötz, Funke, Jochem, & Wietschel, 2017).

### 2.2.4 China

China holds the top spot as the world's largest market for EVs. This growth has been caused by several key factors, including strong government subsidies, strict limits on license plates for traditional gas-powered cars, and heavy support for local EV production. Together, these policies have made EVs more accessible and appealing to Chinese consumers. Interestingly, research from China shows that environmental concern is not the main reason people choose EVs. Instead, most buyers focus more on practical features and financial benefits, like lower running costs and avoiding license plate restrictions (Huang, Qian, & Yang, 2021).

## 2.3 Challenges in the Swedish Context

Even though Sweden has a high rate of EV adoption, there are still a few challenges that need to be addressed. One major issue is the difference between urban and rural areas. Cities tend to have more public charging stations and stronger local support programs, making it easier for residents to own and use EVs. In contrast, people living in rural regions often struggle with limited access to charging points and fewer EV models to choose from (Lindgren & Olsson, 2023). Another challenge is the cold climate in Sweden. Low temperatures can cause batteries to lose efficiency and increase energy use for heating, which adds to people's concerns about how far they can drive on a single charge, especially during the long winter months (Yang & Yao, 2019).

On top of these challenges, recent changes in government policy have added some uncertainty. When the national climate bonus was suddenly removed in 2022, it raised questions about how reliable future support for EV buyers might be (Norwegian EV Association, 2023). This unpredictability can make people hesitate, especially if they're unsure whether new incentives will come or existing ones will stick around. Lastly, even though environmental awareness is generally strong in Sweden, that alone is not always enough to push people to switch to EVs. For many, the decision still comes down to whether the car's features and costs match their daily needs, habits, and budget.

## 2.4 Discrete Choice Model

A discrete choice model is usually used to predict how individuals make decisions regarding a set of two or more discrete alternatives (Train, 2009). It also aims to make predictions about how the objective attributes or the socioeconomic characteristics influence when decision-makers select their choices (Columbia University Mailman School of Public Health, n.d.). Discrete choice models are widely used in various fields to analyze and predict individual decision-making behavior when faced with a finite set of alternatives (Train, 2009). For instance, it can make research in travelers' preferences among different modes of transport, such as car, public transportation, or bicycle, by quantifying the influence of different factors like cost, travel time, and convenience in transportation research (Ortúzar & Willumsen, 2011). Discrete choice models are also widely applied in marketing, environmental economics, health care, and urban planning fields, where they can help in modeling consumer choices, policy evaluation, and strategic planning by evaluating the weights of attributes that decide people's selections (MIT Professional Education, n.d.).

The key point of the discrete choice model is the random utility model (Ben-Akiva et al., 1997). Individuals typically choose one option from a set of alternatives, that is, the one with the highest utility (Train, 2009). However, the highest utility varies from different people because they prioritize different factors (Saylor Academy, n.d.). Take the choice task between ICE car and EV car as an example, some people focus on cost efficiency, while others might pay more attention to environmental impact or convenience (Hong et al., 2024). Additionally, personal characteristics such as age, income, and gender can also have significant impacts on decision-making (Delaney, 2014). The utility can be expressed as Equation 2.1:

$$U_n = V_n + \varepsilon \tag{2.1}$$

where $\varepsilon$ is the error term, associated with different alternatives and observations, which is assumed to follow an identical and independent distribution, and $V_n$ is the deterministic part of the utility, defined as Equation 2.2:

$$V_n = \alpha + \beta \times X_n \tag{2.2}$$

where $\alpha$ is a constant, reflecting the baseline level of utility when the explanatory variables are all zero. $\beta$ is a coefficient that indicates the strength and direction of the relationship between the attributes $X_n$ and the utility. $X_n$ denotes the observed attributes or characteristics associated with alternative n. (Balakrishnan & Ramanujam, 2011).

### 2.4.1 Binary Logit Model

Logistic regression is considered an extension of traditional linear regression and is specifically applied when the dependent variable is categorical (IBM, n.d.). In binary logistic regression, the dependent variable consists of two outputs, often marked numerically as 0 and 1(PubMed Central, 2022). These two outputs can represent any pair of opposing outcomes in various fields (Wikipedia, 2025). The binary logistic regression is usually used to obtain the most appropriate model that explains the relationship between the independent variables and the dependent variable (GeeksforGeeks, 2024).

Ngene is a specialized software tool used in decision science research for the design and analysis of experimental choice models (Ngene, 2018). It supports the development of orthogonal, optimal orthogonal, and efficient stated choice designs. The software also allows for the estimation of multinomial and binary logit models, which are commonly applied in analyzing discrete choice behavior. A key advantage of using this model is its capacity to handle large datasets involving multiple alternatives, enabling the estimation of a utility function for each option. However, one limitation is that the distribution of choices across alternatives must be relatively balanced. If the distribution is highly uneven, the results may become unreliable and difficult to interpret (Ngene, 2018).

### 2.4.2 Maximum likelihood estimation

In many econometric models and discrete choice modeling studies, Maximum Likelihood Estimation (MLE) as the core method of parameter estimation has been widely verified for its effectiveness and applicability (Balakrishnan & Ramanujam, 2011). Ben-Akiva and Lerman (1985) systematically explained the application of MLE in models such as Logit and Nested Logit in their classic book Discrete Choice Analysis, pointing out that MLE can provide efficient parameter estimation under the premise of ensuring consistency and asymptotic normality.

Train (2009) further extended MLE to mixed Logit and random parameter models in

Discrete Choice Methods with Simulation and proposed that when facing high-dimensional individual heterogeneity, the maximum likelihood estimation combined with the simulation method can significantly improve the flexibility and fit of the model（Train, 2009）. The implementation details of MLE in the software in the Biogeme development manual proposed that the evaluation of robust standard errors and gradient norms is of great significance for the interpretation of results when faced with finite samples and high variance estimates (Bierlaire, 2020).

In addition, many applied studies have also confirmed the reliability of MLE in actual travel behavior analysis. For example, Hensher et al. (2005) used MLE to estimate the transportation mode selection model and accurately identified the influence direction and significance of key variables such as price, time, and comfort. Zhao et al. (2021) used MLE to estimate the multinomial Logit model in the analysis of the willingness to purchase new energy vehicles, revealing the nonlinear interaction between socioeconomic characteristics and policy factors.

Therefore, this study draws on the theoretical basis and methodological practices of the above literature and uses MLE to estimate the parameters of the constructed binary logit model, thereby maximizing the likelihood function of the observed selection results and ensuring that the obtained results have statistical consistency and practical explanatory power. Through this method, this study can effectively identify the effects of vehicle attributes and individual characteristics on choice behavior and provide a solid foundation for policy simulation.

# 3. Methods

This chapter mainly shows the methodology steps of this paper. At first, a literature review was conducted to find the differences between gasoline and EVs, and to identify some key attributes, that is, the main factors that affect people's purchase behaviors, such as range, car price, charging time, etc. Secondly, the approximate data range of these key attributes in Sweden was determined, and Ngene software was used to generate several choice scenarios. Then, a survey containing scenario selection and personal socioeconomic background was created, and it was distributed using several means on the online platform. Additionally, a Biogeme model specification and estimation pipeline for a binary logit model is determined in Python, which is based on the choice data results of the survey. Finally, a data analysis was conducted based on the survey results, aiming to analyze the key factors that affect the Swedish people's purchase of gasoline and EVs, and to give some prospects for the government and vehicle manufacturers.

## 3.1 Vehicle Attributes Research

In this part, a comprehensive survey of key vehicle attributes influencing consumers' choices between ICE vehicles and EVs is conducted. In Sweden, EVs and ICE vehicles have their pros and cons in terms of purchase cost and operating cost. In general, the purchase price of EVs is higher than that of fuel vehicles of the same level, but EVs have obvious advantages in terms of operating costs.

Sweden is one of the countries with the lowest rental costs for EVs in Europe, according to the Ayvens 2025 Vehicle Cost Index, which is less than 820 euros monthly. In addition, EVs also have lower costs in energy and maintenance. For example, ChargePanel's analysis shows that even in southern Sweden, where electricity prices are higher, the cost of home charging for EVs per 10 kilometers is about 5.5 SEK, while the fuel cost of gasoline vehicles is about 15.2 SEK (Mobility Sweden, 2023). However, the purchase price of EVs is still higher than that of ICE vehicles of the same level. For example, Swedish market data in 2025 shows that the average price of EVs is approximately 350,000 SEK, while that of ICE vehicles is approximately 30,0000 pounds (Ayvens, 2025). Therefore, although the initial purchase cost of EVs is higher, their lower use and maintenance costs may bring economic advantages in long-term use circumstances, which is most people's usage style. Meanwhile, there are no subsidies for purchasing electric cars in Sweden currently.

In Sweden, the availability of home charging is a very important factor for EV (EV) users (Roland Berger, 2024). Home charging not only provides great convenience but also significantly reduces the cost of charging. According to a survey by gridX, European EV users generally prefer to charge at home, mainly because of its convenience, and cost and reliability are also important advantages (gridX, 2025). The Swedish government supports the construction of home charging infrastructure actively (AMPECO, 2024; Mobility Portal Europe, 2024). For example, the “Ladda bilen” program provides up to 50% subsidies for the installation of charging stations at homes and workplaces, up to 15,000 Swedish kronor (European Alternative Fuels Observatory, 2025). The program is applicable to apartment associations, companies, and other organizations and aims to provide EV charging facilities for residents and employees (AMPECO, 2024; Mobility Portal Europe, 2024). In addition, private enterprises in Sweden are also paying attention to the development of home charging availability. For example, CTEK offers a variety of home charging products, such as CHARGESTORM CONNECTED 2 and NJORD GO, which can support charging power up to 22kW and have load balancing functions to ensure the safety and charging efficiency of the home grid (CTEK, 2025). In summary, having a home charging station is becoming an important consideration for EV users in Sweden, because it not only improves the convenience of using EVs, but also reduces the user’s total cost of ownership through government subsidies and technical support from private enterprises (AMPECO, 2024).

Based on the above research, several important attributes are initially determined, the attributes include vehicle price, range, energy cost, annual maintenance costs, average refueling or charging time, $CO_2$ emissions per kilometer, and home charging availability. Then, the approximate value range of each attribute will be presented. A mid-range ICE car in Sweden will cost between SEK 250,000 and 800,000, while a comparable electric car will cost SEK 350,000 to 900,000. In addition, average driving ranges vary greatly, with ICE cars typically getting 500-900 kilometers on a full tank of gas, while electric cars can get 300-700 kilometers on a full charge of battery. The energy cost range of an electric car, which is between SEK 0.22/km and SEK 0.3/km, is significantly lower than that of an ICE car, which is between SEK 1.1/km and SEK 1.5/km. Additionally, annual maintenance costs for ICE cars, which are 4,000-7,000 SEK, are higher than for electric cars, which are 2,000-3,500 SEK. Different charging infrastructures influence charging time. Therefore, a range of 20 to 100 minutes of charging time is determined. However, for ICE cars, it can be assumed that a 5-minute refuel time is suitable for most of the ICE cars. Finally, environmental impact is also be considered, average $CO_2$ emissions is a representative index when it comes to ICE vehicles, and its range is approximately around 100 to 200 grams per kilometer regards of various engines, while there are no $CO_2$ emissions for electric cars hence it can be considered as zero pollution to the environment because Sweden relies on renewable energy.

