Technical University of Munich

Light Electric Vehicle utility model to realise adaption behavior in Germany.

Exploring Consumer Preferences Through Hybrid Choice Models

Scientific work to obtain the degree

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List of Abbreviations

AIC	Akaike Information Criterion
ASC	Alternative Specific Constant
BIC	Bayesian Information Criterion
DCE	Discrete Choice Experiment
DCM	Discrete Choice Model
EV	Electric Vehicles
HCM	Hybrid Choice Model
IIA	Independence of Irrelevant Alternatives
IID	Independent and Identically Distributed Terms
LCA	Latent Class Analysis
LCM	Latent Class Model
LEV	Light Electric Vehicles
LVM	Latent variable Model
MEV	Micro Electric Vehicles (Microcars)
MiD	Mobility in Germany
MNL	Multinominal Logit Model
RP	Revealed Preference
SC	Stated Choice
SP	Stated Preference

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1. Introduction

The transport sector alone is a major source of greenhouse gas emissions and air pollution, and the population's rapid development has resulted in significant traffic congestion and a dependency on private passenger cars (Ewert et al., 2021). Passenger cars alone account for over 61% of emissions in Germany, requiring the development of new approaches to lower transportation-related carbon emissions and create mobility solutions for congestion. (Brost et al., n.d.; Karaca et al., 2018).

The lack of infrastructure for large vehicles in the city, the growing number of more energy-efficient vehicles that might result in reduced energy consumption per kilometre, and cost-effectiveness are among several factors driving the need for mobility solutions, increased by the more significant emissions resulting from existing traffic congestion. (Brost et al., n.d.; Karaca et al., 2018). Microcars and other light electric vehicles (LEVs), such as e-scooters, e-bikes, motorcycles and mopeds, have become popular. They can help bring about the necessary change, especially for shorter city trips, and bridge the distance between public transportation and final destinations, which can help with last-mile issues in rural areas (Brost et al., n.d.; Mesimäki & Lehtonen, 2023).

LEVs can substitute most private car trips as these can compensate for an average trip length of 12km in urban regions of Germany (Brost et al., n.d.). These LEVs are characterized by their small and compact size, less energy consumption and minimal environmental impact; however, due to a lack of awareness, concerns regarding the safety of small vehicle market adoption of LEVs are hindered (Brost et al., n.d.; Mesimäki & Lehtonen, 2023). The advantages mentioned above can be achieved by addressing these obstacles while understanding people's perspectives regarding microcar adoption through policy implementation, developing the required infrastructure, and conducting awareness campaigns, which may contribute to future market demand for microcars. (Böhrk & Radlwimmer, n.d.; Zhao et al., 2024, p. 2021).

Note: In the current study, specifically medium-range battery electric vehicles (BEVs) were considered comparable with small microcars but referred to as electric vehicles (EVs) throughout the study.

1.1. Research Motivation

According to research on the Mobility in Germany (MiD) survey, LEVs have the larger potential to substitute for the total number of passenger car trips in Germany. With an average occupancy rate of 1.4 passengers per car, about 80% of the trips are under 20km, and almost 98% are shorter than 100km, which can be substituted by microcars. In total, microcars have the potential to substitute about 75% of the total motorised trips and replace almost half of the total mileage. Greenhouse gas (GHS) emissions of microcars alone are 25% of the replaced passenger car GHG emissions (weighted mileage average) (BMVI, n.d.; Brost et al., n.d.).

While carbon dioxide equivalent (CO2eq) emissions substitution of LEVs is about 44% and microcars alone can contribute to about 14%, which sounds significant, there is a need to realise specific changes required for actual emissions reduction potential (Brost et al., 2022). This requires analysing individual preferences for microcars over an electric car while evaluating key attributes that affect their adoption. Furthermore, it was noticed that no current research has analysed the potential of microcar adoption using discrete choice modelling to the best of the author's attention and knowledge. Therefore, this study aims to examine a behaviour model and the acceptance of microcars as a particular interest.

1.2. Objective and Research Questions

Even though the theoretical realisation potential is at its highest, the actual changes required to encourage this shift might require further policy implementation through push and pull measures to change mobility habits, which can be realized by understanding the factors affecting the adoption (Brost et al., 2022). Which brings us to our main objective:

Utilising Hybrid Choice Modelling (HCM) methodology to understand independent variables influencing the adoption of microcars and potentially identify the classes (population groups) who are more likely to adopt Micro-electric Vehicles (MEVs) considering Electric Vehicles (EVs) as an alternative and how these insights can provide strategies to increase microcar adoption.

The research questions answered in the study include:

1. How can a discrete choice experiment (DCE) be designed effectively to collect mode choice data in analysing individual preferences for microcars (MEVs) compared to EVs

2. What are the major vehicle attributes and latent variables that might influence consumer adoption behaviour, particularly for microcars in Germany?

3. Who are the potential users more likely to adopt microcars, and how do these group-specific socio-demographic characteristics affect their likelihood of adopting microcars in Germany?

4. How well do predicted choice probabilities for microcars versus BEVs reflect the potential adoption of microcars in Germany?

1.3. Overall Research Workflow

The thesis consists of 7 significant parts: Problem definition, Literature Review, Methodology, Analysis, Results, Discussion and Conclusion, for which the workflow is shown below in Figure 1.

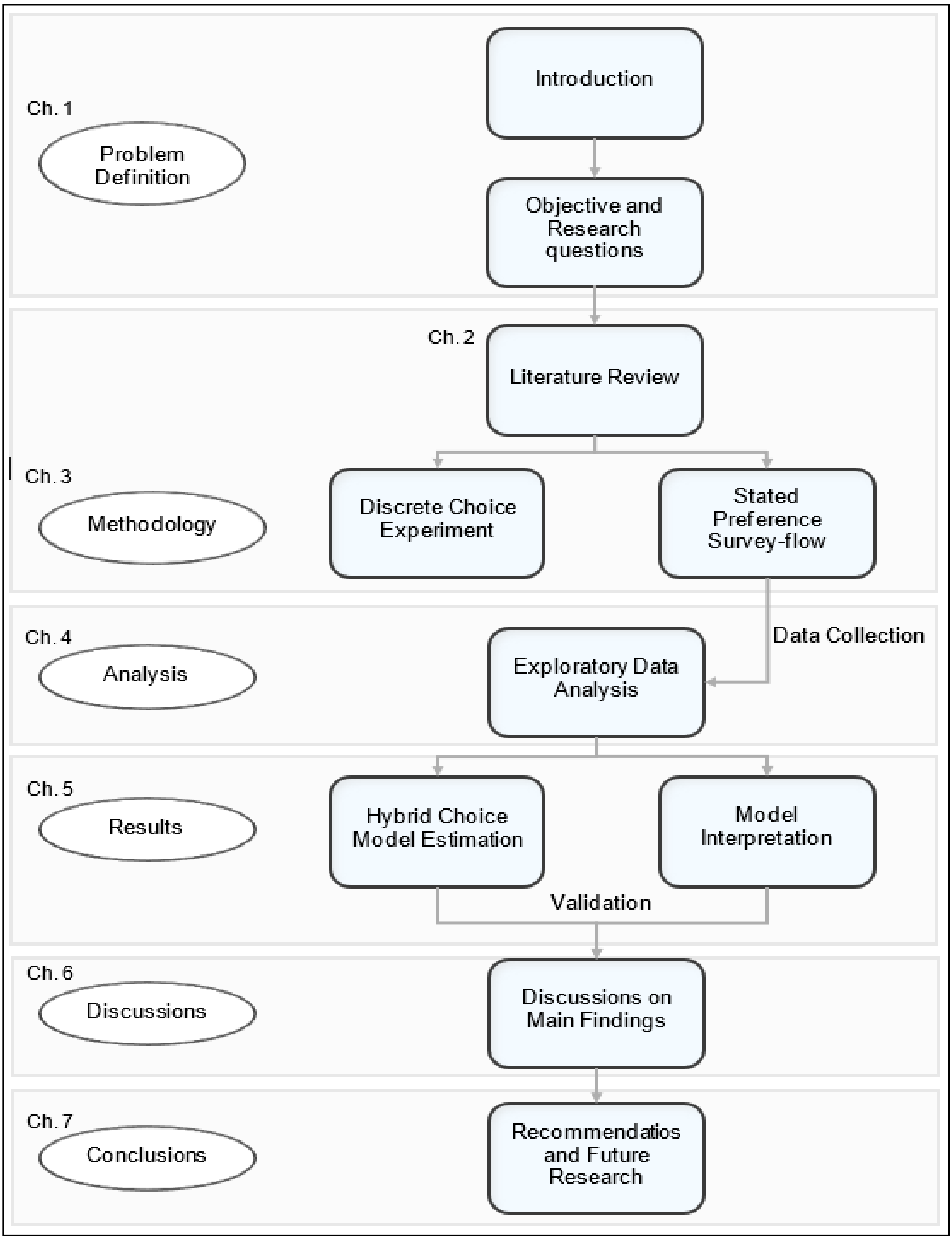


Figure 1. Overall Research Framework

1.4. Research Contributions

1.4.1. Analytical Contributions

1. Survey Methodology: A stated preference survey design was conducted to understand preferences, which offers an approach to collect reliable insights from consumers and their choices.

2. Consumer Behavior: A Hybrid Choice Model (HCM) integrated with identified latent variables built from the survey results can be considered for further research, which can validate and improve choice models in predicting individual behavior in vehicle adoption.

3. Further Work: Limitations and possible future works have been identified in the study, and these insights can be helpful for future research in sustainable transport vehicle adoption.

1.4.2. Practical Implications

1. Findings from the study provide actionable possible policies that can be developed further to target specific groups of individuals to increase and promote market demand.

2. While emission reduction was not directly calculated, the study can act as a starting point to understand the potential environmental advantages of microcars in real-world adoption environments.

2. Literature Review

2.1. Electric Vehicles and Microcars and their Market Adoption

Electric vehicles (EVs) have gained significant attention nowadays, showing the possibility of sustainable transportation solutions in reducing environmental and energy-related challenges. They promise reduced GHG emissions and urban air quality improvements through shifts in personal mobility usage (Liao et al., 2017). Microcars, on the other hand, have a high potential to transform urban transportation. In addition to EV advantages, microcars are space-efficient and adaptable to urban needs (Alam et al., 2024; Brost et al., 2022; Karaca et al., 2018). So, governments worldwide have developed policies to encourage the adoption of these vehicles, which can transform living environments in the future.

2.1.1. Electric Vehicles (EVs)

BEVs are identified to be the most feasible option to reduce traffic emissions and also road population caused by conventional vehicles and others (Zhao et al., 2023). However, despite all these advantages and policy interventions like discounts and purchase grants offered for green-labelled cars, the adoption and market demand for BEVs are still low (Darup et al., n.d.). There are further individual concerns in EV adoption other than environmental advantages, such as range anxiety and insufficient charging infrastructure. So, these economic, technical and other factors are acting as barriers to EV adoption (Broadbent et al., 2018).

Consumer preferences in EV adoption play a significant role as other than technological and financial attributes such as purchase price, charging time and infrastructure and other costs, how consumers perceive technological advantages and disadvantages, cost, and environmental concerns affect the adoption behavior on a large scale (Broadbent et al., 2018).

Although the government implemented policies to increase the demand, not all the incentives were seen to be effective, and not enough recharging station networks seems to be one of the major concerns for EV adoption due to both range anxiety and limited vehicles (Broadbent et al., 2018). It was seen that EV adoption in Germany would be greatly beneficial if driving experience combined with car-sharing opportunities were provided for consumers (Darup et al., n.d.).

Despite all other factors, consumer satisfaction remains the primary factor for EV adoption, and it remains a critical area that needs improvement (Zhao et al., 2023). Furthermore, a few other attributes, such as noise isolation and the top range of BEVs, need significant improvement for customer satisfaction (Zhao et al., 2023). In conclusion, although EVs have the advantages of reducing emissions and providing environmental benefits over conventional vehicles, their adoption is influenced by technical, financial, and other behavioral characteristics (Darup et al., n.d.).

2.1.2. Microcars (MEVs)

Microcars are well known for their small and compact sizes, as they can replace large traditional vehicles because the average per-car occupancy rate is only 1.4 persons (BMVI, n.d.). They can also be an alternative solution for major traffic problems caused by passenger cars, especially in cities (Karaca et al., 2018). These vehicles can be an effective solution for congestion problems and environmental concerns as they reduce both energy and space-related transportation problems (Karaca et al., 2018; Mesimäki & Lehtonen, 2023).

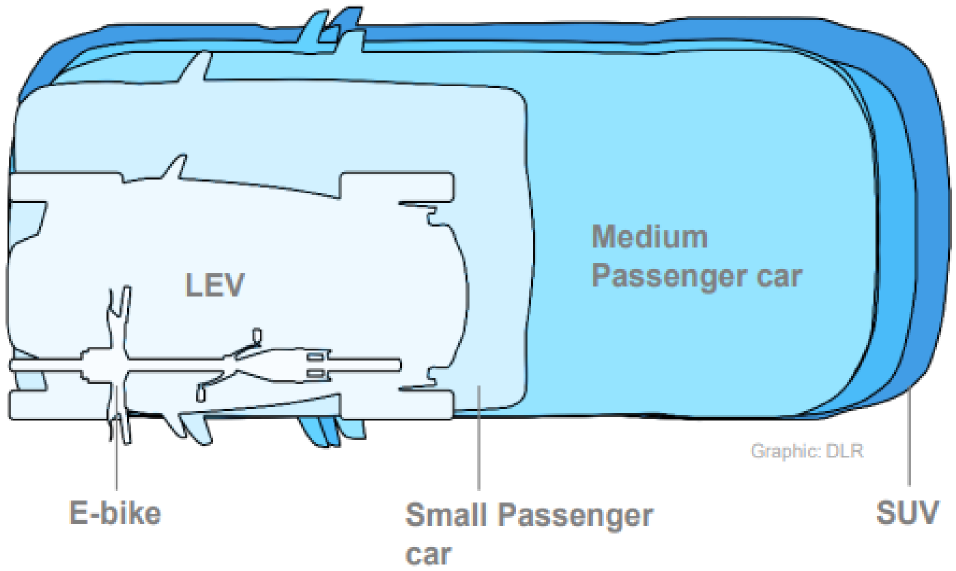


Figure 2. Size Comparison of Microcar with Other Types of Cars Available in the Market (LEV Represents Microcar) (Brost et al., 2022)

Despite their advantages, their market and research are less explored. Even though research on their potential for emissions reduction has been theorised to some extent (Brost et al., 2022), the possibility of real-world reduction is not well known. This requires understanding the research gap on adopting microcars or LEVs.

Furthermore, market adoption is greatly influenced by political frameworks and acceptance from society, so in Germany, the adoption of the smallest vehicle categories has been a big challenge (Böhrk & Radlwimmer, n.d.). Although shared mobility is not taken into account in the current research, research suggests that, as a part of shared mobility schemes, these microcars have significantly been promoted for their use, which has led to the advantage of vehicle accessibility to consumers without the need to pay upfront costs (Mesimäki & Lehtonen, 2023). This also aligns with Brost et al. (2022) findings that shared mobility has the potential yet requires many measures to implement and encourage consumers to switch from large vehicles to small ones (Brost et al., 2022).

In large cities, major traffic congestion is developed by large conventional cars, which occupy a great amount of space; these can be replaced by small urban cars, which are compact and have better drivability to tackle congestion, emissions and space constraints (Karaca et al., 2018). Congestion problems can be solved by microcar adoption as stated by one of the examples that Renault Twizy acquires about 20m2 less space when compared to Mercedes B-class when considered in terms of reaction time, stopping distance and the situation that both are at 30km/hr speed (Ewert et al., 2021).

However, with all the above challenges mentioned, Mesimäki and Lehtonen (2023) mention that despite all the benefits LEVs pursue, less familiarity with their usage has been one of the hurdles to tackling the increase in their adoption. This could be a significant step in encouraging uptake, especially among non-users. So, future work should focus on user mode choice behavior and acceptance of these preferences (Brost et al., 2022), which are pursued in the current study. In summary, the combination of user acceptance, familiarity with the technology, shared mobility, public awareness, and other technical frameworks for adopting microcars over regular conventional cars can be tackled.

2.2. Factors Influencing Transport Mode Choice

The attributes and their levels were decided extensively based on an in-depth literature review of the 24 works of literature, as the region division of these totals is shown in Figure 2. below. The major attributes affecting consumer adoption were decided based on the total number of times each attribute was included in the entire list of literature. Attributes with maximum total count were prioritised to be included in the study, and a few other attributes based on expert reviews and personal curiosity were considered in this study. Further, a detailed attribute-identifying procedure table from the literature review has been included in Table 1 below. The green counts represent the most repeated, orange represents medium representation, and red represents the least in that section. The repeated numbers along rows for each piece of literature represent the time that attribute was identified in that literature's review.

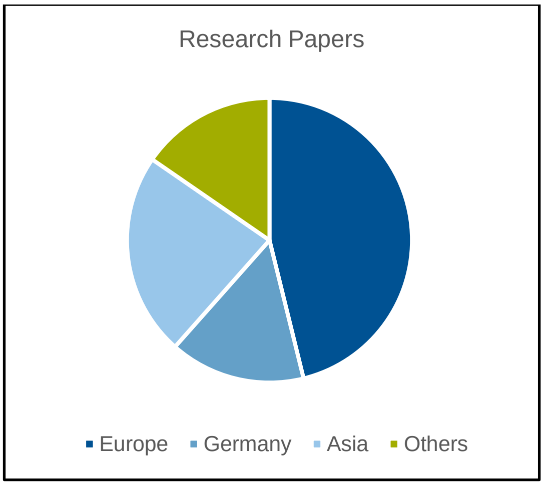


Figure 3. Division of Research Papers Reviewed

Table 1. Summary of Attributes Identified from Literature

Attributes	Count	(Secinaro et al., 2022)	(Junguera et al., 2016)	(Encarnação et al., 2018)	(Jansson et al., 2017)	(Helveston et al., 2015)	(Mersky et al., 2016)	(W. Zhang et al., 2022)	(Adu-Gyamfi et al., 2022)	(Schneidereit et al., 2015)	(Cellina et al., 2016)	(Dong, 2022)	(Bennett et al., 2016)	(Brost et al., 2022)	(Darup et al., n.d.)	(Broadbent et al., 2018)	(Sica & Deflorio, 2023)	(Liao et al., 2017)	(Ling et al., 2019)	(Bryla et al., 2022)	(Lebeau et al., 2016)	(Lashari et al., 2021)	(Wang et al., 2017)	(Smith et al., 2017)	(X. Zhang et al., 2014)
Vehicle attributes																									
Purchase price	32	2	2	0	1	1	1	1	1	1	1	0	1	0	1	6	0	1	6	1	1	1	1	2	0
Battery/recharging	33	1	2	1	1	1	1	1	1	1	1	1	1	1	1	7	0	1	5	1	1	1	1	1	0
Driving range	31	0	2	0	1	1	1	1	1	1	1	1	1	1	1	7	0	1	5	1	1	1	1	1	0
Top Speed	24	0	1	1	0	0	1	0	1	0	0	1	1	0	1	4	0	1	5	1	1	1	1	1	2
Acceleration	9	0	0	0	1	1	0	0	0	0	1	0	1	1	1	0	0	1	2	0	0	0	0	0	0
Operating cost	16	1	0	0	1	1	0	1	1	1	1	1	1	0	1	0	0	1	1	1	1	0	1	1	0
Other attributes																									
Environmental concerns	28	4	0	1	1	1	1	0	1	1	1	0	1	0	1	5	0	1	3	1	1	1	1	1	1
Knowledge/experience	27	1	1	0	1	0	0	1	1	1	1	0	1	0	1	9	0	1	3	1	1	1	1	1	0
Charging stations	16	2	0	1	0	1	1	0	0	0	1	1	0	0	1	4	0	1	1	1	1	0	0	0	0
Willingness to buy	7	0	1	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	3	0	0	0	0	0	0
Policy incentives	28	0	1	1	0	0	1	0	1	0	0	1	1	0	1	8	0	1	5	1	1	1	1	1	2
User Attributes																									
Age	16	0	1	0	1	1	0	1	1	1	0	1	1	1	0	0	0	1	1	1	1	1	1	1	0
Gender	14	0	1	1	0	1	0	1	1	1	0	1	1	0	1	1	0	1	0	1	0	1	1	0	0
Daily Range	14	0	1	0	0	0	1	1	0	1	1	1	1	1	1	1	0	1	0	1	1	1	0	0	0
Education	16	0	0	0	1	1	0	1	1	1	0	1	1	0	0	1	1	1	1	1	1	1	1	1	0
Income	18	0	0	0	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	0
HH_size/status	15	0	0	0	1	1	0	1	1	0	0	1	1	1	1	1	1	1	1	0	1	1	0	1	0
Region	12	0	1	0	1	1	0	0	1	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0
Employment status	7	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	1	0	1	1	1	0	0	0
No of cars	16	0	1	1	0	0	1	0	1	0	1	1	1	0	1	0	1	1	1	1	1	1	1	1	0
Access to charging	12	0	0	0	0	1	1	0	0	0	0	1	1	0	1	2	1	1	1	1	0	1	0	0	0
Childern	8	0	0	0	1	1	0	1	1	0	0	0	0	0	1	0	1	1	0	0	0	1	0	0	0
Car model	3	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Past EV ownweship	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0

The selection procedure for attributes from the above literature review for further discrete choice experiment will be explained in detail in Chapter 3.

2.3. Stated Preference Methods and Survey Design

2.3.1. Stated Preference Method

Stated Choice (SC) experiments need to be designed to understand the decisions made by an individual over a given choice situation based on the influence of independent attributes (Twaddle, 2011). SC generally contains revealed preference (RP) and stated preference (SP) experiments, but in the current study, only SP is adopted. Many SP experiments can be adopted in transport research experiments; one such technique adopted in this study was discrete choice experiments (DCE), which, based on hypothetical situations, is known to produce trade-offs between different attributes considered (Shah et al., 2015).

DCE comprises several choice sets presented to respondents, where each choice set contains different alternatives, which are described using attributes and their levels. So, respondents will be presented with a series of hypothetical choice sets and asked to choose between them, which will be further used to estimate the utility of the selected alternative (Shah et al., 2015). However, SP data reliability under hypothetical situations is limited as what each respondent chose across all the choice sets is inconsistent with their preference (Mengying Fu, n.d.).

2.3.2. Alternatives, Attributes and Their Levels

Identifying alternatives, attributes, and their levels for DCE is one of the important tasks; these attributes can be qualitative and quantitative, and these attributes should be less than 10 to obtain the most reliable experiment output (Szinay et al., 2021).

Based on an in-depth literature review, as stated before and shown in Table 1, alternatives and their levels will be adopted. Additionally, a content validation of the identified alternatives that are relevant to the study has to be done (Szinay et al., 2021). Further, after defining the number of alternatives, selected attributes can be shared or explicitly defined among the alternatives (Twaddle, 2011).

Further, with the identified alternatives and their validation, “none of the above” alternative was included in the study in order to make choice scenarios more realistic and to reduce hypothetical bias (Mengying Fu, n.d.). Respondents can choose none of the above options for two stated reasons: if either of the options was unattractive and if both were equally attractive (Mengying Fu, n.d.).

Once attributes have been identified, their levels can be defined, ensuring trade-offs between attributes. Here, trade-off refers to respondents giving up on one attribute to gain from another attribute (Szinay et al., 2021). It is seen that a balance between less number of attribute levels and a simple design with less content reduces the burden on respondents (Szinay et al., 2021).

2.3.3. Experiential Design

An experimental design method is adopted to define choice sets that will be presented to the respondents, which is the base for high-quality data (Szinay et al., 2021). A few considerations should be defined to obtain reliable design, such as previously defined analytical model, labelled or unlabeled design, type of design, and how well the attribute levels are balanced (Szinay et al., 2021).

The analytical model, such as the discrete choice model (DCM), which describes the probability of choosing a specific alternative, can be considered; this probability is defined as a function of independent variables (attributes) and their levels that are specific to alternatives, which indicated the probability of a dependent variable which is the choice of an alternative. A basic DCM, multinominal logit model (MNL), which can act as a strong base point for further model variations, can be considered (Szinay et al., 2021).

Further, deciding on labelled or unlabeled experiments depends on whether to have specific and different alternatives with alternative specific attributes that could be defined or have the same attributes along with unspecified alternatives. So, labelled experiment should be considered for a DCE as it estimates each alternative and their parameters considering alternative-specific attributes (Szinay et al., 2021). Once the model and its parameters are defined, DCE can be further generated based on the selected design.

The next step in DCE is to generate a number of choice tasks for each individual. To reduce the respondent's burden and loss of interest, the number of tasks defined should be considered within a certain limit. The literature suggests that most studies have choice tasks between 7 and 16 to obtain robust estimations (Szinay et al., 2021). So, here, 8 choice tasks per respondent were chosen to avoid any cognitive burden on respondents.

Further, there are many defined designs to perform DCE; full factorial or fractional factorial designs can be adopted depending on a number of attributes and research. Although full factorial design provides full combinations of attributes and levels which explain maximum possibilities, this is often not considered practical due to the high number of combinations generated (Szinay et al., 2021).

In the current study, if two alternatives with eight attributes (A) and four levels (L) each were considered, it would result in a total of LA (65536) number of possible alternatives from full factorial design. Still, with the help of fractional factorial designs such as random, efficient or orthogonal, this number can be reduced and arranged in required choice sets (Szinay et al., 2021).

However, an orthogonal design might not be practical for studies with more than five attributes, with each of more than two levels. It is only optimal with fewer levels (Szinay et al., 2021). On the other hand, efficient design requires prior information about attributes and their behaviour in the model, which are called priors. Further, efficient design is divided into many D-efficient designs (Szinay et al., 2021). So, to reduce the complexity of the experiment efficient design was also not considered in the current study.

Another simple yet efficient option was random design, where alternatives are randomly selected from full-factorial design (Mengying Fu, n.d.). Few pieces of literature argue that random design performs well in any design considerations, and it is expected to perform well when the presence of dominating alternatives is removed through applied constraints (Mengying Fu, n.d.).

So, a random design, as an efficient option for large samples that offered realism, was chosen as the final design for the current study (Loder, 2024). Further, to obtain more unbiased choices, each choice set was developed using unrepeated attribute levels, which were less used previously to ensure that the choice options presented were distinct.

2.4. Choice Modelling in Transport Research

2.4.1. Utility Model (Utility and Error terms, alternative specific constants)

The utility of an alternative is generally defined with attributes and their levels; DCM generally develops a model to maximize this utility across individuals (Mengying Fu, n.d.). Each respondent chooses an alternative based on the maximum utility calculated over each alternative. So, the utility equation 2.1 is given by.

$$Uiq = Viq + \mathcal{E}iq \qquad (2.1)$$

Where, Uiq: Utility calculated for i th alternative and q th individual,

Viq: Deterministic utility for i th alternative and q th individual,

$\mathcal{E}iq$: Error component.

(Mengying Fu, n.d.)

2.4.2. Utility of Choice Theory

The above-formulated utility in the utility model can be adjusted for choice theory, which can be explained by equation 2.2, where the deterministic part of the utility is further defined to contain mathematical functions that have attributes and their levels and characteristics of an individual (Koppelman & Bhat, 2006).

$$Uiq = ASCiq + V(Xiq) + V(Sq) + V(Xiq, Sq) + \mathcal{E}iq \qquad (2.2)$$

Were

$ASCi$: Alternative-specific constant for alternative i,

Uiq: Utility value of the i th alternative for the q th individual,

$V(Xiq)$: Deterministic element of the i th alternative for person q,

$V(Sq)$: Characteristics of individual q,

$V(Xiq, Sq)$: Interactions between the attributes of alternative i and the of individual q,

$\mathcal{E}iq$: Unknown Error component.

(Koppelman & Bhat, 2006)

Error Component

Since the error term is unknown, including it becomes important while accounting for each respondent's decision-making (Mengying Fu, n.d.). With the assumption that error terms have less impact on the value of an alternative considering missing components of each alternative. Errors will be generally distributed according to the central limit theory, which helps identify a DCM's mathematical form (Koppelman & Bhat, 2006).

2.4.3. Multinominal logit Model (MNL)

Based on the error term assumption above, probit models are formulated, but due to their limitations, an alternative Gumbel or extreme value distribution assumptions for error term leads to the formulation of logit models (Mengying Fu, n.d.).

MNL majorly holds for Independence from irrelevant alternative (IIA), which states that an individual's probability of choosing one alternative over the other presented alternative is unaffected by their presence (Louviere et al., 2000). So, this IIA property of MNL states that the error term here is independently distributed across alternatives and is identical (IID). So, MNL assumes that error is distributed according to extreme value type one (EV1); considering this, IIA and IID with EV1 MNL probability of an alternative can be formulated in equation 2.3 below (Louviere et al., 2000; Mengying Fu, n.d.).

$$P_{iq} = \frac{e^{V_{iq}}}{\sum_{j=1}^{J} e^{V_{jq}}} \qquad (2.3)$$

where Piq: the probability of selecting alternative i, Viq: deterministic component of the utility of alternative i, VJq: deterministic component of the utility of alternative j.

(Train, 2009; Mengying Fu, n.d.)

However, MNL assumes that the entire population is homogeneous and that all alternatives are equally likely to be selected by the respondent for their IIA properties. To overcome this limitation, other models are defined further (Koppelman & Bhat, 2006; Mengying Fu, n.d.).

2.4.4. Hybrid Choice Model (HCM)

DCM has become a standard approach nowadays, especially for transport research. However, these simple models based on the utility of an alternative, attributes, and characteristics of an individual fail to capture respondents' decision-making latent variables, attitudes, perceptions, beliefs, etc, which are expected to influence the decision process. So, HCM attempts to define and include these variables in DCM, such as MNL (Kim et al., 2014a).

So, HCM is a framework which combines different types of models into a single framework. HCM adopts a defined latent variable model (LVM) into DCM to improvise its explanatory power. Latent variables are obtained by considering attitudinal variables while defining them. LVM is expected to identify the underlying latent construct from the defined attitudinal variables (Kim et al., 2014a).

Although there many methods exist to identify underlying latent structures from a set of attitudinal variables, such as factor analysis (FA) and sequential equation modelling (SEM), each of those has its limitations, especially when adopting these latent constructs into discrete choice models (Kim et al., 2014a). FA identifies latent variables, but it has limitations, such as it only considers attitudinal variables included and not the actual choice behavior of the respondents, which makes identified latent variables to be alternative-specific variables (Kim et al., 2014a).