## 3.2 Survey Design

The survey of this thesis was designed to understand and analyze Swedish consumers' willingness to purchase EVs and examine the influence of different vehicle attributes, as well as consumers' socioeconomic background, and then conduct quantitative research on these attributes and the social context of individuals. Hence, there are four parts to this survey. Initially, a clear introduction was written to explain the survey's purpose and reassure participants of their anonymity and data confidentiality.

### 3.2.1 Driving & Purchase Experience

In this part, basic information about respondents' car ownership and driving habits was collected, including their experiences and satisfaction with EV driving, as well as their typical daily commute distance. This can help categorize respondents, therefore, the analysis of differences in personal attitudes and choices among various user groups can be conducted. The respondents were also asked about their average daily driving distance. The purpose here was to identify whether daily travel habits might affect the purchase of EVs, particularly regarding range anxiety, which is one of the common concerns influencing EV adoption. This information is essential for accurately interpreting responses in the following parts of the survey, where respondents make choices among different vehicle options. In addition, as the first part of the survey, these questions do not involve sensitive privacy issues of the respondents, which also helps respondents to continue to complete the survey and improve the completion rate of the survey.

### 3.2.2 Scenario-based Questions

To minimize respondents' burden and cognitive load, each choice set was presented as a single question with three options rather than multiple binary questions. This approach reduces the number of questions while still yielding statistically robust data, helping to prevent respondent fatigue and frustration. The scenarios in this survey were generated using Ngene software, where a Multinomial Logit model was used as the underlying design. Each respondent was presented with three choices for each scenario, including one ICE vehicle and two EVs. The design can ensure variation across key attributes, and different options are varied systematically across several attributes, which is designed based on the vehicle attributes research in chapter 3.1.

The stated example scenarios in Figure 3.1 and Figure 3.2 presented three alternatives for each respondent: two EVs and one ICE vehicle. Each alternative was characterized by a set of attributes, including price, range, maintenance cost, driving cost, charging/refueling time, and carbon emissions. Following random utility theory, the utility function of each alternative was specified as a function of its attributes (Train, 2009). The utilities of the three vehicles were modeled as equations shown below.

$$U_{ICE} = \beta_{price} \cdot B_{ICE_{Price}} + \beta_{Range} \cdot B_{ICE_{Range}} + \beta_{Maintenance} \cdot B_{ICE_{\mathrm{Maintenance}}} + \beta_{Drivingcost} \cdot B_{ICE_{Drivingcost}} + \beta_{Chargingtime} \cdot B_{ICE_{Chargingtime}} + \beta_{Emission} \cdot B_{ICE_{Emission}} \quad (3.1)$$

$$U_{EV1} = ASC_{EV1} + \beta_{EV1_{price}} \cdot B_{EV1_{price}} + \beta_{EV1_{range}} \cdot B_{EV1_{range}} + \beta_{EV1_{\mathrm{maintenance}}} \cdot B_{EV1_{\mathrm{maintenance}}} + \beta_{EV1_{\mathrm{driving}cost}} \cdot B_{EV1_{\mathrm{driving}cost}} + \beta_{EV1_{\mathrm{charging}time}} \cdot B_{EV1_{\mathrm{charging}time}} + \beta_{EV1_{emission}} \cdot B_{EV1_{emission}} + \beta_{EV1_{charging\_home}} \cdot B_{EV1_{charging\_home}} \quad (3.2)$$

$$U_{EV2} = ASC_{EV2} + \beta_{EV2_{price}} \cdot B_{EV2_{price}} + \beta_{EV2_{range}} \cdot B_{EV2_{range}} + \beta_{EV2_{\mathrm{maintenance}}} \cdot B_{EV2_{\mathrm{maintenance}}} + \beta_{EV2_{\mathrm{driving}cost}} \cdot B_{EV2_{\mathrm{driving}cost}} + \beta_{EV2_{\mathrm{charging}time}} \cdot B_{EV2_{\mathrm{charging}time}} + \beta_{EV2_{emission}} \cdot B_{EV2_{emission}} + \beta_{EV2_{charging\_home}} \cdot B_{EV2_{charging\_home}} \quad (3.3)$$

where $U_{ICE}$ represents the total utility of an ICE vehicle, which is composed of the weighted sum of multiple attribute variables. For $U_{EV1}$ and $U_{EV2}$, there are specific constants $ASC_{EV}$. Attributes include price, range, maintenance cost, driving cost, refueling time, and emission level. Each attribute consists of two parts, $\beta$ coefficient represents the respondents' sensitivity and preference for the attribute, while $B$ value represents the actual value level of the ICE vehicle on this attribute.
There are in total of 12 questions for this part, which are divided into 2 groups based

on the availability of charging at home. Each respondent will be presented with only one group, because according to the feedback from our small-scale trial survey, six questions are an appropriate design, and it will not make respondents feel tired and bored, to increase the survey completion rate. Two example questions of these two groups are shown in Figure 3.1 and Figure 3.2. The explanation of attributes is shown in Table 3.1 below.

*Table 3.1 The explanation of attributes.*

| **Attributes** | **Range of attributes** |
|---|---|
| Price | The purchase cost including taxes |
| Range | The maximum distance the vehicle can travel on a full tank (for fuel vehicles) or full charge (for EVs) |
| Maintenance per year | Annual maintenance expenses |
| Cost per km | Operational costs calculated based on fuel or electricity consumption |
| Refueling/Charging Time | The time required to fully refuel or recharge the vehicle |
| Emissions per km | $CO_2$ emissions |
| Availability of charging at home | Specifically relevant to EVs |

The value range of ICE vehicles and EVs is also shown in Table 3.2 below:

*Table 3.2 The value range of ICE vehicles and EVs.*

| **Attributes** | **ICE Vehicles** | **EVs (EV)** |
|---|---|---|
| Price | SEK 250,000 - 800,000 | SEK 350,000 - 900,000 |
| Range | 500 - 900 km | 300 - 700 km |
| Maintenance per year | SEK 4,000 - 7,000 | SEK 2,000 - 3,500 |
| Cost per km | SEK 1.1 - 1.5 | SEK 0.22 - 0.3 |
| Refueling/Charging Time | Approximately 5 minutes | 20 - 100 minutes |
| Emissions per km | 100 - 200 grams $CO_2$ | 0 |
| Availability of home charging | Not applicable | Yes or No |

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price Kr | 250000 | 350000 | 350000 |
| Range(km) | 500 | 500 | 600 |
| Maintenance per year Kr | 4000 | 2000 | 3500 |
| Cost per km Kr | 1.3 | 0.26 | 0.26 |
| Public Refuel/Recharging Time(min) | 5 | 60 | 80 |
| Emission per km(g) | 130 | 0 | |
| Availability of charging at home | / | YES | |

*Figure 3.1: The figure shows one example in Group A, where home charging is available for all six questions.*

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 250000 | 750000 | 350000 |
| Range(km) | 600 | 600 | 400 |
| Maintenance per year | 5000 | 2500 | 3000 |
| Cost per km | 1.1 | 0.26 | 0.26 |
| Public Refuel/Recharging Time(min) | 5 | 80 | 80 |
| Emission per km(g) | 200 | 0 | |
| Availability of charging at home | / | NO | |

*Figure 3.2: The figure shows one example in Group B, where home charging is not available for all six questions.*

Each respondent answered six choice scenarios, either from group A (with home charging availability) or group B (without charging availability), and selected their preferred vehicle in each. Respondents were instructed to carefully review the provided attributes and then select their preferred vehicle option in each scenario, which is completely based on their own judgment and lifestyle. It was clearly stated that there were no right or wrong answers, which can encourage respondents to answer honestly according to their real preferences.

### 3.2.3 Sociodemographic Information

The third part gathered respondents' socioeconomic information, including gender, age, education level, household income, and family size. By collecting this information, it allows researchers to analyze how personal attributes can influence the purchase behavior of EVs. The options level of each question is shown in Table 3.3, Table 3.4, Table 3.5, and Table 3.6.

*Table 3.3 Gender Level.*

| Level | Gender |
|---|---|
| 0 | Male |
| 1 | Female |
| 2 | Diverse |

*Table 3.4 Age Level.*

| Level | Age |
|---|---|
| 0 | 0-18 |
| 1 | 18-44 |
| 2 | 45-59 |
| 3 | 60-74 |
| 4 | 75 and above |

*Table 3.5 Highest Education Level.*

| Level | Highest Education |
|---|---|
| 0 | High school or below (or similar) |
| 1 | Bachelor's degree (or similar |
| 2 | Postgraduate degree or above (or similar) |

*Table 3.6 Household Income Level.*

| Level | Household Income |
|---|---|
| 0 | Less than 300,000 |
| 1 | 300,000–499,999 |
| 2 | 500,000–699,999 |
| 3 | 700,000 and above |

*Table 3.7 Number of Household Members Level.*

| Level | Number of Household Members |
|---|---|
| 0 | 1 |
| 1 | 2 |
| 2 | 3 |

| | |
|---|---|
| 3 | 4 and above |

## 3.3 Model Estimation Process

The scenario-based questions must be carefully designed; for this survey, a software named Ngene was used to generate scenarios, which can ensure the rationality and distinguishability of the scenarios. The design of the choice scenarios was generated based on D-efficient criteria. However, this survey aims to find out the adoption level between ICE vehicles and EVs, so during data processing and model estimation, each three-alternative question was systematically decomposed into two binary comparisons, each contrasting the ICE vehicle against one EV alternative (i.e., ICE vs. EV1 and ICE vs. EV2). Only the pairwise comparison was retained for estimation. For example, if a respondent selected ICE vehicle, then the comparisons were transformed to ICE vs. EV1 and ICE vs. EV2; if the EV1 was selected, only the comparison ICE vs. EV1 remained.

This transformation enabled the use of the binary logit model, which is a specific case of MNL. It can offer advantages in model tractability, interpretability, and alignment with the study's focus on identifying the trade-offs respondents make between ICE and EV options. Although this approach simplifies the estimation process and gives a clearer comparison between ICE vehicles and EVs, it relies on the assumption that the Independence of Irrelevant Alternatives (IIA) holds between the decomposed pairs (Train, 2009). This should be acknowledged as a trade-off between design simplicity, respondent comfort, and modeling precision. Finally, the model was implemented by using the Biogeme package in Python when analyzing the collected data.

### 3.3.1 Binary Logit Model

This utility function is one of the key components in this discrete choice model, and it is used to predict the probability of respondents choosing among three vehicles. Then, a binary logit model was used to model this survey, the utility was calculated as shown in Equation 3.4:

$$U_n = V_n + \varepsilon_{price} + \varepsilon_{range} + \varepsilon_{\text{maintenance}} + \varepsilon_{\text{driving\_cost}} + \varepsilon_{\text{charging/refueling\_time}} + \varepsilon_{emission} + \varepsilon_{\text{charging\_infrastructure}} \quad (3.4)$$

Where $V_n$ is an observed part, and $\varepsilon_n$ is the unobserved part for each attribute. The survey assumes that respondents' answers are rational, and they will choose the alternative that provides them with the highest utility.

### 3.3.2 Utility Functions

In the binary logit model, to ensure the identifiability of the model, a baseline option must be set for the utility function. Since the logit model predicts the relative probabilities between the options, the utility itself is only meaningful in terms of the difference, and the absolute utility cannot be directly estimated (Train, 2009). Specifically, to ensure the uniqueness of the utility difference, the constant term (ASC) of the utility function of one of the options in the model needs to be set to zero. Here, we choose to set the constant term of the ICE vehicles to 0 and estimate a separate intercept term $ASC_{EV}$ for the EVs, so that the utility of the EV represents the additional attractiveness relative to the ICE vehicles (Train, 2009).

This setting does not affect the model's actual explanatory power, because the logit model relies on the relative difference between utilities, rather than their absolute level. Therefore, this method can uniquely and accurately identify the preference direction and intensity of the attributes of EVs (Train, 2009). Following random utility theory, the utility function of each alternative was specified as a function of its attributes (Train, 2009). The utilities of the two vehicles were modeled as equations shown below.

$$\begin{aligned} U_{ICE} = {} & \beta_{price} \cdot B_{ICE_{Price}} + \beta_{Range} \cdot B_{ICE_{Range}} + \beta_{Maintenance} \cdot B_{ICE_{\text{Maintenance}}} \\ & + \beta_{Drivingcost} \cdot B_{ICE_{Drivingcost}} + \beta_{Chargingtime} \cdot B_{ICE_{Chargingtime}} \\ & + \beta_{Emission} \cdot B_{ICE_{Emission}} \end{aligned} \tag{3.5}$$

$$\begin{aligned} U_{EV} = {} & ASC_{EV} + \beta_{price} \cdot B_{EV_{Price}} + \beta_{Range} \cdot B_{EV_{Range}} + \beta_{Maintenance} \cdot B_{EV_{\text{Maintenance}}} \\ & + \beta_{Drivingcost} \cdot B_{EV_{Drivingcost}} + \beta_{Chargingtime} \cdot B_{EV_{Chargingtime}} \\ & + \beta_{Homecharging} \\ & \cdot B_{EV_{Homecharging}} \end{aligned} \tag{3.6}$$

Where $U_{EV}$ represents the total utility of an EV, and $U_{ICE}$ represents the total utility of a ICE vehicle, which are composed of a specific constant $ASC_{EV}$ and the weight, sum of multiple attribute variables. Attributes include price, range, maintenance cost, driving cost, refueling time, and emission level. Each attribute consists of two parts: $\beta$ coefficient represents the respondents' sensitivity and preference for the attribute, while $B$ value represents the actual value level of the vehicle on this attribute. For example, $\beta_{price}$ is usually negative, meaning that the higher the price, the lower the utility. It can be explained as the more expensive the car, the less inclined people are to buy it, which makes sense. $\beta_{Range}$ may be positive, meaning that the longer the range, the greater the possibility people will have to choose this option.

### 3.3.3 Model Estimation

The model parameters are usually estimated using maximum likelihood estimation. The estimation was carried out with the Biogeme package in Python. In this study, MLE is used to estimate the parameters of discrete choice models. The goal is to find a set of parameters that maximizes the probability of actual choice in the sample, given known individual choice data, see Equation 3.5(Train, 2009).

$$L(\alpha, \beta) = N \prod_{i=1}^{n} P(c_i|C_i) \tag{3.5}$$

Where $L(\alpha, \beta)$ is the likelihood function, which is a function of the model parameters $\alpha$ (constant terms such as intercept) and $\beta$ (weights of various attributes); $P(c_i|C_i)$) represents the probability that individual i chooses $c_i$ from its alternative set $C_i$. n is the number of samples; $N$ is a normalization constant or constant multiple, which is sometimes used for overall scaling.

The cleaned dataset included only respondents with valid and complete responses. The model's performance was evaluated using standard indicators, including log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC).

# 4. Results and Discussion

This chapter expounds data analysis process, and several discussions of this survey are based on the collected results from the respondents.

## 4.1 Descriptive statistics

Over the two-week online distribution period, we received several hundred responses. After removing incomplete submissions during data cleaning, 373 valid samples were obtained, 188 samples from Group A and 185 samples from Group B.

To understand the demographic background of respondents, several key socioeconomic characteristics were analyzed, including car ownership, daily commute distance, gender, age, education level, household income, and household size. Table 4.1 shows the overall distribution of the survey respondents in terms of socioeconomic characteristics. This analysis helps to understand the basic structure and distribution of the sample and provides background support for the following analysis about EV adoption.

In terms of vehicle ownership situation, hybrid EVs (HEV) are the most common type according to the sample, accounting for 49.8%; as for the proportion of pure EVs is 27%, and the proportion is 23.2% for ICE vehicles. This shows that the sample has a high acceptance of EVs, which may be caused by the respondents' high environmental awareness and relatively high penetration rate of EVs in Northern Europe.

In terms of commuting distance, 10 to 20 kilometers is the most common commuting range, accounting for 39.7%, followed by 26% of 5 to 10 kilometers and 18.2% of 20 to 50 kilometers. Only 6.4% of the respondents commute less than 5 kilometers every day, while 9.7% of the respondents commute more than 50 kilometers. This shows that most of the respondents are at the medium distance commuting level and may not be very sensitive to vehicle range.

In terms of gender, female respondents accounted for 47.5%, male respondents accounted for 44.5%, and another 8% (30 people) chose non-binary gender. This gender ratio is relatively balanced, and the use of non-binary gender options enhances the inclusiveness and diversity of the sample.

In terms of age distribution, the 18 to 44 age group accounted for the highest proportion, accounting for 47.2%, followed by 33.5% of 45 to 59 years old level, while the proportion of 0 to 18 years old is 9.9% and over 60 years old is 9.4% in total, which are relatively low. Overall, the sample is mainly composed of people of working age, which is consistent with the profile of the main population that purchases and uses vehicles.

Regarding education level, nearly half of the respondents have a bachelor's degree (49.3%, 184 people), 35.7% (133 people) have a high school degree or below, and only 15% (56 people) have a master's degree or above. This shows that the overall education level of the sample is relatively high, which may mean that they have a high level of new technology acceptance.

In terms of family income, most respondents are concentrated in the income range of 300,000 to 500,000 SEK (37.5%, 140 people), followed by 500,000-700,000 SEK (26.8%) and less than 300,000 SEK (24.1%). Only 11.5% of people have an income of more than 700,000, and the overall structure shows that middle-income families are dominant, which is also in line with common sense.

Regarding family size, three-person families are the most common (58.7%, 219 people), followed by four-person and above families (25.5%), two-person families account for 11.8%, and single-person families account for only 4%. This shows that the sample is mainly composed of medium-sized and large families, who may pay more attention to vehicle space, economy, and convenience in their daily lives.

In summary, the sample group is mainly composed of middle-aged and young people with middle income and high education, who may have a certain degree of environmental awareness and the potential to accept new technology such as EVs. Although such a sample structure cannot fully represent the entire social population, it can represent the potential early adopters of EVs and provide an effective view for the following modeling analysis.

*Table 4.1 The distribution of socioeconomic characteristics of the results.*

| Characteristic | Level | Sample | Distribution |
|---|---|---|---|
| Car Ownership | EV | 101 | 27% |
| | HEV | 182 | 49.8% |
| | ICE | 90 | 23.2% |
| Commute Distance | Less than 5km | 24 | 6.4% |
| | 5-10km | 97 | 26% |
| | 10-20km | 148 | 39.7% |

| | | | |
|---|---|---|---|
| | 20-50km | 68 | 18.2 |
| | 50+ km | 36 | 9.7% |
| Gender | Female | 177 | 47.5% |
| | Male | 166 | 44.5% |
| | No-binary | 30 | 8% |
| Age | 0-18 | 37 | 9.9% |
| | 18-44 | 176 | 47.2% |
| | 45-59 | 125 | 33.5% |
| | 60-74 | 22 | 5.9% |
| | 75 and above | 13 | 3.5% |
| Education | High school or below (or similar) | 133 | 35.7% |
| | Bachelor's degree (or similar | 184 | 49.3% |
| | Postgraduate degree or above (or similar) | 56 | 15% |
| Household Income | Less than 300,000 | 90 | 24.1% |
| | 300,000–499,999 | 140 | 37.5% |
| | 500,000–699,999 | 100 | 26.8% |
| | 700,000 and above | 43 | 11.5% |
| Household Members | 1 | 15 | 4% |
| | 2 | 44 | 11.8% |
| | 3 | 219 | 58.7% |
| | 4 and above | 95 | 25.5% |

## 4.2 Vehicle Attributes Model Results

In this thesis, the Binary Logit Model is used to model and analyze respondents' choice behavior between EVs and ICE vehicles. The model is based on the maximum likelihood estimation results of 7266 valid binary choice results, which have been processed from the initial obtained results based on the method mentioned in chapter 3.3. The model estimation results are shown in Tables 4.2 and 4.3, presenting the statistical significance and direction of different influencing attributes. Generally speaking, a p-value less than 0.05 is considered to be significant.

*Table 4.2 Estimated parameters of attributes.*

| Attribute | Value | Rob. Std err | Rob. t-test | Rob. p-value |
|---|---|---|---|---|
| ASC_EV | -3.1 | 0.38 | -8.27 | < 0.01 |
| B_CHARGE | -0.02 | 0.02 | -1.07 | 0.29 |
| B_CHARGING_EV | 2.81 | 0.11 | 25.56 | < 0.01 |
| B_DRIVE | -0.21 | 0.36 | -0.59 | 0.56 |
| B_EMISS_ICE | 0 | 0.16 | 0 | 1.00 |
| B_MAINT | -0.11 | 0.05 | -2.31 | 0.02 |
| B_PRICE | -0.08 | 0.03 | -2.64 | < 0.01 |
| B_RANGE | 0.05 | 0.04 | 1.26 | 0.21 |

*Table 4.3 Evaluation of model estimation.*

| Metric | Value |
|---|---|
| Number of estimated parameters | 8 |
| Sample size | 7266 |
| Excluded observations | 0 |
| Init log likelihood | -1980.59 |
| Final log likelihood | -1487.16 |
| Likelihood ratio test | 986.86 |
| Rho-square | 0.25 |
| Rho-square-bar | 0.25 |
| Akaike Information Criterion | 2990.32 |
| Bayesian Information Criterion | 3039.90 |

From the overall model performance, as Table 4.3 shown, the model has a good fit. The final log-likelihood value is -1487.16, which is significantly higher than -1980.59 of the log-likelihood of the initial model, and the corresponding likelihood ratio test value is 986.86, indicating that the combination of all variables has a significant improvement in predicting choice behavior. The Rho-square value is 0.25, indicating that the model has a strong explanatory power, which is better than 0.2, the threshold referred to by the general literature for good fitness. AIC and BIC are 2990.32 and 3039.90, respectively, which further proves the robustness of the model.