So, SEM was considered to account for this limitation, where SEM accounts for both latent attitudinal construct and choice behavior across alternatives. Even though SEM is similar to HCM, it has limitations. SEM generally adopts a regression model to estimate continuous variables but has a limitation regarding discrete variables. So, to overcome both FA and SEM's limitations, HCM has been adopted in the current research (Kim et al., 2014a).

HCM consists of an LVM and a DCM, where LVM consists of two parts: the measurement equation (FA) and the structural equation (SEM), which are defined in equations 2.4 and 2.5. (Kim et al., 2014a).

$$X_n^L = \Gamma^{LZ} X_n^Z + \zeta_n^L, \quad \zeta_n^L \sim \mathcal{N}\left(0, \sigma_{\zeta LL}\right) \qquad (2.4)$$

Where: 1. X_n^L is a $(L \times 1)$ vector representing the latent variables for individual n. 2. X_n^Z denotes a $(Z \times 1)$ vector of observable explanatory variables. 3. Γ^{LZ} represents a $(L \times Z)$ matrix of unknown parameters that link explanatory variables to latent variables. 4. ζ_n^L is a random error term accounting for unobserved factors, which follows a multivariate normal distribution $\mathcal{N}(0, \sigma_{\zeta LL})$ with zero mean and a covariance matrix $\sigma_{\zeta LL}$.

$$I_n^D = \Lambda^{DL} X_n^L + \epsilon_n^D, \quad \epsilon_n^D \sim \mathcal{N}(0, \sigma_{\epsilon DD}) \qquad (2.5)$$

Where: 1. I_n^D is a $(D \times 1)$ vector of observable indicator variables, such as responses to survey questions, for individual n. 2. Λ^{DL} is a $(D \times L)$ matrix of unknown parameters linking latent variables to observable indicators. 3. ε_n^D is a random disturbance term representing measurement error, assumed to follow a multivariate normal distribution $\mathcal{N}(0, \sigma_{\varepsilon DD})$ with zero mean and a covariance matrix $\sigma_{\varepsilon DD}$.

Further, the logit model comprises both of the above equations. Then, the defined SEM equation is incorporated into the utility, which comprises the defined latent variables. As the FA equation is defined for utility maximization, the utility function of the model is defined below in equations 2.6 and 2.7. (Kim et al., 2014a).

$$U_{in} = \beta_Z(i) X_n^Z(i) + \beta_L(i) X_n^L(i) + \beta_M(i) X_n^M(i) + \epsilon_{in}, \quad \epsilon_{in} \sim \mathcal{G}(0, \sigma_{\epsilon_i}) \qquad (2.6)$$

$$y_{in} = \begin{cases} 1, & \text{if } U_{in} = \max_j \{U_{jn}\} \\ 0, & \text{otherwise} \end{cases} \qquad (2.7)$$

Where:

Where U_{in} is the random utility of alternative i for individual n. The notation (i) after a variable matrix indicates the ith column vector corresponding to the variable matrix. Notation (i) after a parameter matrix indicates the ith row vector corresponding to the parameter matrix. Thus, the notation (i) represents the components in terms of the ith alternative in each variable and parameter matrices.

Further, the latent vector's matrices are expanded to account for individual alternative utility; thus, their dimensions become (Z × J), (L × J) and (M × J). Thus, $ß_Z$, $ß_L$, and $ß_M$ correspond to unknown matrix parameters that were estimated through individual specific, latent and other variables that will take the dimensions of (J × Z), (J × L) and (J × M). (Kim et al., 2014a).

Note: The explanations were generated using latex, and a snapshot of them has been added to Word due to the complexity of writing these symbols in Word.

2.4.5. Latent Class Analysis (LCA)

In addition to HCM with logit model adoption, Latent Class Analysis (LCA) with the model (LCM) was adopted to analyse the class behavior of individuals across the choice selection.

Further, categorical variables with similar patterns in LCA form a latent class variable, C. If Y_1 …., Y_m represents binary indicators (categorical variables), an attempt will be made to identify response patterns in Y_i indicators defined. So, to estimate distinct C in $Y_{i,}$ a latent class model (LCM) will be incorporated as shown in equation 2.8 below(Tompsett, n.d.):

$$P(Y) = \sum_{j=1}^{c} P(C = j) \prod_{k=1}^{m} \prod_{l=1}^{R_k} P(Y_k = l \mid C = j)^{I_{Y_{k}=l}} \qquad (2.8)$$

Were,

P (C = j) was the structural element that models the C with other non-indicator variables, and the second part was the measurement element that links the latent classes defined with the categorical indicator variables.

(Tompsett, n.d.)

Once the C value is specified, the output parameters will be calculated based on equation 2.8; once the posterior probabilities of each individual belonging to a class are determined, each can be assigned to a class based on their maximum posterior probability (Tompsett, n.d.).

$$W = \arg\max_{j}\big(P(C = j \mid Y_1, \ldots, Y_m)\big) \qquad (2.9)$$

Were W defines the maximum probability output.

(Tompsett, n.d.)

Once individuals are assigned to a defined class based on their maximum posterior probability, utility equations adopted from equations 2.6 and 2.7 will be incorporated to understand class-wise utility values.

2.4.6. Maximum Likelihood Estimation

In logit models considered, estimated probabilities are of closed form to which a maximum likelihood estimation can be applied, but maximizing the log function is much simpler and has been adopted for estimation. So, the function can be maximized by deriving a derivative concerning each parameter and setting it to zero (Train, 2009; Mengying Fu, n.d).

3. Methodology

In this section, two major methodologies are described. Considering the research objectives, the stated choice experiment was adopted with the modelling framework for further analysis of mode choice data. The first section, 3.1, describes the choice experiment workflow to survey data collection methods involved. Section 3.2 describes the initial data analysis adopted for mode choice data analysis and the methodological framework adopted in this study for further insights into collected data.

3.1. Stated Choice Experiment

Since the study was focused on the entire Germany, data was collected for the same. The section below explains the methodology for building the survey and data collection.

3.1.1. Selection of Alternatives, Attributes and Levels

The study is majorly based on the LEV4Climate Study's theoretical adoption possibility of LEVs conducted by the German Aerospace Center (DLR), where the possibility of a shift from regular conventional vehicles to LEVs was analysed based on vehicle, individual and other characteristics (Brost et al., 2022). However, this study's primary focus was comparing the adoption of microcars over regular BEVs available in the market and understanding individual perceptions of EVs and microcars. As EVs and microcars majorly belong to the electric vehicle category, the need to understand this small microcar's acceptance over existing EVs in the market was derived. Hence, EVs versus microcars were the two alternatives to be included in the discrete choice experiment (DCE). None of the above was included as an alternative to understanding more realistic choice behavior.

Once these alternatives were decided to be included in the choice experiment, the attribute levels of each attribute were defined based on the characteristics of EVs and microcars available in the real-world market. A list of EVs and microcars that are considered is shown in Figure 5. The actual levels of these vehicles are represented in Appendix A and, further, based on identifying all alternative attributes from the literature review in Table 1 in Chapter 2.2. the below-explained attributes and their levels were selected to obtain a more efficient design.

Vehicle Attributes

Based on the literature review shown in Table 1. and with a theoretical understanding of each attribute and its importance in the study, the final attributes shown below were selected based on the maximum counts of each attribute accounted for across all literature (Figure 4).

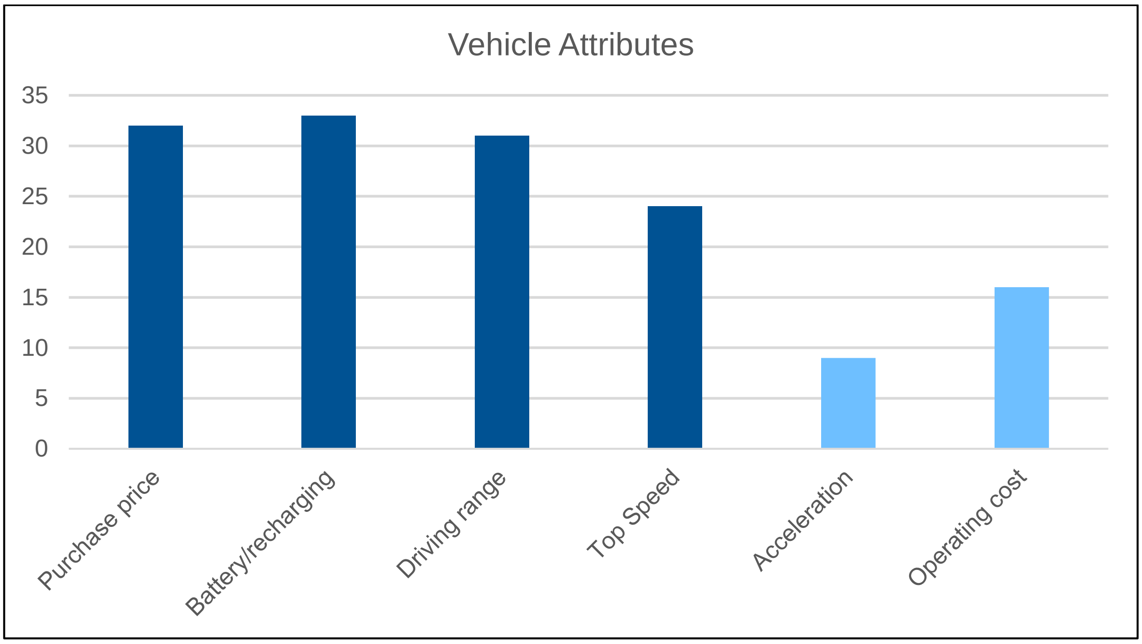


Figure 4. List of Vehicle Attributes from Literature

The above graph shows all the attributes identified from the literature, and the highlighted bars represent the chosen attributes for the choice set experiment. Purchase price and battery charging were among the most reviewed vehicle characteristics in the literature. Acceleration and operation cost still seem to be well reviewed but not considered in the choice experiment and the study as a greater number of variables might cause increased dimensionality during the choice set experiment. So, to simplify the choices, the most mentioned four variables were chosen.

Microcars	**Battery Electric Vehicles**
1. SmartForTwo	1. Dacia Spring Electric 45
2. Microlino	2.Hyundai INSTER Long Range
3. Renault Twizy	3. Renault 5 E-Tech 40kWh 95hp
4. Varaneo	4. Mini Cooper S
5. Citroen Ami	5. MG ZS EV Standard
6. Eli Zero	6.Smart #1 Pure

Figure 5. List of Market Available Vehicles Chosen to Define Attribute Levels

Even though the set of selected attributes for both the alternatives are the same, different levels were defined based on the actual values from the above-listed vehicles. This was done to ensure that respondents were well exposed to real-world choice options even though choice set creation was random from defined levels. Charging time, top speed, and purchase price had the same number of levels in both microcars and EVs, but for range, EVs had an additional level defined as EV ranges that are vastly wider compared to microcars in the current market. Levels for both EVs and microcars are shown in Tables 2 and 3.

Attitudinal and Other Attributes

While microcars offer advantages with parking, cost, charging satisfaction and compact size, they also raise controversy regarding safety concerns, which need to be addressed (Ling et al., 2019). Another factor of comfort is also well recognized with microcars and needs to be given particular attention (Zhao et al., 2023). Although other factors drive microcar adoption, in addition to vehicle attributes, safety and comfort attributes, which are mainly of microcar interest, were adopted in the study and analysed for their perception.

Considering the above vehicle-specific attributes, there were other attributes literature reviews identified that affect the adoption of EVs and microcars. Concerning Table 1, some additional attributes like environmental concern, knowledge about existing EVs and their performance, and policy incentives implemented by the government in adopting these vehicles were identified, as shown in Figure 6 below, where highlighted bars represent selected variables. While policy incentives had a more significant impact on adoption, only environmental concerns and knowledge about electric cars were included as variables in the model, as policy incentives alone can be a different research question.

Further, the attribute environmental concern was adopted in the choice set based on the levels defined from the Life Cycle Assessment (LCA) of each vehicle mentioned in Figure 5, and the levels were kept constant for all the vehicles considered in the choice set. Nevertheless, the summary tables 2 and 3 explain all the levels included. Further, Appendix B shows the LCA calculations of all the vehicles in a table.

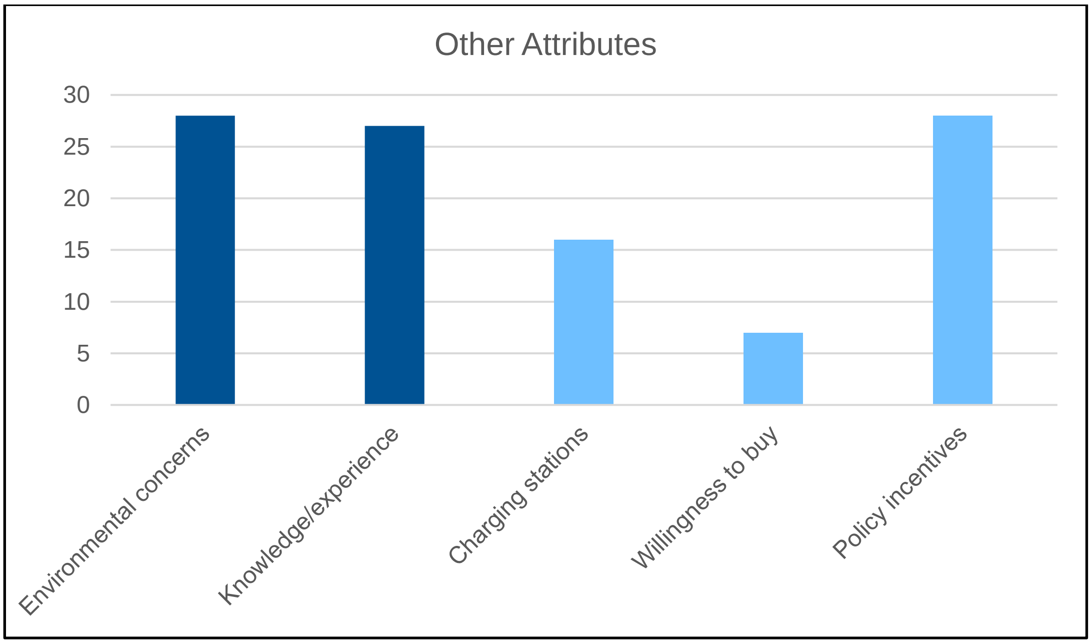


Figure 6. List of Other Attributes from Literature

Now, concerning additional attributes considered, comfort levels for both alternatives were kept constant while considering the number of seats as a reference. Since most microcars possess two seats, the Basic (Two seaters) level was set, and the Standard (Four seaters) was set for regular EVs.

While defining safety levels was tricky as it can be a personal perception, ADAC, in collaboration with EURO NCAP, conducts a study called “Crashtests” based on a few vehicle criteria. These tests led to defined safety ratings out of five. Based on these ratings, safety levels for considered (Figure 5) vehicles were identified, two levels (4 stars and 5 stars) were defined for EVs, and a constant level (3 stars) was identified for microcars (Crashtests | ADAC, n.d.; The Ratings Explained | Euro NCAP, n.d.).