According to the parameter estimation results above, respondents' preferences for attributes can be analyzed in depth. Then, the parameters of attributes were estimated, namely price (B_PRICE), range (B_RANGE), charging time (B_CHARGE), maintenance (B_MAINT), drive cost (B_DRIVE), ICE emissions (B_EMISS_ICE), home charging availability of EV (B_CHARGING_EV), and a constant term (ASC_EV). It is well known that the absolute numerical differences between vehicle attributes are very large. In order to make the estimated parameters of attributes easier to compare, these attributes need to be scaled. The attributes were scaled as follows: the price unit is per 100,000 SEK, the range unit is per 100 kilometers, the maintenance unit is per 1000 SEK, the emission of ICE vehicles unit is per 100g, and the charging time unit is per 10 minutes, and home charging availability is a dummy variable indicating whether there is a charging pile at home, 1 for yes and 0 for no.

In this model estimation, although most attribute coefficients are statistically significant, which can be evaluated by the p-values of attributes' coefficients less than 0.05. It indicates that they have a big impact on consumers' vehicle purchase decisions; there are still several attribute coefficients that are not statistically significant, that is, their p-values are higher than the commonly used significance judgment threshold of 0.05. These attributes include charging time (B_CHARGE), driving cost (B_DRIVE), emissions of ICE vehicles (B_EMISS_ICE), and range (B_RANGE). This shows that under this survey sample, these variables do not show a sufficiently stable or strong trend in the utility changes when respondents choose between EVs and ICE vehicles.

From the perspective of charging time (B_CHARGE), although the coefficient is negative and the direction is in line with expectations, its t-value is not enough to reject the null hypothesis, indicating that under the current model setting, the marginal impact of charging time on overall utility is not statistically significant. It may be because the time sensitivity of different respondents in the sample varies greatly, or some have expectations about the accessibility of fast charging facilities, thus reducing their attention to the indicator of charging time.

When it comes to the driving cost (B_DRIVE), it also shows a negative coefficient, which is in line with the common sense that respondents prefer lower driving costs, but its p-value also does not reach the significance level. Possible explanations can be drawn that respondents' consideration of daily driving costs is lagging at the car purchase stage, or because in this survey, the value range of driving cost does not differ greatly among different alternatives, it cannot be counted as a decisive attribute in the decision-making process.

Then, regarding the carbon emissions of ICE vehicles (B_EMISS_ICE), the coefficient of this attribute is 0 as a limit less than zero was set. This is done because, in reality, no one will increase the probability of buying a car because of higher emissions. Mostly, they just don't care about the emission, so this setting is more reasonable in terms of the model design. This finding reflects that in the actual car purchase choice, although the public has a certain understanding of environmental protection and sustainable development, consumers have not yet internalized it as a decision-making basis with obvious utility differences in terms of carbon emissions alone. In other words, although environmental awareness is increasing, it is still not enough to form a strong punitive preference for ICE vehicles.

Although range (B_RANGE) is one of the important technical indicators of EVs, and its coefficient is also positive, indicating that the longer the range, the more popular it is, it still does not reach the significance standard in the current data sample. This may suggest that under the cognitive structure of the current sample, respondents' concerns about range anxiety have been masked by other attributes such as home charging availability and price, or the value range difference in this survey is also not large enough, resulting in insufficient effect.

These statistically insignificant attributes do not mean that they are completely ineffective in reality, but reflect that their marginal utility changes in the sample and model settings of this study are not enough to form a stable behavior pattern.

In the estimation results of the model, the coefficients of multiple attributes show high statistical significance, indicating that they have clear, stable, and significant marginal utility effects on respondents' choice between EVs and ICE vehicles. It is worth noting that these attributes are not only in line with expectations, but their p-values are generally lower than 0.05, and some attributes even show extremely significant statistics, of which the p-values are less than 0.01, indicating that these attributes play a key role in car purchase behavior and have been widely included in the real decision-making process by consumers.

The constant term ASC_EV of EVs is negative and extremely significant, indicating that after controlling all observable attributes, consumers still have a preference disadvantage for EVs under the assumption that there is no interference from other attribute information. This to a certain extent reflects the hidden concerns or inherent biases of respondents when facing the choice of EVs, which may come from factors such as unfamiliarity with brand awareness, concerns about battery life, uncertainty in charging network coverage, low expectations for second-hand residual value, or psychological barriers to adapting to new technologies. The significance of this constant term reinforces the fact that even if EVs have advantages in some observable attributes, they still face inherent challenges in overall attractiveness.

The availability of home charging (B_CHARGING_EV) has a value of -3.1, and is one of the attributes with the highest and most significant coefficients in this model, showing that this attribute has a particularly significant role in promoting the preference for EV selection. Home charging availability represents charging convenience, time autonomy, and continuity of use, which are the core dimensions of the user experience of EVs. Respondents in the survey sample recognized the convenience and sense of security brought by home charging availability, especially in the context of the reality that public charging infrastructure is still imperfect and charging pile queues are common. The existence of charging piles at home is almost equivalent to giving EVs a positive signal of availability guarantee. Therefore, the marginal utility corresponding to this attribute is significantly positive, and the p-value is close to 0, which can be considered as one of the primary attributes for consumers to choose EVs.

The coefficient of maintenance cost (B_MAINT) is also negative and statistically significant, indicating that respondents are sensitive to the cost of later use during the car purchase process. Compared with the purchase price, maintenance costs are periodic expenses, representing the time and money required for the use of the car. Especially in the era of ICE vehicles, accumulated stereotypes of “high frequency of maintenance and uncertain cost” have taken deep root in people’s minds; they tend to take maintenance certainty and cost performance into overall consideration when buying a car. The significant influence of maintenance cost on this marginal utility also reflects, from one aspect, that the automotive industry is evolving from a purchase-oriented to a use-oriented trend.

When it comes to the coefficient of price (B_PRICE), it is -0.08 and significant, which is completely consistent with the assumption of negative correlation between price and utility in a common sense. Price is one of the most intuitive and oppressive information in respondent decision-making. It not only reflects the immediate economic threshold of the product, but also often implies the psychological trade-off between risk, burden, and investment return. From the estimated value, its coefficient is not only significantly negative, but also forms a reliable marginal rate of substitution basis with the ratio relationship of multiple other attributes, which can be further used to analyze the probability of selection on EVs and ICE vehicles in terms of consumers.

Overall, these statistically significant variables together constitute the dominant factors in the attractiveness structure of EVs. They not only pass the significance test in a mathematical sense, but also gain strong support from behavioral logic, psychological motivation, and actual usage experience.

## 4.3 Further Analysis

In this part, in order to gain a deeper understanding of the specific impact of home charging conditions on consumers' car purchase preferences, a set of representative average attribute combinations is constructed and simulated the changes in the selection probability of EVs in two scenarios, "having" and "not having" home charging piles. The results show that when an EV has a home charging pile, its comprehensive utility is -1.51, and the corresponding selection probability is as high as 87.1%; when this attribute is removed (i.e., consumers cannot charge at home), the utility of EVs drops sharply to -4.32, and the selection probability also drops sharply to 28.8%, an overall decrease of more than 58%. This significant change highlights the decisive influence of home charging conditions on car purchase decisions, which is much higher than many traditional performance attributes such as driving range, price, or maintenance cost.

Under the premise of controlling other attributes to the sample average, a further analysis on the impact of EV price reduction on the probability of selection in the absence of home charging piles was conducted. Specifically, the price of EVs was reduced from 625,000 SEK to 525,000 SEK, that is, a reduction of 100,000 SEK, and its selection probability was recalculated based on the utility function and model estimation parameters. The results show that the probability of EV selection is 28.8% under the original price and without charging piles; when the price drops by 100,000 SEK, the selection probability only rises to 30.5%, an increase of 1.67 %. This small change indicates that in the absence of home charging infrastructure, consumers' acceptance of EVs is still significantly limited, and a single price incentive is not enough to significantly change their decision-making tendency. From the perspective of behavioral economics, this means that the weight of car buyers' consideration of charging convenience in decision-making is significantly higher than the price factor. Even if the price is significantly reduced, if the basic supporting facilities cannot be improved simultaneously, consumers' behavioral response will still appear slow.

According to our survey statistics, the selection proportion of EVs in group A is 64.8%, and the ratio of group B is 10.1%. The significant difference between group A and group B is whether there is a charging pile. While the other attribute values are very average and reasonable. This can also indirectly confirm the importance of decisiveness of the home charging pile option for EV purchases.

The results show that consumers are extremely sensitive to “convenient charging” when buying cars, especially when choosing between EVs and ICE vehicles. Even if EVs have certain advantages in technical parameters, their attractiveness will be significantly reduced if there is a lack of home charging conditions. Therefore, improving the accessibility of charging facilities in residential areas, especially encouraging and simplifying the installation process of home charging piles, can not only alleviate users’ range anxiety but may also become a key strategy to promote the popularization of EVs. This finding provides clear empirical support for the government to formulate support policies during the transition to electric transportation.

Although the coefficients of the two attributes of EV range (B_RANGE) and charging time (B_CHARGE) did not pass the significance test in the model estimation results of this study, with p values of 0.21 and 0.29 respectively, indicating that their statistical impact on consumers’ utility in choosing EVs is not stable enough, analysis can still be conducted to reveal their potential economic significance in actual decision-making through the calculation of the marginal rate of substitution.

Specifically, under the condition that other attributes remain constant, consumers are willing to pay an additional 62,500 SEK on average for every additional 100 kilometers of range. Although this value comes from a statistically insignificant coefficient, its direction is consistent with expectations, that is, consumers are more inclined to choose models with longer range. This tendency is driven by the psychology of “range anxiety”, especially in the context of the fact that public charging facilities are not yet fully popularized, and range is still regarded as a safety redundancy when choosing a car.

In addition, consumers’ “Willingness To Pay” for charging time is about 25,000 SEK per 10 minutes shorter. The negative value of this value is also consistent with common sense, indicating that faster charging time can bring higher overall utility. Although this attribute did not pass the statistical significance test, this value reveals that consumers generally prefer a more efficient and faster charging experience when other conditions are the same. Although the current data has not significantly confirmed its importance, the result is still of reference value, indicating that in the future EV market, the increase in charging speed may bring actual consumer utility gains.

In this study, although the range and charging time have not shown a significant impact at present, they still have certain practical significance from the perspective of marginal substitution rate, especially in the future, with the popularization of EVs and the improvement of user awareness, they may gradually become an important factor affecting car purchase decisions. Therefore, in policy design and product optimization, it is still recommended to pay attention to the improvement potential of these two attributes.

## 4.4 Demographic Model Results

In this part, the impact of personal socioeconomic characteristics on EV preferences is analyzed. To avoid multicollinearity problems, a base group is set for each group of categorical characteristics, and these reference groups do not appear in the model as dummy variables. In terms of gender, men are set as the reference group, so only variables of women and non-binary gender are included in the model; in terms of age, the group under 18 years old is used as the reference group, and the remaining age groups such as 18 to 44 years old, 45 to 59 years old, 60 to 74 years old, and over 75 years old are included in the form of dummy variables; in the educational level characteristic, high school and below education level is used as the reference group, compared with undergraduate and postgraduate education; in terms of income, people with an annual income of less than 300,000 SEK are used as the reference group, and the model includes income ranges of 300,000 to 500,000 SEK, 500,000 to 700,000 SEK, and more than 700,000 SEK; in the household member characteristic, the model involves household member of two, three, and four or more people, taking the single-person household member as the benchmark. Through this setting, the model can estimate the tendency of various groups to choose EVs relative to the reference group, and it can analyze the impact of personal characteristics on vehicle choices more accurately.

*Table 4.3: Estimated parameters of personal characteristics.*

| Characteristic | Value | Rob. Std err | Rob. t-test | Rob. p-value |
|---|---|---|---|---|
| B_AGE_18_44 | -0.5 | 0.43 | -1.17 | 0.24 |
| B_AGE_45_59 | -0.44 | 0.43 | -1.03 | 0.3 |
| B_AGE_60_74 | -0.58 | 0.6 | -0.95 | 0.34 |
| B_AGE_75p | -0.24 | 0.88 | -0.27 | 0.79 |
| B_BACHELOR | 0.35 | 0.35 | 0.99 | 0.32 |
| B_POSTGRAD | -0.02 | 0.48 | -0.04 | 0.97 |
| B_FEMALE | 0.56 | 0.3 | 1.89 | 0.06 |
| B_HH_2 | -1.22 | 0.49 | -2.48 | 0.01 |
| B_HH_3 | -1.79 | 0.42 | -4.22 | 0 |
| B_HH_4p | -1.14 | 0.43 | -2.66 | 0.01 |
| B_INC_30_50 | -0.19 | 0.37 | -0.52 | 0.6 |
| B_INC_50_70 | 0.32 | 0.37 | 0.86 | 0.39 |
| B_INC_70p | -1.41 | 0.7 | -2.02 | 0.04 |
| B_NONBINARY | 0.6 | 0.52 | 1.17 | 0.24 |

The results show that gender and family size are significant variables, as shown in Table

4.3. Female respondents are more likely to choose EVs than male respondents (B_FEMALE is 0.56, p value is about 0.06), which is close to significant at the 95% confidence level, which may be related to the fact that women pay more attention to environmental protection concepts and urban travel convenience. The household members are the most influential characteristic. Compared with single-person families, the coefficients of the number of family members of two(B_HH_2), three(B_HH_3), and four or more(B_HH_4) are -1.22, -1.79, and -1.15, respectively, and all are significant at the 95% confidence level, indicating that the family which have more than one person prefer to choosing ICE vehicles. This may be due to the higher demand for vehicle range, space, and travel stability in multi-person families, and it is difficult for EVs to completely replace ICE vehicles in these aspects at this stage.

In addition, the value of B_INC_70p, which represents the high-income group (income over 70,000 SEK per month), has a significantly lower preference for EVs, which may reflect that EVs have not yet established sufficient performance appeal and brand recognition in the high-end market. In contrast, the variables of low- and middle-income groups, different age groups, and educational levels do not reach a significant level in the model. Although the directions of these values may have some explanatory power, they still need richer samples or stronger variable controls to further confirm their effects. Overall, the model reveals the impact of some socioeconomic characteristics on EV selection behavior, especially emphasizing the key role of family size, gender, and family income level in consumer decisions.

## 4.5 General Discussion

Comparing the results of this study with relevant literature can provide a more comprehensive understanding of its theoretical and practical significance.

In this study, emissions of ICE vehicles were included in the utility function as an explanatory attribute and forced the corresponding coefficient to be set to less than zero in the model setting. It is to avoid illogical estimation results at the explanatory level of the model. And the estimated result is zero, indicating that the coefficient has no effect in this model. Similarly, in the study of Dumortier et al. (2015), they found that providing total cost of ownership (TCO) information significantly increased users' acceptance of new energy vehicles and pointed out that if the saving fuel cost is not accurately understood by consumers, it may not have a significant impact (Dumortier et al., 2015). The insignificant effect of emissions also reflects that emissions as an attribute may not be correctly understood and recognized by respondents in this study. This also shows that, to a certain extent, under the current information transmission and market cognitive structure, consumers' sensitivity to environmental factors still does

not have a strong enough decision-making weight.
In the research report “Consumer Behavior and the Plug-In EV Purchase Decision Process”, researchers summarized multiple factors that affect consumer behavior, such as individual attributes such as gender, age, and income, and emphasized the role of infrastructure and vehicle performance on consumers (Taylor & Fujita, 2018). This thesis also estimated the impact of multiple socioeconomic characteristics on preference for EVs in the model, among which gender, household members, income, etc., did show statistical significance. This is basically consistent with the analysis results of the thesis and was further quantitatively verified through model estimation.

It was empirically found that the availability of fast charging facilities (such as walking distance and whether they are available at home) has a significant positive effect on the choice preference of EVs (U.S. Department of Transportation, 2021). This is also highly consistent with the result that the dummy variable “whether can charging at home” in this study has a significant positive coefficient, which verifies that users are highly sensitive to charging convenience when choosing EVs. This preference is also reflected in our probability analysis, that is, consumers show a high probability of purchasing EVs when having home charging piles.

There is an article that emphasizes the core position of EV price and range in influencing users’ choices, especially in the context of low-carbon demands that have not yet formed a unified value consensus. Consumers still mainly evaluate from the perspective of economic and practical (Purwanto & Irawan, 2024). Although our model’s estimation result for the attribute of driving range is not significant, the attribute of price is very significant.

# 5. Conclusion

This study presents a comprehensive discrete choice analysis of Swedish consumers' preferences between ICE vehicles and EVs, based on 7266 binary choices from 373 valid respondents. A binary logit model was developed using key vehicle attributes, including purchase price, maintenance cost, driving range, charging time, emissions for ICE vehicles, and home charging availability for EVs, to examine their influence on vehicle choice behavior. The analysis also included socioeconomic attributes to investigating their moderating effects.

The results indicate that charging convenience, purchase price, and maintenance cost are the three most statistically significant vehicle attributes affecting consumer decisions. In particular, the availability of home charging shows a strong positive influence, with its coefficient being both large and highly significant. This suggests that enabling convenient at-home charging infrastructure can greatly increase the probability of EV selection. The estimated negative coefficient of vehicle price confirms that cost is still one of the most dominant barriers to EV adoption, while the significance of maintenance costs reflects consumers' attention to long-term economic burdens in their vehicle decisions. Furthermore, the negative and highly significant constant term for EVs suggests that even after controlling for all observable attributes, consumers still exhibit a fundamental preference disadvantage for EVs, which may reflect brand unfamiliarity or technological uncertainty. Several probability calculation analyses reveal the behavioral implications of these attributes. When a home charging pile is available, the predicted EV choice probability can reach up to 87.1%, compared to 28.8% without it. However, even with no home charging availability, a price reduction of SEK 100,000 still only increases the probability of choosing an EV by 1.67%, suggesting that price incentives alone are not enough if charging barriers remain.

Although attributes such as driving range and charging time do not reach the conventional significance threshold in this model, the direction of their coefficients remains consistent in theory. Further marginal substitution calculations show that on average, consumers are willing to pay about 62,500 SEK for each additional 100 km of driving range and 25,000 SEK for a 10-minute reduction in charging time, which to some extent reflects their potential preferences for longer driving range and faster energy replenishment, although these preferences are not statistically significant in the current data set.

Overall, this study confirms that Swedish consumers are highly sensitive to charging convenience, economic costs, and long-term vehicle maintenance, but still have some resistance to making electric vehicles the default choice. These findings provide policymakers with a solid quantitative basis to help them increase the penetration of EVs by focusing on infrastructure investment and economic policy tools, especially charging access at the household level. Future research can integrate psychological constructs or attitudinal variables to better capture the hidden preferences behind EV resistance and acceptance.

# 6. Limitations

Despite the valuable insights obtained from this study, some limitations must be acknowledged. First, the sample size of 373 respondents, while sufficient for basic discrete choice modeling, is relatively limited when generalizing the findings to the wider population of Swedish car users. Such a small sample limits the statistical power of the model and may reduce the robustness of the estimated parameters.

Second, the design of the choice experiment sets a fixed number of six choice tasks for each respondent, each of which contains one ICE vehicle and two EV alternatives. Although the choice set was constructed by Ngene based on the MNL model design, the final model estimation used a series of binary logistic regression models for pairwise comparisons. This transformation introduces the independence of irrelevant alternatives (IIA) assumption at the binary level, which may not fully realize the substitution pattern between multiple alternatives.

Third, although individual analyses incorporate a range of sociodemographic characteristics, including gender, age, education level, income, and household members, other potentially important psychological or attitudinal factors, such as environmental awareness and acceptance of new technologies, are not included in the main choice model.

Finally, respondents were faced with hypothetical scenarios, and their choices may not fully reflect actual behavior under real market constraints, budget considerations, or policy incentives. The difference between stated and revealed preferences is a common limitation of discrete choice models and is worth noting when interpreting the WTP estimates.