These ratings were defined based on five important areas and their scores: Adult occupant protection, which was defined for driver and passenger safety; child occupant protection; pedestrian protection; and overall safety assistance (The Ratings Explained | Euro NCAP, n.d.). In the current choice experiment, only driver's safety and overall safety assistance were identified as the most important due to limited explainability on presented choice cards for respondents. The driver's safety score was determined based on impact from front and lateral (Adult Occupant Protection | Euro NCAP, n.d.). The safety assistance was determined from the performance of vehicles during regular driving and simulated accident scenarios (Safety Assist | Euro NCAP, n.d.). A table explaining safety considerations for selected vehicles is represented in Appendix C at the end of the document.

In addition to all the identified attributes, the study added battery swapping availability as an attribute, as knowledge of using the battery swapping technology was found important in considering the adoption of EVs (Adu-Gyamfi et al., 2022).

Socio-Demographic Attributes

In reference to Table 1, all the above variables in Figure 7 from the user attributes section were considered in the survey. While the highlighted ones were included during model development, car models and past EV ownership were considered in respondents' exploratory data analysis (EDA).

The levels for all the highlighted bars in the above graphs were adopted solely from the Mobility in Germany (MiD) 2017 household survey; all the adopted levels are shown in a table in Appendix D at the end of the report.

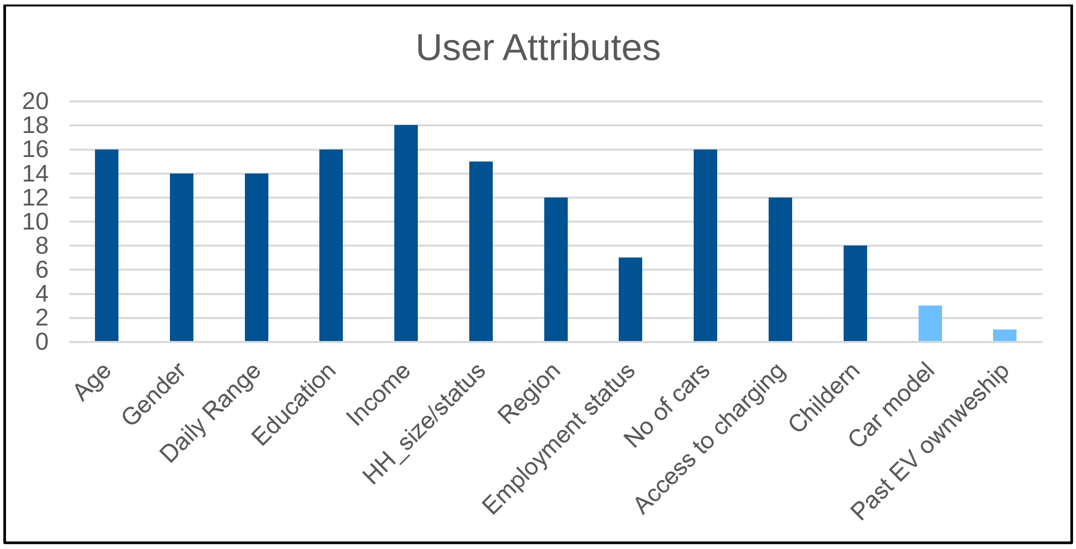


Figure 7. Socio-demographic Attributes from Literature

Summary of Alternatives, Attributes and Their Levels

The two tables below summarise the attributes and their levels for respective alternatives. In addition to the two below, “None of the above” was included as an alternative in the choice cards.

Table 2. Microcars Attributes and Attribute Levels

Microcars	Levels	1	2	3	4	5
	Vehicle					
	1. Purchase price	8,000 euros	10,000 euros	13,000 euros	17,000 euros	20,000 euros
	2. Charging time (Home Charging)	3hrs	4hrs	5hrs		
	3. Top speed	45km/hr	80km/hr	120km/hr		
	4. Range	75km	100km	120km		
	Others					
	1. Environmen-tal effects (Compared to e-SUV)	Co2 reduction of 60%	Co2 reduction of 70%	Co2 reduction of 80%		
	2. Comfort	Basic (Two-seater)				
	3. Safety	3 Stars (50% safety assist and 70% driver safety)	4 Stars (60% safety as-sist and 80% driver safety)			
	4. Battery Swapping	Widely Available	Available only at se-lected lo-cations	Not Availa-ble		

Table 3. Electric Vehicles Attributes and Attribute Levels

BEVs	Levels	1	2	3	4	5
	Vehicle					
	1. Purchase price	18,000 euros	22,000 euros	26,000 euros	30,000 euros	34,000 euros
	2. Charging time	4hrs	6hrs	8hrs		
	3. Top speed	140km/hr	160km/hr	180km/hr		
	4. Range	200km	230km	270km	300km	
	Others					
	1. Environmen-tal effects	Co2 reduction of 40%	Co2 reduction of 50%	Co2 reduction of 60%	Co2 reduction of 70%	
	2. Comfort	Standard (Four - seater)				
	3. Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety as-sist and 95% driver safety)			
	4. Battery Swapping	Widely Available	Available only at se-lected lo-cations	Not Availa-ble		

3.1.2. Choice Sets

After finalizing the alternative, attributes, and attributes levels, constraints were applied to further design the choice experiment. An overview of constraints considered particularly for microcars (MEVs), EVs and others is shown in Figure 8.

Further, a random design method strategy was adopted to define eight choice sets for each respondent based on theoretical minimum design size (A statistical requirement for any design), as shown in the equation below (Loder, 2024).

Minimum Theoretical Design Size > (number of parameters) / (number of alternatives – 1)
where,
number of parameters = 8,
number of alternatives = 3,
Therefore, the minimum design size = 4.

Although the theoretical minimum was four, eight choice sets were defined to increase the statistical significance of the study. Further, Appendix E contains a figure of all eight choice cards.

Microcar	
Attribute/Level	Constraint
Price 8k	Cannot have 5hrs charging
Price 8k	Can only have 45kmph
Price 8k	Can only have 75km range
Price 8k	Can only have 3 stars
Price 20k and 17k	Cannot have 3hrs charging, 75km range, and 3 stars
45kmph top speed and 75km range	Goes only with 8k price

BEVs	
Attribute/Level	Constraint
Price 34k	Cannot have 4hrs charging, 140kmph, and 200km range
Price 18k	Can only have 4hrs charging, 140kmph, and 200km range

Others	
Attribute	Constraint
Non-overlapping attributes	Charging time, battery swapping, and safety across choice sets
Price pairing	BEVs (18k) should not be paired with MEVs (17k or 20k)
Charging comparison	MEVs (3hrs) should not be compared with BEVs (4hrs); MEVs should be compared with longer BEV charging times (6hrs or 8hrs)
Speed comparison	MEVs (120kmph) should be compared with BEVs (140kmph)

Figure 8. Overview of Constraints Used in the Choice Experiment (Note: BEVs refer to EVs)

Additionally, to provide real-world comparison and imagination to respondents, each choice set had images of vehicles attached to them solely based on the purchase price attribute of that choice set. An example of the choice cards is shown in Figure 9 below.

Choice Set 4	Choice A	Choice B
		
Purchase Price	8,000 euros	34,000 euros
Charging Time (Home Charge)	4 hrs	8 hrs
Top Speed	45 km/hr	180 km/hr
Range	75 km	230 km
Safety	3 Stars (50% safety assistance and 70% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO_2 reduction of 80% compared to electric-SUV	CO_2 reduction of 60% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Widely Available	Not Available

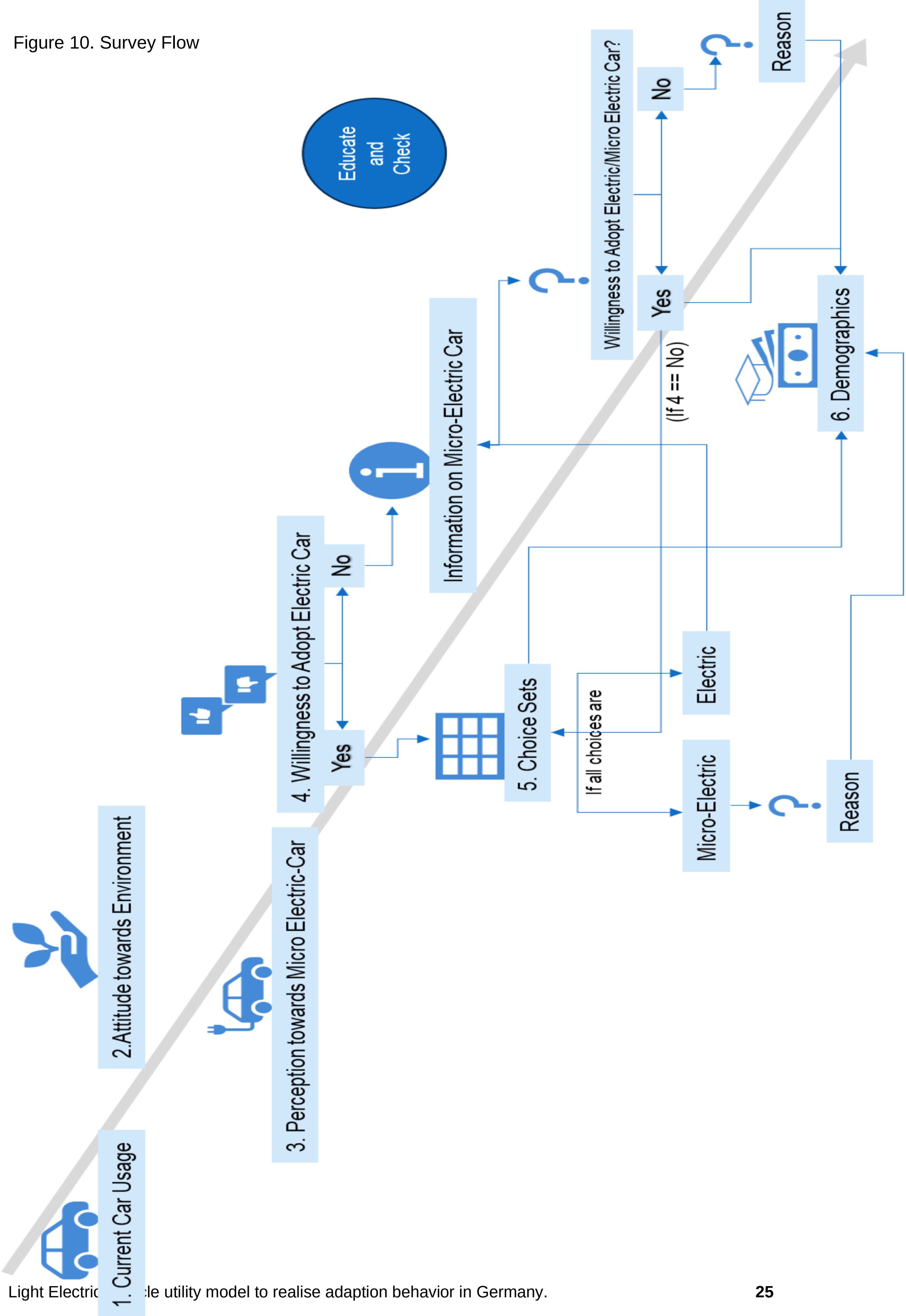
Figure 9. Example of Choice Card

3.1.3. Survey Framework

Given that the study analysed a hypothetical situation, the possibility of choosing a microcar over an EV, a stated preference (SP) survey was designed and conducted. The survey consists of six major sections, as shown in Figure 10. The flow starts with filtering people younger than 18 due to extensive legal driving age rules in Germany, even though the presented situations are hypothetical. Further, the survey starts by asking respondents about their current car usage and its daily to yearly patterns, followed by their attitude towards the environment through Likert scale questions and a section to understand perception towards microcars, on charging time, range, and, most importantly, features while adopting them. Then, respondents were asked about their willingness to adopt an electric vehicle soon, and accordingly, they were led to eight choice sets, or they were educated about microcar’s advantages and yet again led to choice sets if the respondent was convinced to buy a microcar based on the provided information. Further, reasons for adopting and not adopting the presented vehicles were asked, and a demographic section was concluded at the end, considering that providing personal information can be sensitive.

Note: The complete survey, including all the sections and questions, is provided **in Appendix F**.

Figure 10. Survey Flow



3.1.4. Survey Data Collection

Initial data collection started with distributing surveys online through company mailing systems, LinkedIn pages, and Facebook. However, the selected target area for the study was Germany, so the primary requirement of the survey was to get a representative sample of the entire country. So, an online survey distribution platform called CINT was utilized, and the survey was distributed through the same. The platform, which gave access to the target group of people, also ensured that the sample was representative based on pre-defined quotas of respondents. The sample was representative of all the states of Germany and throughout the categories considered in the study, as shown in Table 4. The data collection for this study was funded by the German Aerospace Center (DLR), which covered all the costs associated with the considered survey platform.

The minimum sample size for DCE based on the general thumb rule was defined to make sure sample size N satisfies the inequality and to obtain a statistically reliable sample, which is called ‘Omre’s formula”, as shown below (Assele et al., 2023):

$$N \geq 500 \frac{L^{max}}{J\,S} \qquad (3.1)$$

Where Lmax is the largest number of attribute levels considered across both alternatives, i.e. 5, J is the number of alternatives represented in each choice task (excluding ‘None of the above’ options), i.e. 2, S is the total number of choice sets presented for each individual i.e. 8, and value 500 is defined for the general population (Assele et al., 2023). The current study's resulting N (minimum sample size) value was 157.

The survey was conducted during September 2024. A total of 456 complete responses were collected and valid throughout Germany. Out of a total of 145 respondents showed their unwillingness to own any kind of electric car anywhere in the near future, and 22 out of these respondents chose yes to adopt a vehicle after being informed about the advantages of a microcar adoption (An information card represented to respondents is shown in Appendix G). So, 333 (N) respondents were chosen for further analysis.

3.2. Model Framework

This section explains the initial exploratory analysis before the model. It provides an overview of the general framework considered in the model development and analysis process, further explained in Chapter 5.

3.2.1. Exploratory Data Analysis (EDA)

EDA was done in two significant parts of factor analysis: Confirmatory factor analysis (CFA) and Exploratory factor analysis (EFA). Based on survey data, three potential latent variables were hypothesized for CFA: Car usage intensity based on the car usage pattern section of the survey, environmental concern based on the environmental concern Likert scale section, and knowledge about microcars based on the knowledge section of the survey. Based on factor loadings and standard error in identifying the loadings of each variable on each hypothesized latent variable, a latent variable was identified, and further factor scores were calculated based on the final identified variables for each latent variable.

Furthermore, EFA was done on socio-demographic variables to identify which characteristics led to potential groups of people in the survey. Based on the number of factors defined in EFA, their calculated factor scores were utilized to identify potential clusters of individuals using the K-means clustering methodology. Further, these identified clusters of individuals were utilized in model estimation to determine their potential behavior towards microcar adoption. Further, a detailed explanation of EDA is provided in Chapter 4.

3.2.2. Model Development and Estimation

The framework of model flow is shown in Figure 11, which follows a Hybrid Choice Model (HCM); the framework includes a latent variable model (LVM) and latent class analysis (LCA) into the discrete choice model (DCM) to understand individual preferences of presented vehicles based on stated choice data collected from the survey. The adopted DCM type in the current study was the Latent Class Model (LCM).