# References

International Energy Agency. (2023). *Transport – Tracking Report 2023*. IEA. https://www.iea.org/reports/transport

Government Offices of Sweden. (2021). *Sweden's climate policy framework*. https://www.government.se/articles/2021/06/swedens-climate-policy-framework/

Rezvani, Z., Jansson, J., & Bodin, J. (2015). Advances in consumer EV adoption research: A review and research agenda. *Transportation Research Part D: Transport and Environment, 34*, 122–136. https://doi.org/10.1016/j.trd.2014.10.010

Sovacool, B. K., Axsen, J., & Sorrell, S. (2018). Promoting novelty, rigor, and style in energy social science: Towards codes of practice for appropriate methods and research design. *Energy Research & Social Science, 45*, 12–42. https://doi.org/10.1016/j.erss.2018.07.007

Gnann, T., Plötz, P., Funke, S. Á., & Wietschel, M. (2018). What is the market potential of plug-in EVs as commercial passenger cars? A case study from Germany. *Transportation Research Part D: Transport and Environment, 62*, 658–672. https://doi.org/10.1016/j.trd.2018.04.021

Hardman, S., Shiu, E., & Steinberger-Wilckens, R. (2017). Comparing high-end and low-end early adopters of battery EVs. *Transportation Research Part A: Policy and Practice, 88*, 40–57. https://doi.org/10.1016/j.tra.2016.12.003

Axsen, J., & Kurani, K. S. (2013). Developing sustainability-oriented values: Insights from households in a green mobility program. *Global Environmental Change, 23*(5), 1241–1252. https://doi.org/10.1016/j.gloenvcha.2013.07.001

Hidrue, M. K., Parsons, G. R., Kempton, W., & Gardner, M. P. (2011). Willingness to pay for EVs and their attributes. *Resource and Energy Economics, 33*(3), 686–705. https://doi.org/10.1016/j.reseneeco.2011.02.002

Franke, T., & Krems, J. F. (2013). Understanding charging behavior of EV users. *Transportation Research Part F: Traffic Psychology and Behaviour, 21*, 75–89. https://doi.org/10.1016/j.trf.2013.09.002

Egbue, O., & Long, S. (2012). Barriers to widespread adoption of EVs: An analysis of consumer attitudes and perceptions. *Energy Policy, 48*, 717–729. https://doi.org/10.1016/j.enpol.2012.06.009

Greene, D. L., Park, S., & Liu, C. (2014). Analyzing the transition to electric drive vehicles in the U.S. *Futures, 58*, 34–52. https://doi.org/10.1016/j.futures.2014.01.008

Helveston, J. P., et al. (2015). Will subsidies drive EV adoption? Measuring consumer preferences in the U.S. and China. *Transportation Research Part A: Policy and Practice, 73*, 96–112. https://doi.org/10.1016/j.tra.2015.01.002

Jenn, A., Springel, K., & Gopal, A. R. (2018). Effectiveness of EV incentives in the United States. *Energy Policy, 119*, 349–356. https://doi.org/10.1016/j.enpol.2018.04.065

Li, W., Long, R., Chen, H., & Geng, J. (2017). A review of factors influencing consumer intentions to adopt battery EVs. *Renewable and Sustainable Energy Reviews, 78*, 318–328. https://doi.org/10.1016/j.rser.2017.04.076

Yang, X., & Yao, E. (2019). The influence of low temperature on EV range: Evidence from Chinese test data. *Journal of Advanced Transportation, 2019*, 1–8. https://doi.org/10.1155/2019/3514193

Train, K. (2009). *Discrete Choice Methods with Simulation* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511805271

Jansson, J., Nordlund, A., & Westin, K. (2017). Examining drivers of sustainable consumption: The influence of norms and environmental concern on EV adoption. *Journal of Consumer Behaviour, 16*(4), 291–301. https://doi.org/10.1002/cb.1624

Bierlaire, M. (2020). *A short introduction to pandasbiogeme*. EPFL. https://transp-or.epfl.ch/documents/technicalReports/Bier20.pdf

Ben-Akiva, M., & Lerman, S. R. (1985). *Discrete choice analysis: Theory and application to travel demand*. MIT Press.

Barbarossa, C., Beckmann, S. C., De Pelsmacker, P., & Moons, I. (2015). A self-identity based model of electric car adoption intention. *Journal of Environmental Psychology, 44*, 124–135. https://doi.org/10.1016/j.jenvp.2015.06.006

Whitmarsh, L., & O'Neill, S. (2010). Green identity, green living? *Journal of Environmental Psychology, 30*(3), 305–314. https://doi.org/10.1016/j.jenvp.2010.01.003

Degirmenci, K., & Breitner, M. H. (2017). Consumer purchase intentions for EVs: Is green more important than price and range? *Transportation Research Part D: Transport and Environment, 51*, 250–260. https://doi.org/10.1016/j.trd.2017.01.001

Wang, N., Tang, L., & Pan, H. (2017). Analysis of public acceptance of EVs: An empirical study in Shanghai. *Technological Forecasting and Social Change, 126*, 284–291. https://doi.org/10.1016/j.techfore.2017.09.005

Potoglou, D., & Kanaroglou, P. S. (2007). Household demand and willingness to pay for clean vehicles. *Transportation Research Part D: Transport and Environment, 12*(4), 264–274. https://doi.org/10.1016/j.trd.2007.03.001

Bobeth, S., & Kastner, M. (2020). Predicting the adoption of EVs: A psychological approach. *Journal of Environmental Psychology, 71*, 101479. https://doi.org/10.1016/j.jenvp.2020.101479

European Alternative Fuels Observatory. (2024). *Sweden: Vehicle Statistics Dashboard*. https://alternative-fuels-observatory.ec.europa.eu

Reuters. (2022, November 9). *Sweden scraps EV subsidy amid economic pressures*. https://www.reuters.com

Norwegian EV Association. (2023). *EV market share update 2023*. https://elbil.no/english

Zhao, J., Su, Y., Fang, M., & Su, M. (2024). Embracing new energy vehicles: An empirical examination of female consumer perspectives. Journal of Retailing and Consumer Services, 80, 103925. https://doi.org/10.1016/j.jretconser.2024.103925

Figenbaum, E. (2017). Perspectives on Norway's supercharged EV policy. *Environmental Innovation and Societal Transitions, 25*, 14–34. https://doi.org/10.1016/j.eist.2016.11.002

Plötz, P., Funke, S. Á., Jochem, P., & Wietschel, M. (2017). $CO_2$ mitigation potential of plug-in hybrid EVs larger than expected. *Scientific Reports, 7*(1), 16493. https://doi.org/10.1038/s41598-017-16684-9

Huang, Y., Qian, L., & Yang, J. (2021). Understanding Chinese consumers' willingness to adopt EVs: Role of price and performance. *Transport Policy, 100*, 1–9. https://doi.org/10.1016/j.tranpol.2020.10.011

Lindgren, S., & Olsson, L. (2023). Infrastructure and inequality in Sweden's EV rollout. *Sustainability, 15*(4), 2123. https://doi.org/10.3390/su15042123

AMPECO. (2024). *Sweden: Electrifying opportunities for EV charging infrastructure funding*. https://www.ampeco.com/us/ev-charging-grants-incentives/sweden-electrifying-opportunities-ev-charging-infrastructure-funding/

Columbia University Mailman School of Public Health. (n.d.). *Discrete choice model and analysis*. Columbia University. https://www.publichealth.columbia.edu/research/population-health-methods/discrete-choice-model-and-analysis

CTEK. (2025). *Charging an electric car at home*. https://www.ctek.com/ctek-magazine/charging-an-electric-car-at-home

Delaney, R. K. (2014). *Age and gender differences in decision-making style profiles* (Master's thesis, West Virginia University). West Virginia University Research Repository. https://researchrepository.wvu.edu/etd/5465

Dumortier, J., Siddiki, S., Carley, S., Cisney, J., Krause, R. M., Lane, B. W., Rupp, J. A., & Graham, J. D. (2015). Effects of providing total cost of ownership information on consumers' intent to purchase a hybrid or plug-in EV. *Transportation Research Part A: Policy and Practice, 72*, 71–86. https://doi.org/10.1016/j.tra.2014.12.005

European Alternative Fuels Observatory. (2025). *Sweden: Vehicle Statistics Dashboard*. https://alternative-fuels-observatory.ec.europa.eu

GeeksforGeeks. (2024, July 29). *Binary logistic regression*. https://www.geeksforgeeks.org/binary-logistic-regression/

gridX. (2025). *Europe's 2025 EV charging report: Growth, gaps & grids*. https://www.gridx.ai/resources/european-ev-charging-report-2025

Hong, X., Mohamad, W. N. W., Samdin, Z., & Samad, A. R. A. (2024). Consumer preferences and willingness to pay for EVs in China. *Polish Journal of Environmental Studies, 33*(6), 6153–6165. https://doi.org/10.15244/pjoes/184151

IBM. (n.d.). *What is logistic regression?* https://www.ibm.com/think/topics/logistic-regression

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). The implications on willingness to pay of respondents ignoring specific attributes. Transportation, 32(3), 203–222. https://doi.org/10.1007/s11116-004-7613-8

MIT Professional Education. (n.d.). *Discrete choice analysis: Predicting individual behavior and market demand.* https://professional.mit.edu/course-catalog/discrete-choice-analysis-predicting-individual-behavior-and-market-demand

Mobility Sweden. (2023). *It is still cheaper to drive an electric car in Sweden compared to a petrol or diesel car*. https://www.chargepanel.com/cheaper-drive-electric-car/

Ortúzar, J. de D., & Willumsen, L. G. (2011). *Modelling transport* (4th ed.). John Wiley & Sons.

PubMed Central. (2022). *Primer on binary logistic regression*. https://pmc.ncbi.nlm.nih.gov/articles/PMC8710907/

Roland Berger. (2024, August 28). *EV Charging Index: Expert insight from Sweden 2024*. https://www.rolandberger.com/en/Insights/Publications/EV-Charging-Index-Expert-insight-from-Sweden-2024.html

Saylor Academy. (n.d.). *Utility theory*. https://saylordotorg.github.io/text_risk-management-for-enterprises-and-individuals/s07-01-utility-theory.html

Taylor, M., & Fujita, K. (2018). *Consumer behavior and the plug-in EV purchase decision process: A research synthesis*. Lawrence Berkeley National Laboratory. https://seeds.lbl.gov/wp-content/uploads/sites/29/2018/02/Consumer-Behavior-and-the-Plug-In-Electric-Vehicle-Purchase-decision-Process_A-Research-Synthesis.pdf

Train, K. (2009). *Discrete choice methods with simulation* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511805271

Wikipedia contributors. (2025, January 1). *Binary data*. In Wikipedia. https://en.wikipedia.org/wiki/Binary_data

U.S. Department of Transportation. (2021). *Effects of charging infrastructure characteristics on EV adoption* (Report No. DOT-59895_DS1).

https://rosap.ntl.bts.gov/view/dot/59895/dot_59895_DS1.pdf

Purwanto, E., & Irawan, A. P. (2024). The willingness to purchase EVs: A comprehensive review. *IOP Conference Series: Earth and Environmental Science, 1324*(1), 012091. https://doi.org/10.1088/1755-1315/1324/1/012091

# Appendix

English

**Comprehensive Survey on Swedish Consumers' Willingness to Purchase Electric Vehicles (EVs)**

**Introduction:**

**Dear Participant,**

Thank you for participating in this survey on the willingness of Swedish consumers to purchase electric vehicles (EVs). This study aims to better understand people's attitudes, concerns, and intentions regarding EV adoption. The results will provide valuable insights for policymakers, industry stakeholders, and researchers to support the development of the EV market.

**This survey is completely anonymous, and all data will be kept strictly confidential, used solely for academic research purposes.**

**Part I: Driving & Purchase Experience**

1. Do you currently own a car?

- ○ Yes, an EV (electric vehicle)
- ○ Yes, a HEV (hybrid electric vehicle)
- ○ Yes, an ICE (internal combustion engine) vehicle
- ○ No

2.Have you ever driven an electric vehicle?