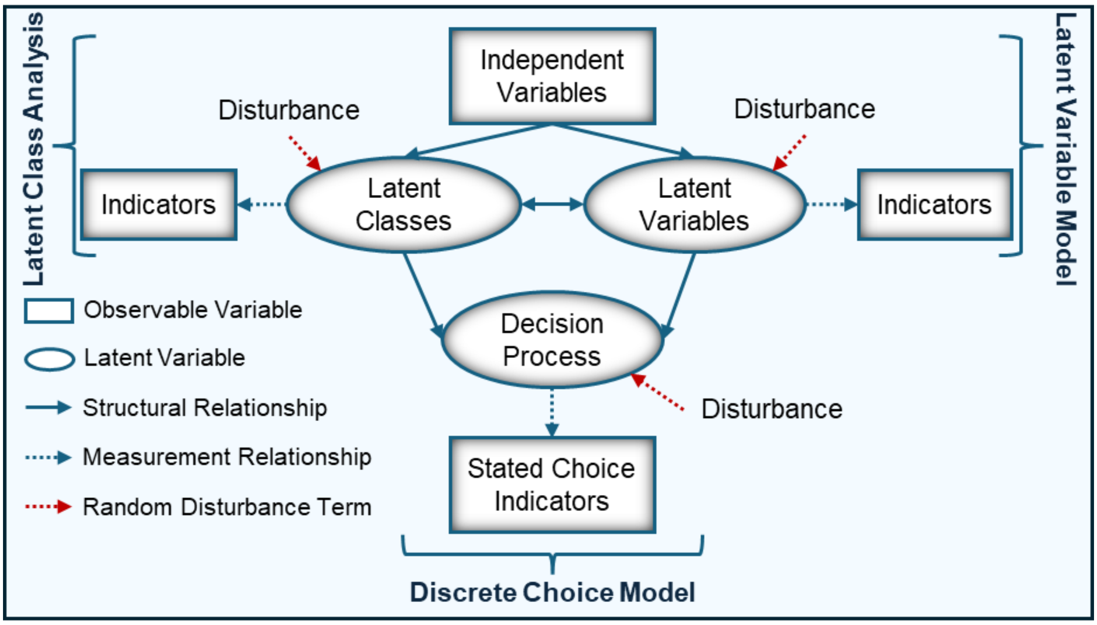


Figure 11. Hybrid Choice Model Framework (adapted for this thesis based on (Kim et al., 2014, pg. 22)

The right part of the framework explains the structure of LVM; indicators are the variables considered while defining the hypothesis for CFA earlier in Chapter 3.2.1. The variables which confirm the latent structure from CFA were adopted for further structural equation modelling (SEM) in LVM. Here, the influence of socio-demographic variables as indicators of these defined latent variables was analysed. The model adopted stepwise variable addition, and only the variables significant for each latent variable were retained for the final SEM. Further, factor scores for each individual were defined based on SEM and were identified to incorporate in LCM.

The left part of the framework explains LCA, where indicators represent observable socio-demographic variables utilized to identify latent classes of individuals from survey responses. Based on similar characteristics among individuals, classes were defined. Random error term was accounted for while identifying a number of classes to account for any unobserved disturbances in the latent class classification process. These identified groups were further incorporated into the model to define utilities based on each class and to understand their class-wise preferences.

Further, LVM and LCA were incorporated with indicator variables from choice sets to define LCM using DCE, where the choice probability of each choice among classes was determined. Additionally, for model comparison, a simple multinomial logit model (MNL) where individuals were analysed and a single class was built, mainly to understand the class division preference compared to one whole class of respondents.

4. Data Analysis

This section explains survey data representation among different variable levels, the overall description of the data, the initial analysis of choice sets, the preliminary analysis of data, and the results of exploratory data analysis, providing insights for further statistical data analysis.

4.1. Survey Data Representation

Table 4. Comparison Tabel of Sample and Population Characteristics Distribution in Germany

	Germany	
Variables	**Sample %**	**Population %**
Gender		
Male	47.37	49.2
Female	52.63	50.8
Age		
18-24 years	10.75	8.87
25-44 years	36.76	29.64
45-59 years	28.51	25.98
60-64 years	7.02	8.04
65 years and older	16.96	27.48
Education		
Primary or secondary school (up to 8th grade)	9.18	19.14
Intermediate school leaving certificate or equivalent (up to 10th grade)	34.48	40.2
High school diploma or vocational training (Abitur, EOS 12th grade)	26.16	12.3
University degree and Other degree	27.43	20.3
No formal qualification yet	2.75	8.05
Employment		
Employed (full-time, part-time and marginal)	66.62	59.1
Student	3.07	4.55
Housewife/Househusband (Others)	5.26	7.29
Pensioners	17.37	25.16
Currently unemployed	7.68	3.9
HH_Size		
1 person	26.1	21
2 people	33.11	30
3 people	23.03	18.2
4 people	11.84	17.9
5 or more people	5.92	12.8
Childern		
Households with children below 18 years (at least 1 kid)	44.08	48.02
Households with no children	55.92	51.98
Households with Net Income		
Less than 500 euros	3.95	Average net income: 3661euros
500 to less than 1,500 euros	15.35	
1,500 to less than 2,000 euros	12.94	
2,000 to less than 3,000 euros	23.03	
3,000 to less than 4,000 euros	20.83	
4,000 to less than 5,000 euros	12.94	
5,000 to less than 6,000 euros	6.58	
6,000 to less than 7,000 euros	2.63	
More than 7,000 euros	1.75	

Table 4 above provides an overview of the comparison of socio-demographics across most variables between sample data collected from the survey and German population data from (Zensus 2022) for N = 456. As the table shows, most of the sample subgroups align closely with the population subgroup. As the sample sufficiently represents the population, weighting was not considered in the sample data in further EDA and model development.

Note: Two individuals preferred not to reveal their gender, and two others chose the “others” option; these four were assigned to the Male category.

4.2. Preliminary Analysis

Initially, choice data with the rest of the available variables was converted from wide format to long data, and hence, it was analysed for its patterns. Each 456 respondents faced eight choice sets, so 3648 observations of long-format data were obtained. Figure 12 below shows the number of times each alternative was chosen.

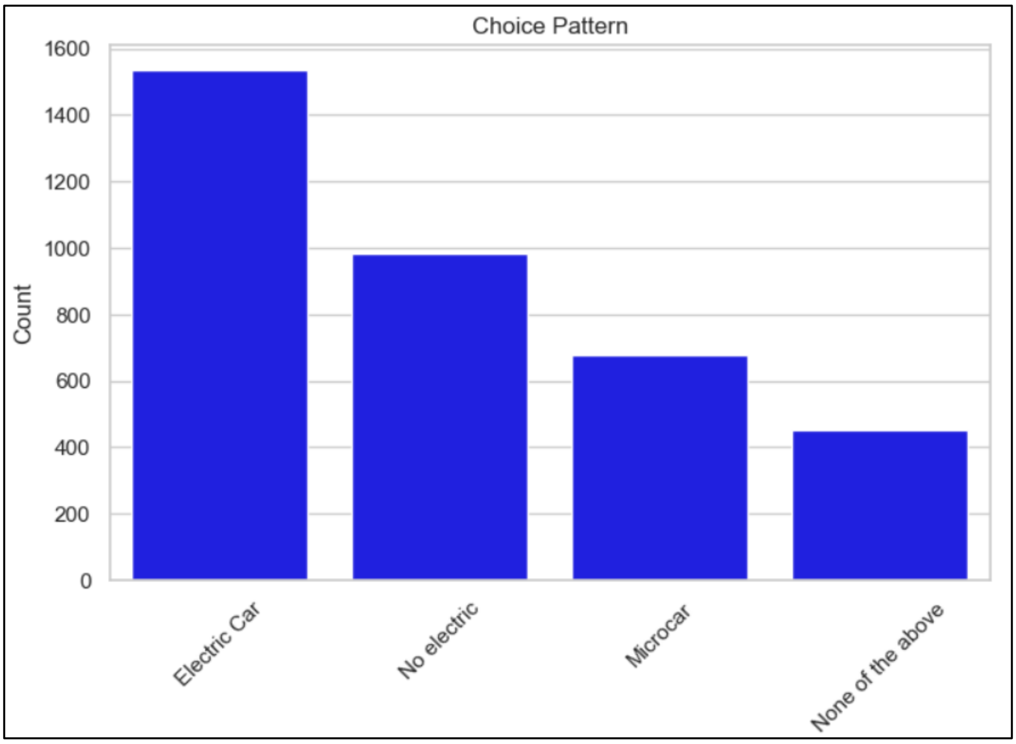


Figure 12. Choice Pattern Across all Alternatives

The figure shows that EVs were the most chosen among all other alternatives, possibly due to the advantages of considerable range, top speed and other characteristics these vehicles possess. No electric choice also accounts for most of the count, indicating respondents might still not be ready to transition to electric vehicles altogether.

Interestingly, most people preferred not buying an electric vehicle over choosing a microcar, which identifies that they might not be considered a prominent choice among respondents, opening the floor for further analysis.

Socio-demographic characteristics are expected to influence the decision-making process. So, a few variables that impact these decisions are shown and explained below from Figures 13 to 15. Three major categorical variables, age, income and gender, are only considered below. The correlation matrix was plotted to understand the independence of these socio-demographic variables versus choice attributes. No significant correlation (>0.70) was observed between any attributes.

4.2.1. Mode Choice Decision Among Age Groups

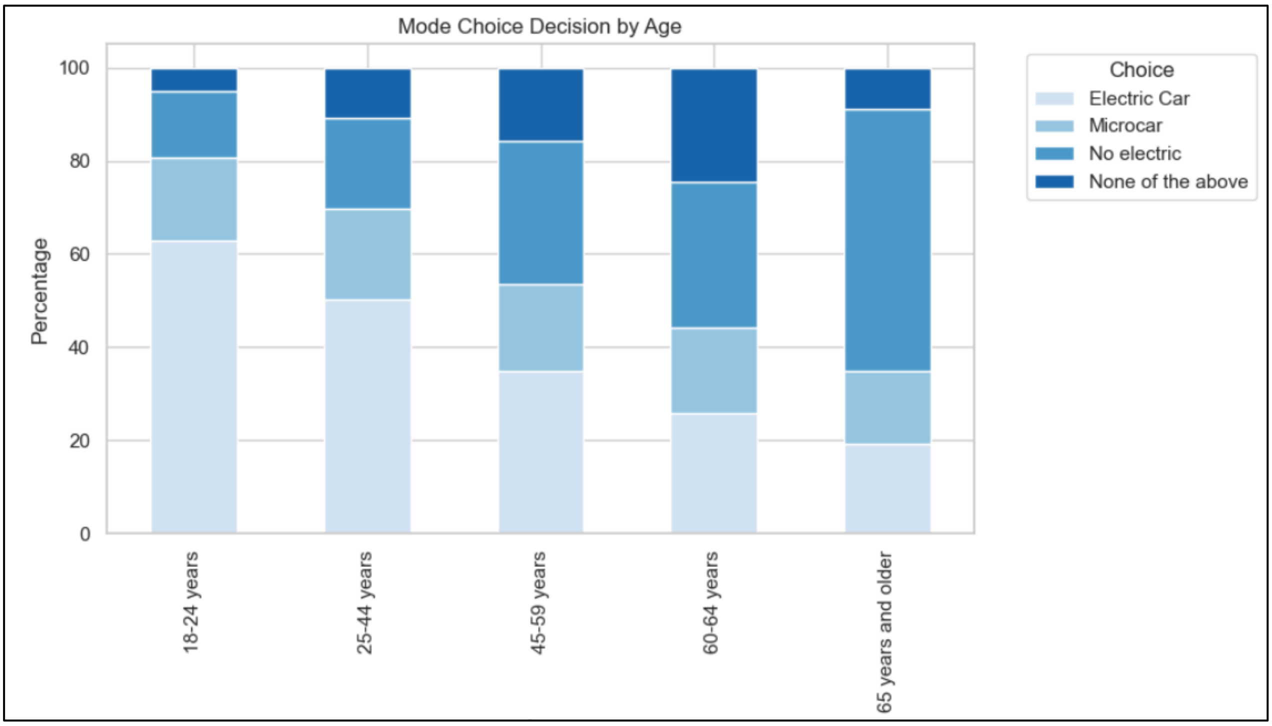


Figure 13. Segmentation of age groups based on their preference for vehicles versus no vehicles.

The graph explains that younger age groups tend to adopt EVs over other options, decreasing age increases. Although the possibility of choosing a microcar across all age groups remains almost similar, the possibility of not being willing to adopt any electric car increases with age. Older people, 65 and above, are much more likely not to choose any electric car, which might depict the possibility of unfamiliarity or other age-related concerns.

4.2.2. Mode Choice Decision Among Gender Groups

Gender groups did not represent much differentiation among different choices, showing that both categories were equally likely to choose any option from the choice set presented, as shown in Figure 14.

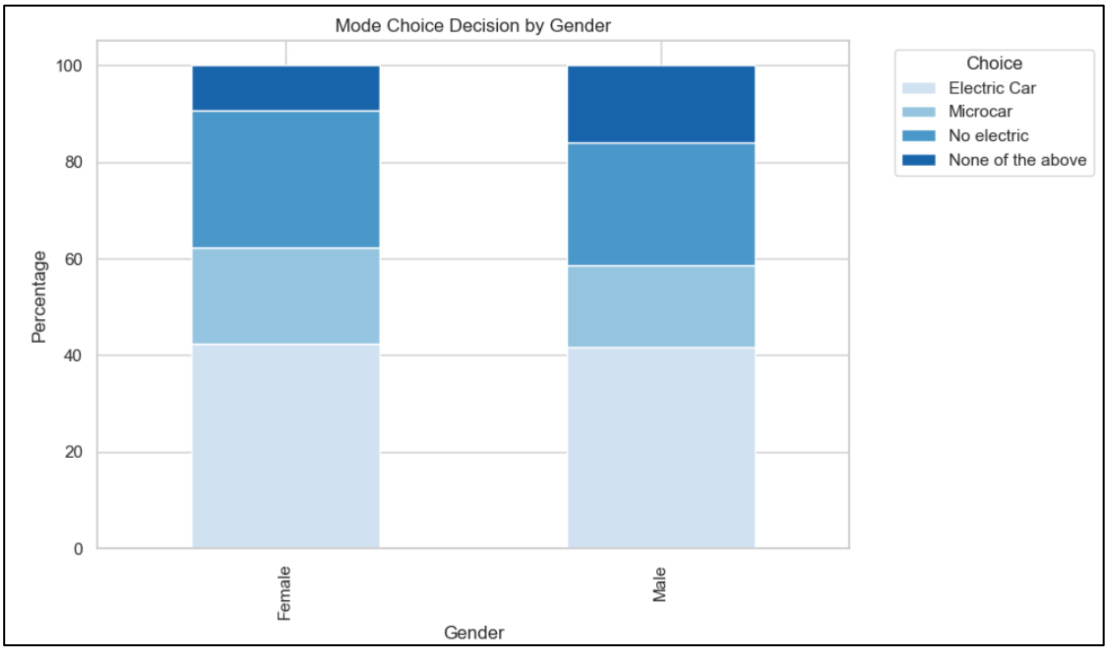


Figure 14. Mode Choice Behavior Among Gender Categories

4.2.3. Mode Choice Decision Among Income Groups

Income groups and their choice decisions showed that less-income people (less than 500 euros per month) are significantly less likely to adopt EVs and microcars and are more likely to choose no electric. This is contradicted by higher-income people, who are more willing to adopt an EV. In contrast, people with more than 7000 euros of income tend to choose none of the above options rather than not buying any electric vehicle, as shown in Figure 15.