- ○ Yes
- ○ No

››

English

3. How satisfied are you with the driving experience of EVs (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree)?

- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5

4. What is your average daily driving distance?

- ◯ Less than 5 km
- ◯ 5-10 km
- ◯ 10-20 km
- ◯ 20-50 km
- ◯ More than 50 km

<<    >>

English

**Part II:Scenario-Based Questions**

There are six tasks in this part, in each task, you will be presented with three vehicle options (one fuel vehicle and two electric vehicles)that **vary across several parameters below :**

**Price** (purchase cost including tax)

**Range** (how far the vehicle can travel on a full tank or full charge)

**Maintenance cost per year**

**Cost per kilometer** (Calculated by fuel or electricity consumption of different vehicles)

**Public Refuel/Recharging time** (include the waiting time and refuel/recharging time)

**CO2 emissions per kilometer**

Availability of home charging (applicable only for EVs): "Yes" indicates that a charger can be installed at home; "No" indicates otherwise.

Each option is hypothetical but reflects realistic values based on the current vehicle market in Sweden.

Please review the information provided in each table carefully and select the vehicle that you would personally prefer, based on your own judgment and lifestyle.

There are no right or wrong answers — we are only interested in your honest preferences.

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English

Question 1:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price (Kr) | 250000 | 750000 | 500000 |
| Range(km) | 800 | 700 | 400 |
| Maintenance per year (Kr) | 7000 | 2000 | 2500 |
| Cost per km (Kr) | 1.5 | 0.3 | 0.3 |
| Public Refuel/Recharging Time(min) | 5 | 20 | 20 |
| Emission per km(g) | 100 | 0 | |
| Availability of charging at home | / | YES | |

- Option A
- Option B
- Option C

Question 2:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price (Kr) | 650000 | 900000 | 750000 |
| Range(km) | 500 | 400 | 300 |
| Maintenance per year (Kr) | 7000 | 3500 | 3000 |
| Cost per km (Kr) | 1.5 | 0.26 | 0.22 |
| Public Refuel/Recharging Time(min) | 5 | 80 | 100 |
| Emission per km(g) | 200 | 0 | |
| Availability of charging at home | / | YES | |

- Option A
- Option B
- Option C

Question 3:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 250000 | 350000 | 350000 |
| Range(km) | 500 | 500 | 600 |
| Maintenance per year | 4000 | 2000 | 3500 |
| Cost per km | 1.3 | 0.26 | 0.26 |
| Public Refuel/Recharging Time(min) | 5 | 60 | 80 |
| Emission per km(g) | 130 | 0 | |
| Availability of charging at home | / | YES | |

- Option A
- Option B
- Option C

Question 4:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 800000 | 500000 | 900000 |
| Range(km) | 700 | 300 | 600 |
| Maintenance per year | 5000 | 3000 | 2500 |
| Cost per km | 1.1 | 0.3 | 0.26 |
| Public Refuel/Recharging Time(min) | 5 | 60 | 20 |
| Emission per km(g) | 160 | 0 | |
| Availability of charging at home | / | YES | |

- Option A
- Option B
- Option C

Question 5

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 650000 | 350000 | 350000 |
| Range(km) | 700 | 700 | 500 |
| Maintenance per year | 6000 | 3500 | 2000 |
| Cost per km | 1.3 | 0.3 | 0.22 |
| Public Refuel/Recharging Time(min) | 5 | 60 | 60 |
| Emission per km(g) | 130 | 0 | |
| Availability of charging at home | / | NO | |

- ◯ Option A
- ◯ Option B
- ◯ Option C

Question 6

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 400000 | 500000 | 900000 |
| Range(km) | 900 | 500 | 700 |
| Maintenance per year | 6000 | 2000 | 3000 |
| Cost per km | 1.5 | 0.3 | 0.22 |
| Public Refuel/Recharging Time(min) | 5 | 100 | 40 |
| Emission per km(g) | 200 | 0 | |
| Availability of charging at home | / | NO | |

- ◯ Option A
- ◯ Option B
- ◯ Option C

English

Question 1:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 250000 | 750000 | 500000 |
| Range(km) | 800 | 700 | 400 |
| Maintenance per year | 7000 | 2000 | 2500 |
| Cost per km | 1.5 | 0.3 | 0.3 |
| Public Refuel/Recharging Time(min) | 5 | 20 | 20 |
| Emission per km(g) | 100 | 0 | |
| Availability of charging at home | / | YES | |

- Option A
- Option B
- Option C

Question 2:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 650000 | 900000 | 750000 |
| Range(km) | 500 | 400 | 300 |
| Maintenance per year | 7000 | 3500 | 3000 |
| Cost per km | 1.5 | 0.26 | 0.22 |
| Public Refuel/Recharging Time(min) | 5 | 80 | 100 |
| Emission per km(g) | 200 | 0 | |
| Availability of charging at home | / | YES | |

- Option A
- Option B
- Option C

Question 3:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 250000 | 350000 | 350000 |
| Range(km) | 500 | 500 | 600 |
| Maintenance per year | 4000 | 2000 | 3500 |
| Cost per km | 1.3 | 0.26 | 0.26 |
| Public Refuel/Recharging Time(min) | 5 | 60 | 80 |
| Emission per km(g) | 130 | 0 | |
| Availability of charging at home | / | YES | |

- ○ Option A
- ○ Option B
- ○ Option C

Question 4:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 800000 | 500000 | 900000 |
| Range(km) | 700 | 300 | 600 |
| Maintenance per year | 5000 | 3000 | 2500 |
| Cost per km | 1.1 | 0.3 | 0.26 |
| Public Refuel/Recharging Time(min) | 5 | 60 | 20 |
| Emission per km(g) | 160 | 0 | |
| Availability of charging at home | / | YES | |

- ○ Option A
- ○ Option B
- ○ Option C

Question 5:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 800000 | 900000 | 750000 |
| Range(km) | 900 | 700 | 600 |
| Maintenance per year | 6000 | 3000 | 3500 |
| Cost per km | 1.1 | 0.22 | 0.22 |
| Public Refuel/Recharging Time(min) | 5 | 40 | 60 |
| Emission per km(g) | 130 | 0 | |
| Availability of charging at home | / | YES | |

- ○ Option A
- ○ Option B
- ○ Option C

Question 6:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 400000 | 350000 | 500000 |
| Range(km) | 900 | 600 | 700 |
| Maintenance per year | 4000 | 3000 | 2000 |
| Cost per km | 1.3 | 0.22 | 0.3 |
| Public Refuel/Recharging Time(min) | 5 | 100 | 80 |
| Emission per km(g) | 160 | 0 | |
| Availability of charging at home | / | YES | |

- ○ Option A
- ○ Option B
- ○ Option C

English

**Part III: Daily Environmental Behaviors**

Please rate the following statements (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree):

11. When shopping, I choose products with eco-friendly packaging whenever possible.

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

12. At home, my family sorts household waste carefully for recycling.

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

13. I avoid using disposable plastic bags by bringing my own reusable bags.

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

14. I prefer using public transportation, biking, or walking instead of driving to reduce emissions.

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

15. I regularly try to reduce electricity and water consumption at home.

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

## Part IV: Sociodemographic Information

16. Gender:

- ○ Male
- ○ Female
- ○ Non-binary

17. Age:

- ○ 0-18
- ○ 18-44
- ○ 45-59
- ○ 60-74
- ○ 75 and above

18. Highest Education Level:

- ○ High school or below (or similar)
- ○ Bachelor's degree (or similar)
- ○ Postgraduate degree or above (or similar)

19. Household Income (in SEK + number of household members):

- ○ Less than 300,000
- ○ 300,000 - 499,999
- ○ 500,000 - 699,999
- ○ 700,000 and above

20. Number of Household Members:

- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4 or more

21.Postcode:

22.Do you have a driver's license?

- ◯ Yes
- ◯ No

<< >>

We thank you for your time spent taking this survey.
Your response has been recorded.

Svenska

## Omfattande undersökning om svenska konsumenters vilja att köpa elfordon (EV)

**Introduktion:**

Bästa deltagare,

Tack för att du deltar i den här undersökningen om svenska konsumenters vilja att köpa elfordon. Denna studie syftar till att bättre förstå människors attityder, oro och avsikter när det gäller adoption av elbilar. Resultaten kommer att ge värdefulla insikter för beslutsfattare, industriintressenter och forskare för att stödja utvecklingen av elbilsmarknaden.

**Denna undersökning är helt anonym och all data kommer att hållas strikt konfidentiell och används endast för akademiska forskningsändamål.**

**Del I: Kör– och köperfarenhet**

1. Äger du en bil för närvarande?

○ Ja, en EV (elfordon)

○ Ja, ett HEV (hybrid elfordon)

○ Ja, ett ICE (förbränningsmotor) fordon

○ Inga

2.Har du någonsin kört ett elfordon?

○ Ja

○ Inga

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Svenska

3. Hur nöjd är du med körupplevelsen av elbilar (1 = Håller helt med, 2 = Instämmer inte, 3 = Neutral, 4 = Instämmer, 5 = Instämmer helt)?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

4. Vad är din genomsnittliga dagliga körsträcka?

- ○ Mindre än 5 km
- ○ 5-10 km
- ○ 10-20 km
- ○ 20-50 km
- ○ Mer än 50 km

<<    >>

Svenska

**Del II: Scenariobaserade frågor**

Det finns sex uppgifter i den här delen, i varje uppgift kommer du att presenteras med tre fordonsalternativ (ett bränslefordon och två elfordon) som **varierar över flera parametrar nedan:**

**Pris** (köpkostnad inklusive moms)

**Räckvidd** (hur långt fordonet kan färdas på full tank eller full laddning)

**Underhållskostnad per år**

**Kostnad per kilometer** (beräknat av olika fordons bränsle- eller elförbrukning)

**Offentlig tankning/laddningstid** (inklusive väntetid och tankning/laddningstid)

**CO2-utsläpp per kilometer**

Tillgänglighet för hemladdning (gäller endast elbilar): "Ja" indikerar att en laddare kan installeras hemma; "Nej" indikerar något annat.

Varje alternativ är hypotetisk men speglar realistiska värden baserade på den nuvarande fordonsmarknaden i Sverige.

Vänligen granska informationen i varje tabell noggrant och välj det fordon som du personligen skulle föredra, baserat på din egen bedömning och livsstil.

Det finns inga rätt eller fel svar – vi är bara intresserade av dina ärliga preferenser.