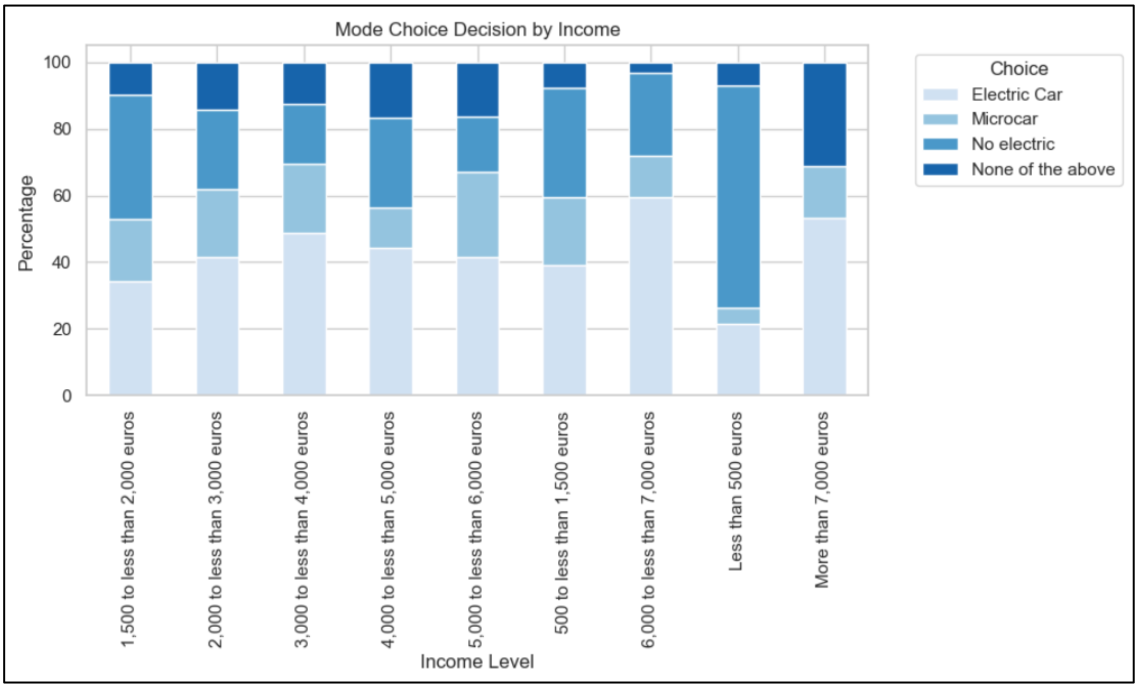


Figure 15. Mode Choice Behavior Among Income Groups

4.2.4. Correlation Matrix

The correlation between all the independent variables identified in the sample data set was plotted, confirming less correlation between all other variables except for between choice attributes. The correlation plot for the same is shown in Figure 16.

The correlation between each alternative specific attribute is considered here. A high correlation exists between the purchase price and top speed in EVs, which is greater than 0.7, and in microcars (MEVs), it exists between the purchase price and range, purchase price and safety, and range and safety. Since all these variables are continuous, an attempt was made to convert these into categorical variables, and yet again, the correlation between these attributes was checked, but the correlation persisted.

So, a decision on combinations of attribute inclusions that were impossible in the model's utility equation was made to mitigate the problem of high correlation. Also, a few interaction terms were introduced between highly correlated variables to reduce the direct impact of it yet include and observe its behavior in the model.

For EVs, the interaction term between the purchase price and speed was defined, and for microcars, two interaction terms, purchase price and range of the vehicle and between the purchase price and safety, were determined.

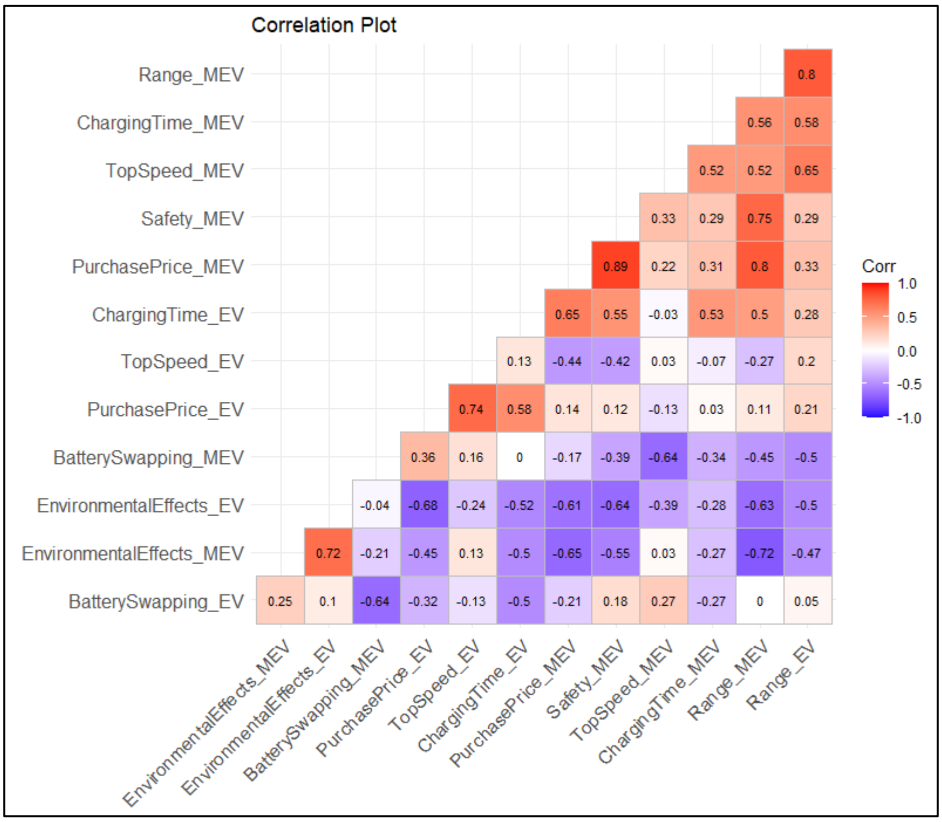


Figure 16. Correlation Matrix Between Choice Attributes

4.3. Results of EDA

4.3.1. Confirmatory Factor Analysis (CFA)

CFA was done by hypothesizing three latent variables: environmental concerns (E_C), knowledge about microcars (K_M) and current car usage intensity (C_U). Environmental concern was hypothesised for five observed indicators (Likert scale questions from 1 to 5 about environmental attitude, five being greatly concerned) where each indicator question was coded as e_1, e_2, e_3, e_4 and e_5, knowledge about microcars was hypothesised for indicators related to familiarity and understanding of microcars such as technological awareness (kn1) level, range perception (kn2) and charging time perception (kn3). Further, current car usage was hypothesised using indicators such as daily car usage patterns (cr_), daily travel distance (dt_), car usage for long distances (c_), yearly travel distances (yr_) and the number of cars available (n_c). All three were defined to form a reliable latent variable.

Initially, all the indicators for all defined latent variables were considered, and each indicator's factor loading was checked on the respective latent variables. All indicators with less than 0.5 loading with an error greater than 80% were removed from latent variables to improve the overall model fit. Figure 17 shows the indicators' initial factors on three defined latent variables.

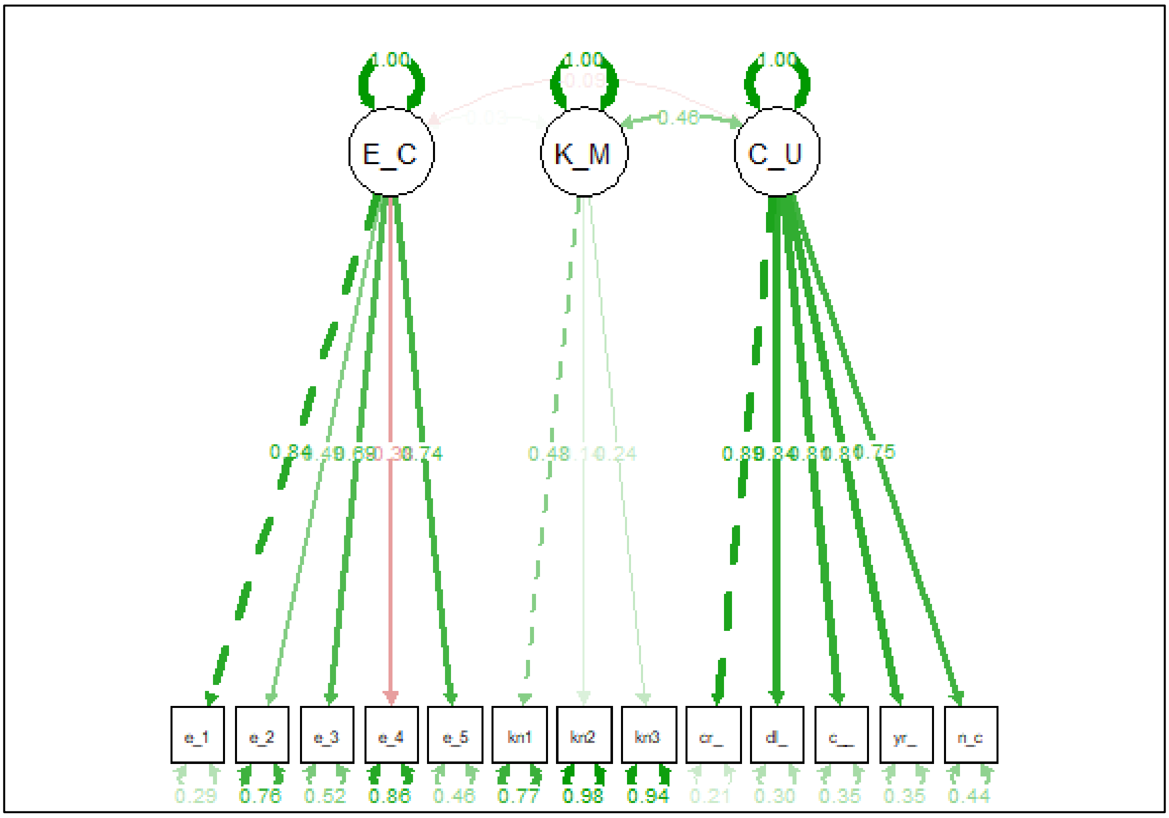


Figure 17. Initial Loadings of Indicators on Latent Variables

The initial dotted line represents the reference indicator to further evaluate the indicator loadings; the linked arrows between latent variables represent the correlation between each other. The last row values on each indicator represent the error value with which the factor ladings were estimated. Further, the e_4 indicator for the E_C latent variable was removed, as theoretically, it was a reversed question about environmental concerns (to check respondents' attention during the survey) to improve the model's overall fit.

As K_M had loadings less than 0.5 from all indicators, the hypothesis of keeping K_M as a latent variable was rejected and was removed from the model to improve overall model fit. Additionally, correlated indicators of each latent variable were defined in the model equation as correlated residuals to increase the model fit indices. The final model fit measures for both of the latent variables once low-loaded indicators have been removed are shown in the tables below.

Table 5. CFA Final Fit Measures for Car Usage Intensity

cfi	tli	rmsea	srmr
0.996	0.973	0.074	0.012

Table 6. CFA Final Fit Measures for Car Usage Intensity

cfi	tli	rmsea	srmr
0.999	0.99	0.058	0.006

The Comparative Fit Index (CFI) and Tucker-Lewis Index (tli) have values above 0.9, indicating a good fit. In contrast, the Root Mean Square Error of Approximation (sea) and Standardized Root Mean Square Residual (some) have values closer to 0, confirming the good fit further. Further, environmental concerns and current car usage intensity factor scores for each individual were obtained for further analysis while accepting them as a latent variable. The distribution of each is shown in Figure 18. Further, the model measurement equation of HCM of CFA for both latent variables is attached in Appendix H. Model outputs are further discussed in section 5.1.2.

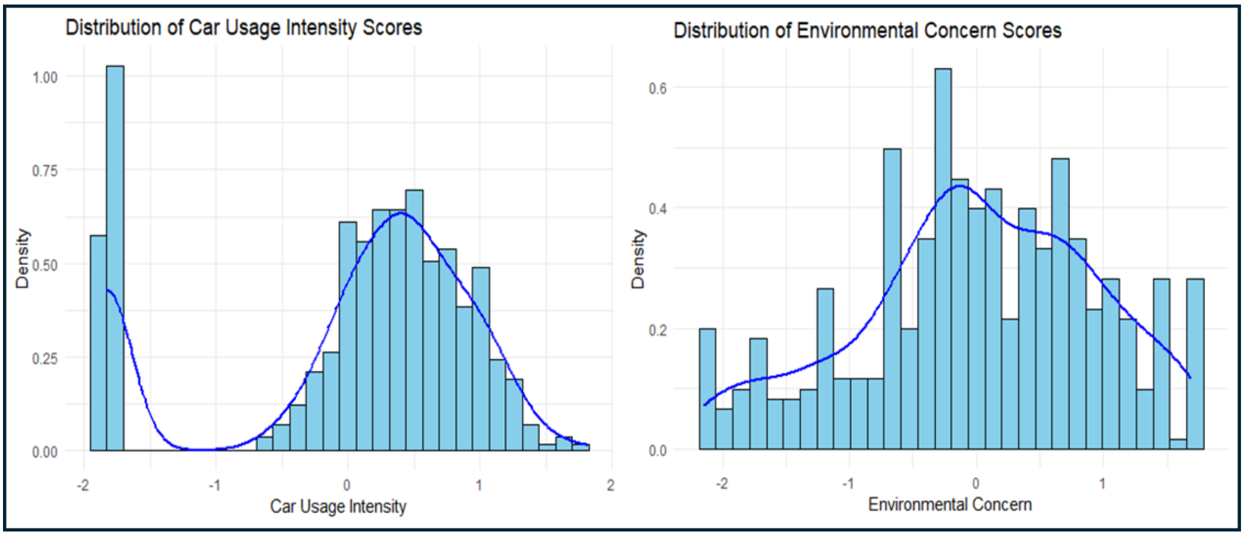


Figure 18. Latent Variable Factor Score Distribution

The distributions of car usage intensity show two modal peaks, where the extremely negative end values represent respondents who rarely use a car or do not own one. In contrast, closer to one and two, the right peak indicates more frequent car users, likely regular car commuters or those who use their cars extensively for long-distance and regular commuting.

Further, environmental concern distribution shows a central peak reflecting participants with moderate environmental concern, which may represent most of the general population's views. Tails of the distribution account for respondents with very low and highest environmental concerns, ensuring a diverse population.

4.3.2. Exploratory Factor Analysis (EFA)

Socio-demographic variables in the sample were used to identify potential groups of people in EFA. Initially, the data was tested for its suitability to perform based on Bartletts's Test chi-square value and its significance. Kaiser-Meier Olkin's Measure of Sampling Adequacy (KMO) was also considered. For Bartlett's test for a chi-square value of 2954.78, the p-value was less than 0.05, making it significant for further consideration.