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Svenska

Fråga 1:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 250000 | 750000 | 500000 |
| Range(km) | 800 | 700 | 400 |
| Maintenance per year | 7000 | 2000 | 2500 |
| Cost per km | 1.5 | 0.3 | 0.3 |
| Public Refuel/Recharging Time(min) | 5 | 20 | 20 |
| Emission per km(g) | 100 | 0 | |
| Availability of charging at home | / | YES | |

- Alternativ A
- Alternativ B
- Alternativ C

Fråga 2:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 650000 | 900000 | 750000 |
| Range(km) | 500 | 400 | 300 |
| Maintenance per year | 7000 | 3500 | 3000 |
| Cost per km | 1.5 | 0.26 | 0.22 |
| Public Refuel/Recharging Time(min) | 5 | 80 | 100 |
| Emission per km(g) | 200 | 0 | |
| Availability of charging at home | / | YES | |

- Alternativ A
- Alternativ B
- Alternativ C

Fråga 3:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 250000 | 350000 | 350000 |
| Range(km) | 500 | 500 | 600 |
| Maintenance per year | 4000 | 2000 | 3500 |
| Cost per km | 1.3 | 0.26 | 0.26 |
| Public Refuel/Recharging Time(min) | 5 | 60 | 80 |
| Emission per km(g) | 130 | 0 | |
| Availability of charging at home | / | YES | |

- Alternativ A
- Alternativ B
- Alternativ C

Fråga 4:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 800000 | 500000 | 900000 |
| Range(km) | 700 | 300 | 600 |
| Maintenance per year | 5000 | 3000 | 2500 |
| Cost per km | 1.1 | 0.3 | 0.26 |
| Public Refuel/Recharging Time(min) | 5 | 60 | 20 |
| Emission per km(g) | 160 | 0 | |
| Availability of charging at home | / | YES | |

- Alternativ A
- Alternativ B
- Alternativ C

Fråga 5:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 800000 | 900000 | 750000 |
| Range(km) | 900 | 700 | 600 |
| Maintenance per year | 6000 | 3000 | 3500 |
| Cost per km | 1.1 | 0.22 | 0.22 |
| Public Refuel/Recharging Time(min) | 5 | 40 | 60 |
| Emission per km(g) | 130 | 0 | |
| Availability of charging at home | / | YES | |

- Alternativ A
- Alternativ B
- Alternativ C

Fråga 6:

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 400000 | 350000 | 500000 |
| Range(km) | 900 | 600 | 700 |
| Maintenance per year | 4000 | 3000 | 2000 |
| Cost per km | 1.3 | 0.22 | 0.3 |
| Public Refuel/Recharging Time(min) | 5 | 100 | 80 |
| Emission per km(g) | 160 | 0 | |
| Availability of charging at home | / | YES | |

- Alternativ A
- Alternativ B
- Alternativ C

Svenska

Fråga 1

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 650000 | 500000 | 500000 |
| Range(km) | 800 | 400 | 500 |
| Maintenance per year | 5000 | 3500 | 3500 |
| Cost per km | 1.3 | 0.22 | 0.3 |
| Public Refuel/Recharging Time(min) | 5 | 20 | 40 |
| Emission per km(g) | 160 | 0 | |
| Availability of charging at home | / | NO | |

- Alternativ A
- Alternativ B
- Alternativ C

Fråga 2

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 800000 | 900000 | 900000 |
| Range(km) | 700 | 600 | 300 |
| Maintenance per year | 4000 | 2500 | 2500 |
| Cost per km | 1.5 | 0.22 | 0.3 |
| Public Refuel/Recharging Time(min) | 5 | 100 | 60 |
| Emission per km(g) | 100 | 0 | |
| Availability of charging at home | / | NO | |

- Alternativ A
- Alternativ B
- Alternativ C

Fråga 3

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 400000 | 750000 | 750000 |
| Range(km) | 600 | 300 | 700 |
| Maintenance per year | 7000 | 2500 | 2000 |
| Cost per km | 1.1 | 0.26 | 0.26 |
| Public Refuel/Recharging Time(min) | 5 | 40 | 100 |
| Emission per km(g) | 100 | 0 | |
| Availability of charging at home | / | NO | |

- Alternativ A
- Alternativ B
- Alternativ C

Fråga 4

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 250000 | 750000 | 350000 |
| Range(km) | 600 | 600 | 400 |
| Maintenance per year | 5000 | 2500 | 3000 |
| Cost per km | 1.1 | 0.26 | 0.26 |
| Public Refuel/Recharging Time(min) | 5 | 80 | 80 |
| Emission per km(g) | 200 | 0 | |
| Availability of charging at home | / | NO | |

- Alternativ A
- Alternativ B
- Alternativ C

Fråga 5

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 650000 | 350000 | 350000 |
| Range(km) | 700 | 700 | 500 |
| Maintenance per year | 6000 | 3500 | 2000 |
| Cost per km | 1.3 | 0.3 | 0.22 |
| Public Refuel/Recharging Time(min) | 5 | 60 | 60 |
| Emission per km(g) | 130 | 0 | |
| Availability of charging at home | / | NO | |

- Alternativ A
- Alternativ B
- Alternativ C

Fråga 6

| | Option A | Option B | Option C |
|---|---|---|---|
| | Internal Conbustion Engine Vehicle | Electric Vehicle 1 | Electric Vehicle 2 |
| Price | 400000 | 500000 | 900000 |
| Range(km) | 900 | 500 | 700 |
| Maintenance per year | 6000 | 2000 | 3000 |
| Cost per km | 1.5 | 0.3 | 0.22 |
| Public Refuel/Recharging Time(min) | 5 | 100 | 40 |
| Emission per km(g) | 200 | 0 | |
| Availability of charging at home | / | NO | |

- Alternativ A
- Alternativ B
- Alternativ C

Svenska

Del III: Dagliga miljöbeteenden

Betygsätt följande påståenden (1 = Håller helt med, 2 = Instämmer inte, 3 = Neutral, 4 = Håller med, 5 = Instämmer helt):

11. När jag handlar väljer jag produkter med miljövänliga förpackningar när det är möjligt.

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

12. Hemma sorterar min familj hushållsavfall noggrant för återvinning.

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

13. Jag undviker att använda engångsplastpåsar genom att ta med egna återanvändbara påsar.

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

14. Jag föredrar att använda kollektivtrafik, cykla eller gå istället för att köra bil för att minska utsläppen.

- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5

15. Jag försöker regelbundet minska el- och vattenförbrukningen hemma.

- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5

Del IV: Sociodemografisk information

16. Kön:

- ◯ Manlig
- ◯ Kvinnlig
- ◯ Icke-binär

17. Ålder:

- ◯ 0-18
- ◯ 18-44
- ◯ 45-59
- ◯ 60-74
- ◯ 75 och uppåt

18. Högsta utbildningsnivå:

- ◯ Gymnasie eller lägre (eller liknande)
- ◯ Kandidatexamen (eller liknande)
- ◯ Forskarexamen eller högre (eller liknande)

19. Hushållsinkomst (i SEK + antal hushållsmedlemmar):

- ◯ Mindre än 300 000
- ◯ 300 000 - 499 999
- ◯ 500 000 - 699 999
- ◯ 700 000 och uppåt

20. Antal hushållsmedlemmar:

- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4 eller fler

21. Postnummer:

22.Har du körkort?

- ◯ Ja
- ◯ Inga

<< >>

```python
 os

# ---------- Step 1: Load and preprocess data ----------
df_full = pd.read_csv("DATA_Wide.csv")

# ✅ Scale numeric variables
df_full["Price_ICE"] = df_full["Price_ICE"] / 100000
df_full["Maintenance_ICE"] = df_full["Maintenance_ICE"] / 1000
df_full["Range_ICE"] = df_full["Range_ICE"] / 100
df_full["ChargeTime_ICE"] = df_full["ChargeTime_ICE"] / 10
df_full["Price_EV"] = df_full["Price_EV"] / 100000
df_full["Maintenance_EV"] = df_full["Maintenance_EV"] / 1000
df_full["Range_EV"] = df_full["Range_EV"] / 100
df_full["ChargeTime_EV"] = df_full["ChargeTime_EV"] / 10
df_full["Emission_ICE"] = df_full["Emission_ICE"] / 100
# ✅ Drop non-key columns with NaN
key_cols = ['Price_ICE', 'Range_ICE', 'Maintenance_ICE', 'DriveCost_ICE',
'ChargeTime_ICE', 'Price_EV', 'Range_EV', 'Maintenance_EV', 'DriveCost_EV',
'ChargeTime_EV','Charging_EV', 'Choice', 'Alternative','Emission_ICE']
non_key_cols = [col for col in df_full.columns if col not in key_cols]
cols_to_drop = [col for col in non_key_cols if df_full[col].isna().any()]
df_full.drop(columns=cols_to_drop, inplace=True)

df_full = df_full.select_dtypes(include=['number'])

# ---------- Step 2: Biogeme database ----------
database = db.Database("choice_data", df_full)

globals().update(database.variables)

# ---------- Step 3: Define parameters ----------
ASC_EV = Beta("ASC_EV", 0, None, None, 0)

B_PRICE = Beta("B_PRICE", 0, None, None, 0)
#B_PRICE_EV = Beta("B_PRICE_EV", 0, None, None, 0)

B_RANGE = Beta("B_RANGE", 0, None, None, 0)
#B_RANGE_EV = Beta("B_RANGE_EV", 0, None, None, 0)

B_CHARGE = Beta("B_CHARGE", 0, None, None, 0)
#B_CHARGE_EV = Beta("B_CHARGE_EV", 0, None, None, 0)

B_MAINT = Beta("B_MAINT", 0, None, None, 0)
#B_MAINT_EV = Beta("B_MAINT_EV", 0, None, None, 0)

B_DRIVE = Beta("B_DRIVE", 0, None, None, 0)
#B_DRIVE_EV = Beta("B_DRIVE_EV", 0, None, None, 0)

B_EMISS_ICE = Beta("B_EMISS_ICE", 0, None, 0, 0)

B_CHARGING_EV = Beta("B_CHARGING_EV", 0, None, None, 0)

# ---------- Step 4: Utility functions ----------
V_ICE = B_PRICE * Price_ICE + \
        B_RANGE * Range_ICE + \
        B_MAINT * Maintenance_ICE + \
        B_CHARGE * ChargeTime_ICE + \
        B_DRIVE * DriveCost_ICE + \
        B_EMISS_ICE * Emission_ICE

V_EV = ASC_EV + \
       B_PRICE * Price_EV + \
       B_RANGE * Range_EV + \
       B_CHARGE * ChargeTime_EV + \
       B_MAINT * Maintenance_EV + \
       B_DRIVE * DriveCost_EV + \
       B_CHARGING_EV * Charging_EV

V = {1: V_ICE, 2: V_EV}

# ---------- Step 5: Model ----------
logprob = models.loglogit(V, None, Choice)
biogeme = bio.BIOGEME(database, logprob, compileExpressions=False)

# ---------- Step 6: Estimate ----------
Results = biogeme.estimate()

# ---------- Step 7: Output ----------
print("\n=== Estimated Parameters ===")
print(Results.get_estimated_parameters())

print("\n=== Estimation Report ===")
for key, value in Results.get_general_statistics().items():
    print(f"{key}: {value}")

print("\n=== Log Likelihoods ===")
print("Init log-likelihood :", Results.data.initLogLike)
print("Final log-likelihood:", Results.data.logLike)
```