Further, while checking for KMO measure, to improve KMO, individual KMO values of all selected variables were checked, and variables with comparatively very low KMO (<0.5) values were dropped to increase overall KMO suitability. The final KMO measure for selected variables was found to be 0.6. While the KMO value should be greater than 0.8, as a rule of thumb, 0.6 is also an acceptable measure (Nkansah, 2018).

Finally, age, education, household size, number of children, the youngest child in the household, categories of gender and categories of the region were finalised for further EFA based on the above two test considerations.

The scree plot for identifying factors was plotted as shown in Figure 19. Although the plot did not specify an evident elbow point as a rule of thumb, a number of factors with an eigenvalue greater than 1.5 were considered. As seen in Figure 19, the number of identified factors was initially three.

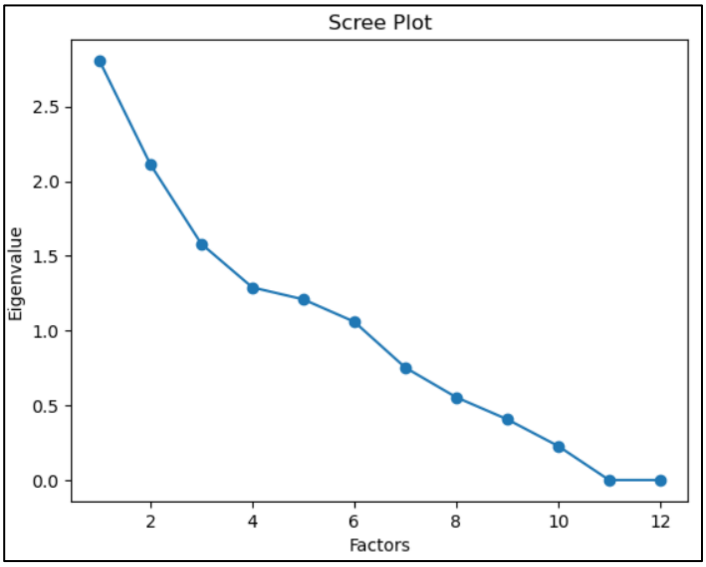


Figure 19. Scree Plot for Identifying Number of Factors

However, the total variance explained by the three factors was only 47.65% for the variables considered. So, all the variables which had loadings less than 0.4, as a rule of thumb, were removed, and it was found that after the removal of a few variables with just two factors, the variance explained was 69.41%. As a significant improvement in the variance explained, only three variables (household size, number of children, and youngest child) were considered, along with two factors. The factor loadings of each variable are shown in Table 6.

Table 6. Factor Loadings of Variables on Each Factor

Variable	Factor 1	Factor 2
Household size	0.69	0.42
Number of Childern	0.66	0.63
Youngest Child	0.41	0.65

Strong loadings of household size (0.692) and children (0.660) on Factor 1 suggest this factor captures the characteristics of large families. Larger household sizes often correlate with the presence of children. The moderate loading of the youngest child (0.415) indicates that the youngest child might be older in these households, as larger families tend to include children across a wider age range.

The strong loading of the youngest child (0.650) and children (0.628) on Factor 2 suggests this factor focuses on families with younger children. The lower loading of household size (0.423) indicates that this factor applies more to medium-sized families rather than huge ones. Medium-sized families focusing more on younger children might prioritize specific child-related needs (e.g., safety or child-friendly products).

Based on these initial interpretations, two-factor scores for each individual were calculated to identify potential clusters based on K-means clustering, explained in the next section, 4.4. To evaluate the reliability of the identified latent from EFA, a Cronbach's Alpha value was calculated, which was found to be 0.84, and the range of reliability for values between 0.80 to 0.89 was found to be good on a scale of unacceptable to excellent as value towards 1 indicates a strong correlation between variables and their ability to measure the underlying construct (Zahreen Mohd Arof et al., 2018). Further, distributions of defined factor scores are attached in Appendix I.

Note: Principal Component Analysis (PCA) was also performed in parallel with EFA; However, PCA for two components explained a total variance of 76.7% for the same set of variables, and yet EFA was the chosen method as its study focused on identifying the underlying constructs rather than maximize the variance across selected variables.

4.4. K-means Clustering

Clustering was performed based on the factor scores obtained from EFA. Before clustering, an optimal number of clusters (k) was identified from the elbow point in the inertia and silhouette score's plot, as shown in Figure 20. While the elbow measures the cohesion of the cluster, it alone will reach zero with an increase in k. So, the Silhouette method, which uses a silhouette score which analyses both the separation and cohesion of cluster, was used (Saputra et al., 2020).

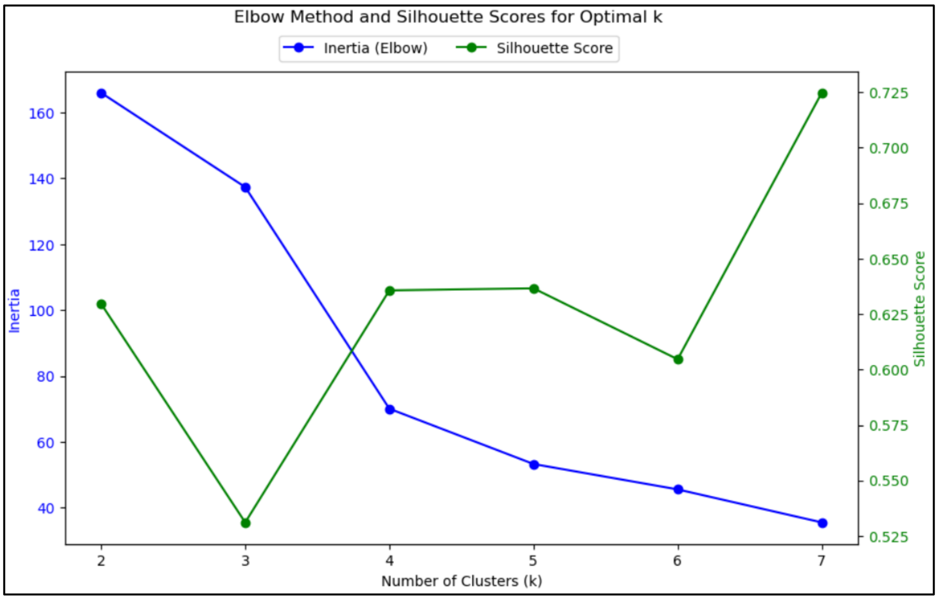


Figure 20. Identifying Optimal k for Clustering

So, as the graph shows, after k =4, the rate of reduction in interim slows down, indicating a diminishing return from adding more clusters, so this was identified as our elbow point in terms of inertia. Although the silhouette score is highest for k = 7, the second highest score at k=4 was retained, leaving k=4 as our most optimal value to defined clusters.

After defining the optimal k value, the mean of factor score values across these defined clusters was calculated to understand the loadings of factor scores and the definition of clusters. Figure 21 shows the clusters defined considering two dimensions. These identified clusters were named further, as shown in the legend.

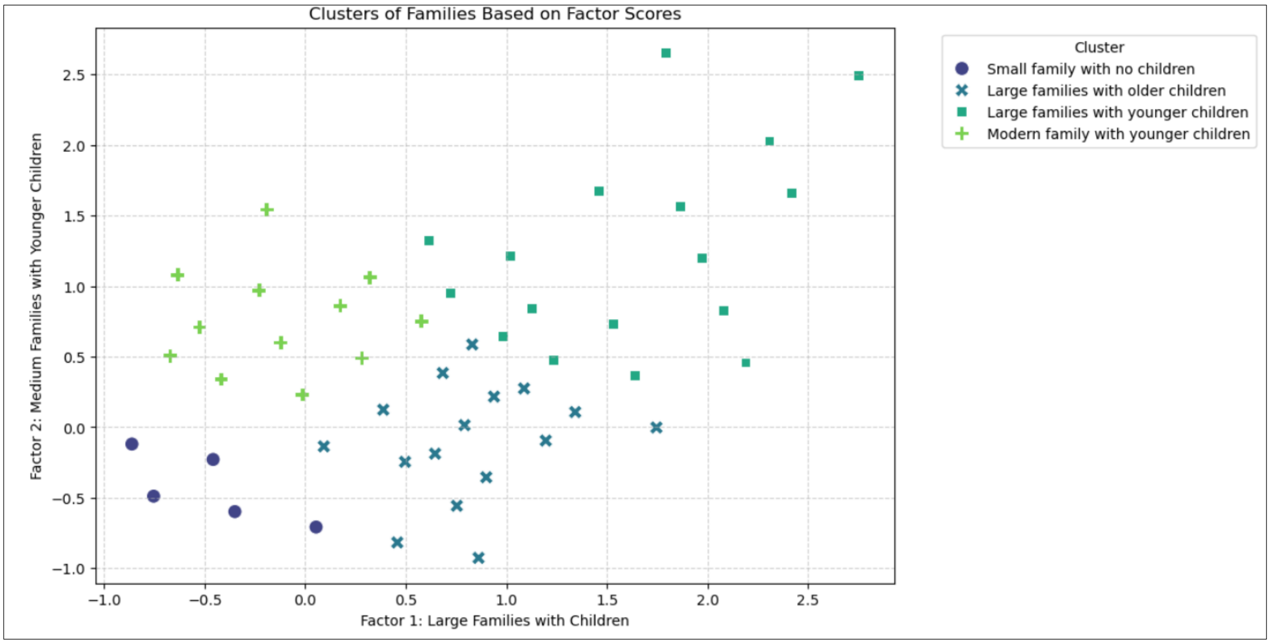


Figure 21. Identified Clusters

The table below represents the factor score across each cluster to define the meaning of each cluster identified. Cluster 0, which has high positive loading on factor 1 and negative loading on factor 2, was identified as a group with “Larger families with older children”. Cluster 1, which shows high and negative loadings on both factors 1 and 2, was identified as “Small family with no children”, which was also found to be the group which accounts for most of the individuals in the entire data set, as shown in Figure 22’s Cluster 0’s cluster width. Cluster 2, which has positive and high loadings on both factors, represents individuals with “Large families with younger children”, and finally, Cluster 3, which had positive high loading on factor 2 and negligible loading on factor 1, was identified as “Medium-sized families with younger children”.

Table 7. Mean Factor Loadings Across Identified Clusters

Cluster	Factor Score 1	Fcator Score 2
0	0.61	-0.16
1	-0.51	-0.55
2	1.36	1.11
3	0.12	0.69

Further, to gain confidence in the defined number of clusters and to validate them, the Silhouette Coefficient for each cluster was calculated, as shown in Figure 22. The average of 0.6 indicates that clusters are well-separated and defined. Cluster 1 is well defined but with less distinction as most respondents belonged to one or two-person households with no children. Cluster 3 and Cluster 2 had high scores with more distinct individuals. Although Cluster 0 had a relatively low score, the overall cluster validation was adopted in the current study, although there might be room for improvement in further research.

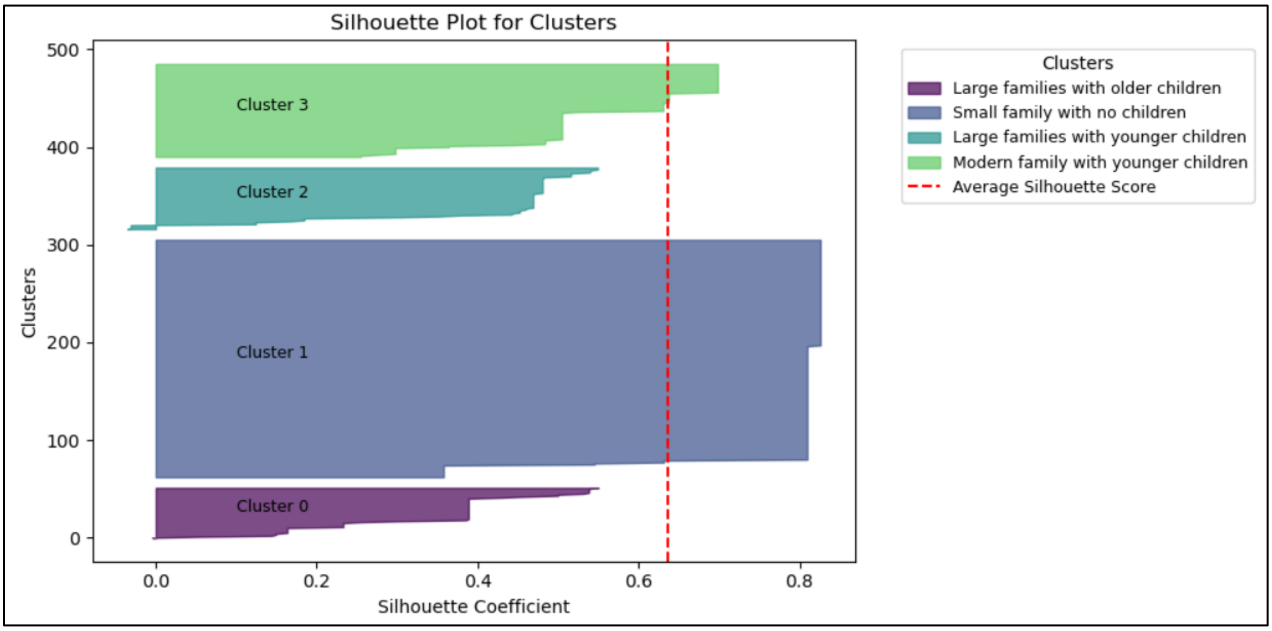


Figure 22. Silhouette Scores of Identified Clusters

4.5. EDA on Identified Clusters

Furthermore, an EDA was performed to understand the income groups, region division and car usage intensity among defined clusters. The two figures below, Figures 23 and 24, show the distribution of income and region across clusters.

Figure 23 shows that small families with no children have less to medium family net income than medium-sized families with younger children and larger families with younger children. Figure 23 shows that small families with no children live primarily in rural and urban areas, which might include older couples and young couples, and their lifestyle preferences for rural and urban regions. Large families with older children tend to be mostly in suburban areas and might include older couples with teenage kids who prefer their lives in the suburbs. In contrast, most medium-sized or large families with young children prefer to stay in the metropolis.

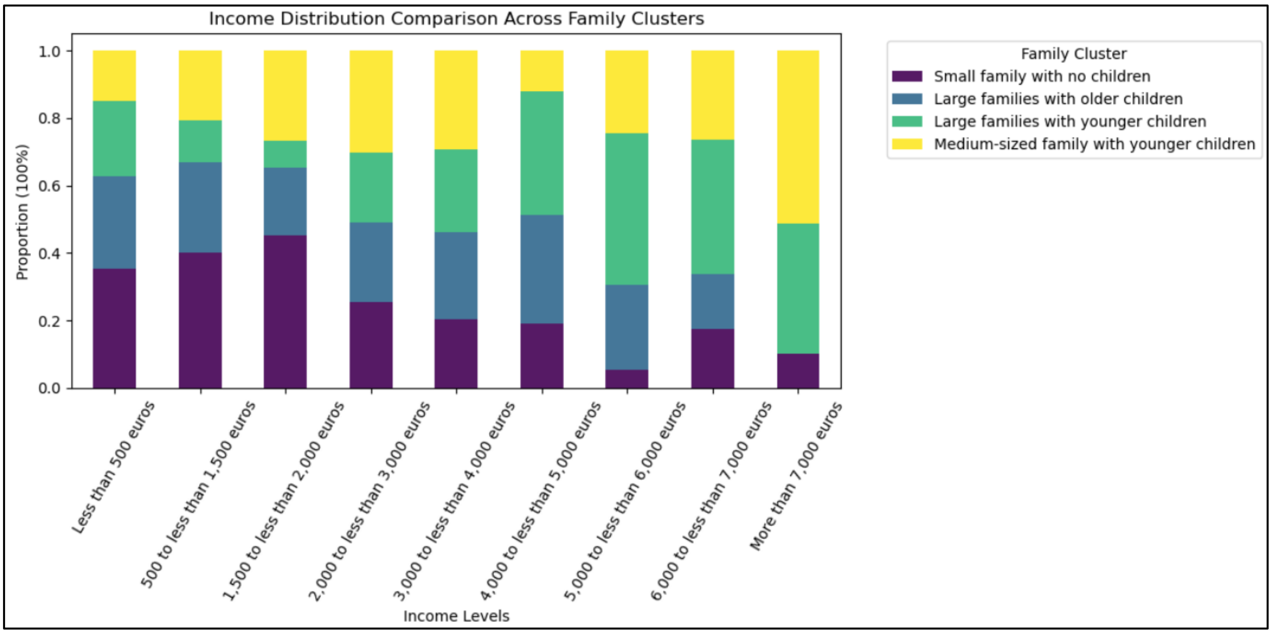


Figure 23. Income Distribution Across Family Clusters

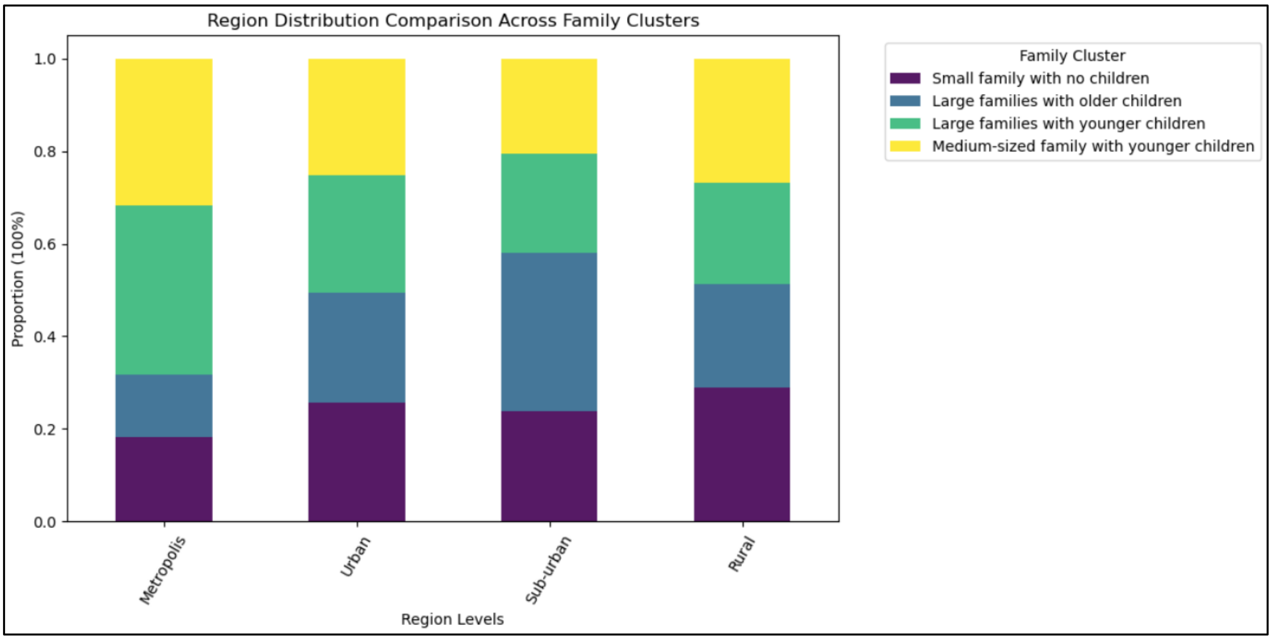


Figure 24. Region Distribution Across Family Clusters

Further, the latent variable “Car Usage Intensity” identified from CFA was considered to understand car usage intensity among family groups. The Kernel Density Estimation (KDE) shows the bimodal distribution across members, where each KDE was normalised to compare the intensity across groups. The left tail in the bimodal of each cluster represents families with no car ownership or usage.

Small families with no children show a high peak in the left tail, indicating that this group does not own a car, most likely due to smaller family sizes and less need for car dependency. Large families with older children show car dependence. However, the intensity is lower compared to small families, which can be interpreted as, although these families own a car, their usage intensity might be distributed across family members or through alternative transport modes. Medium-sized families and large families with younger children exhibit higher usage intensity and dependence on cars. In contrast, larger families have the highest intensity, which signifies more dependence on car usage due to the presence of younger children in the households.

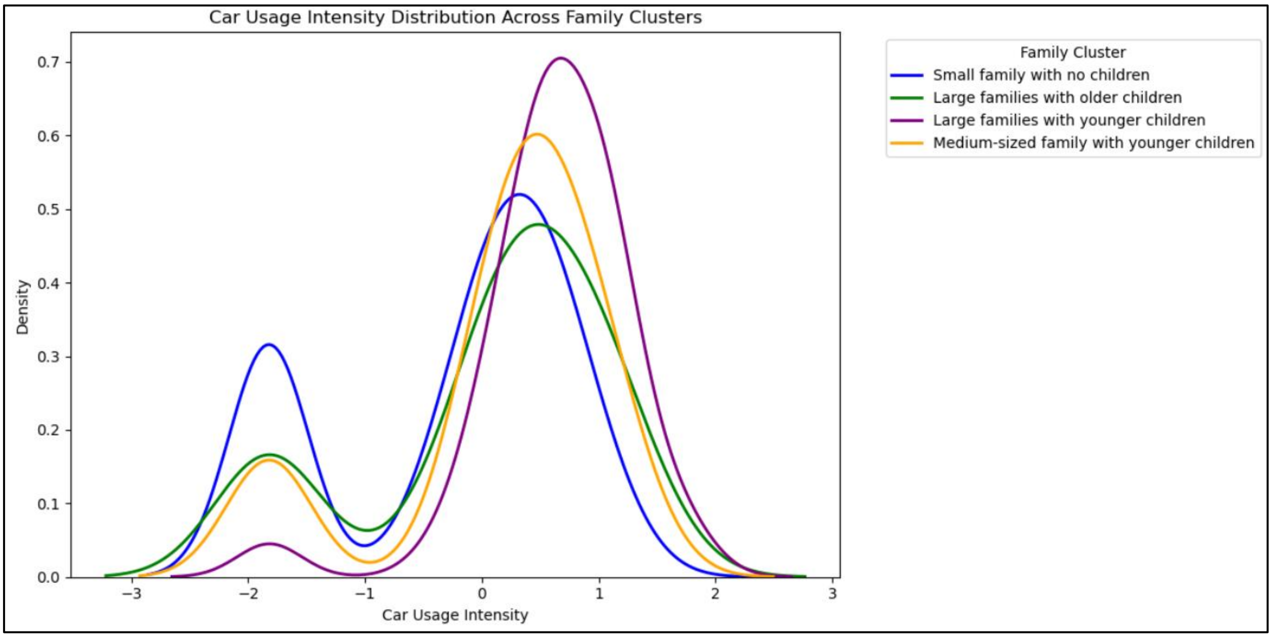


Figure 25. Car Usage Intensity Across Family Clusters

5. Results

This chapter explains model development to define utility for EVs and microcar adoption, understand choice probabilities across alternatives, validate the model by comparing predicted and observed choices, and interpret the estimated significant parameters from defined utility model equations.

5.1. Model Development and Comparison

This section presents the initially expected outcomes, i.e., the hypotheses regarding microcar adoption. This was followed by explaining model formulations, estimations and comparisons, which were explained in detail in section 3.2.2.

5.1.1. Hypotheses

Several hypotheses were identified while working towards defining the model and its predictions on the survey data. The formulated hypotheses are listed below:

Hypothesis 1 The multiple-class model from LCM can provide greater insights into the data than single-class estimation in MNL.

Hypothesis 2 Dividing individuals into classes improves the model performance compared to a single-model class.

Hypothesis 3 A defined latent variable, “Car usage intensity”, has a negative impact on microcar adoption.

Hypothesis 4 A defined latent variable, “Environmental Concerns”, has a positive impact on microcar adoption.

Hypothesis 5 Purchase price significantly affects microcar adoption

Hypothesis 6 Charging time significantly affects microcar adoption

Hypothesis 7 Top speed significantly affects microcar adoption

Hypothesis 8 Range of vehicles significantly affects microcar adoption

Hypothesis 9 Possibility of swapping the battery significantly affects microcar adoption

Hypothesis 10 Knowledge about electric vehicles significantly affects microcar adoption

Hypothesis 11 Presence of public transport nearby significantly affects microcar adoption

Hypothesis 12 Presence of younger children in a family affects microcar adoption significantly

Hypothesis 13 Class of individuals with higher education is more likely to adopt a microcar

Hypothesis 14 Class of individuals with higher income is more likely to adopt a microcar

Hypothesis 15 Urban dwellers are more likely to adopt a microcar

Hypothesis 16 Young individuals are more likely to adopt a microcar

5.1.2. LVM

As the workflow is shown in Figure 11, HCM connects LVM and LCA into a DCM. So, in this section, considering the latent variables identified in section 4.3.1 derived from the measurement equations, the SEM part of LVM, by defining structural equations, was developed to identify the relationship between individuals' socio-demographic characteristics and the defined latent variables.

The model output of the LVM shown in Table 9 comprises CFA (measurement equation) and SEM (structural equation). Further covariance matrix and variance matrix of CFA are included in Appendix K. The overall fit indices of the model are shown in the Table below, where the Comparative Fit Index (CFI) and Tucker-Lewis Index (tli) have values above 0.8, indicating a good fit. In contrast, the Root Mean Square Error of Approximation (sea) and Standardized Root Mean Square Residual (some) have values closer to 0, confirming the good fit of the model further.

Table 8. Fit Indices of LVM

cfi	tli	rmsea	srmr
0.894	0.873	0.053	0.026

CFA output shows that the loadings of each indicator based on high z-values and low p-values (all are significant) confirm their reliability on the defined latent variables, respectively. Further, SEM identified the influence of independent socio-demographic variables on latent variables, where all significant variables are shown in Table 9. Environmental concern had only two affecting variables: high education among individuals had a positive effect, while rural and sub-urban respondents seemed less concerned. On the other hand, car usage intensity had many significant variables affecting it, unlike environmental concerns: employment status, income, education, region, gender, and age affected the usage patterns. Males had slightly higher usage than Females; Full-time employed people and high-income people had increased usage. In contrast, older people were negatively associated, indicating less dependency on private cars with age. Further, the covariance matrix showed a pessimistic estimate between car usage and environmental concerns, indicating that individuals with more environmental concerns are less likely to use cars.

Table 9. Estimated Coefficients of CFA and SEM

Latent Varibale Model Output (N = 3648)							
Confirmatory Factor Analysis							
Latent Variable	**Indicator**	**Estimate**	**Std. Err**	**z-value**	**P(>|z|)**	**Std. lv**	**Std. all**
Environmental Concern	Environmental Concern_1 (Likert)	1	-	-	-	0.97	0.775
	Environmental Concern_2	0.62	0.024	25.737	<0.001	0.602	0.529
	Environmental Concern_3	0.914	0.031	29.126	<0.001	0.887	0.742
	Environmental Concern_4	0.837	0.021	40.492	<0.001	0.812	0.689
Car Usage Intensity	Weekly Car Usage Intensity	1	-	-	-	1.124	0.96
	Total Daily Travel Distance	1.447	0.023	61.934	<0.001	1.626	0.827
	Car Usage Intensity for Long Distances	1.068	0.018	57.992	<0.001	1.2	0.784
	Total Yearly Travel Distance	1.248	0.024	52.555	<0.001	1.402	0.734
	Number of Cars	0.505	0.009	56.029	<0.001	0.568	0.755
Structural Equation Modeling							
Dependent Variable	**Independent Variable**	**Estimate**	**Std. Err**	**z-value**	**P(>|z|)**	**Std. lv**	**Std. all**
Environmental Concern	Education	0.118	0.014	8.389	<0.001	0.122	0.154
	Region (reference = Metropolis)						
	Rural	-0.462	0.046	-9.982	<0.001	-0.476	-0.193
	Suburban	-0.123	0.043	-2.853	0.004	-0.127	-0.055
Car Usage Intensity	**Gender (reference = Female)**						
	Male	0.164	0.032	5.095	<0.001	0.146	0.073
	Employment (reference = Unemployed)						
	Employed Full Time	1.074	0.067	16.034	<0.001	0.956	0.477
	Employed Marginally (below 18 hours)	1.159	0.17	6.828	<0.001	1.032	0.096
	Housewife/Househusband	0.541	0.091	5.951	<0.001	0.481	0.107
	Employed Part Time	0.901	0.07	12.84	<0.001	0.802	0.301
	Pensioners	0.851	0.088	9.72	<0.001	0.758	0.258
	Students	1.023	0.104	9.796	<0.001	0.91	0.157
	Region (reference = Metropolis)						
	Rural	0.439	0.059	7.39	<0.001	0.391	0.159
	Suburban	0.409	0.059	6.974	<0.001	0.364	0.156
	Urban	0.277	0.054	5.111	<0.001	0.247	0.123
	Age (reference = 18 to 24 years)						
	45-59 years	-0.149	0.036	-4.143	<0.001	-0.132	-0.06
	60-64 years	-0.237	0.062	-3.833	<0.001	-0.211	-0.054
	65 and above	-0.305	0.079	-3.867	<0.001	-0.271	-0.085
	Education (reference = University degree)						
	No qualification yet	-0.727	0.117	-6.236	<0.001	-0.647	-0.085
	Other degree	-0.964	0.118	-8.15	<0.001	-0.858	-0.113
	Primary or secondary school (POS 8th grade)	-0.281	0.078	-3.6	<0.001	-0.25	-0.05
	Household Net Income (reference = 1500 to 2000 euros)						
	2000-3000 euros	0.297	0.05	5.922	<0.001	0.265	0.111
	3000-4000 eruos	0.383	0.052	7.366	<0.001	0.341	0.138
	4000-5000 euros	0.618	0.057	10.757	<0.001	0.55	0.185
	5000-6000 euros	0.321	0.071	4.518	<0.001	0.286	0.071
	500-1500 euros	-0.568	0.058	-9.794	<0.001	-0.506	-0.182
	6000-7000 euros	0.613	0.101	6.047	<0.001	0.545	0.087
	Less than 500 euros	-0.867	0.091	-9.492	<0.001	-0.771	-0.15

Further, based on these above results and interpretations, factor scores for each latent variable were computed for further inclusion in model development.

5.1.3. LCA

Further, LCM required defined classes of individuals for model development, so individual socio-demographic characteristics were considered for performing LCA. Since defining the number of classes, which explains the entire data set, was challenging, research says there are several examining criteria for determining the optimal number of classes k (Mindrila, 2020).

The current study considered the goodness of fit indices using the Bayesian Information criteria (BIC) and Akaike Information Criteria (AIC). Lower BIC and AIC generally represent good model fit while keeping that in mind; after a specific number of classes, adding the extra number of classes ceased the improvement in model performance significantly, and this elbow point was identified to be the optimal k (Mindrila, 2020).

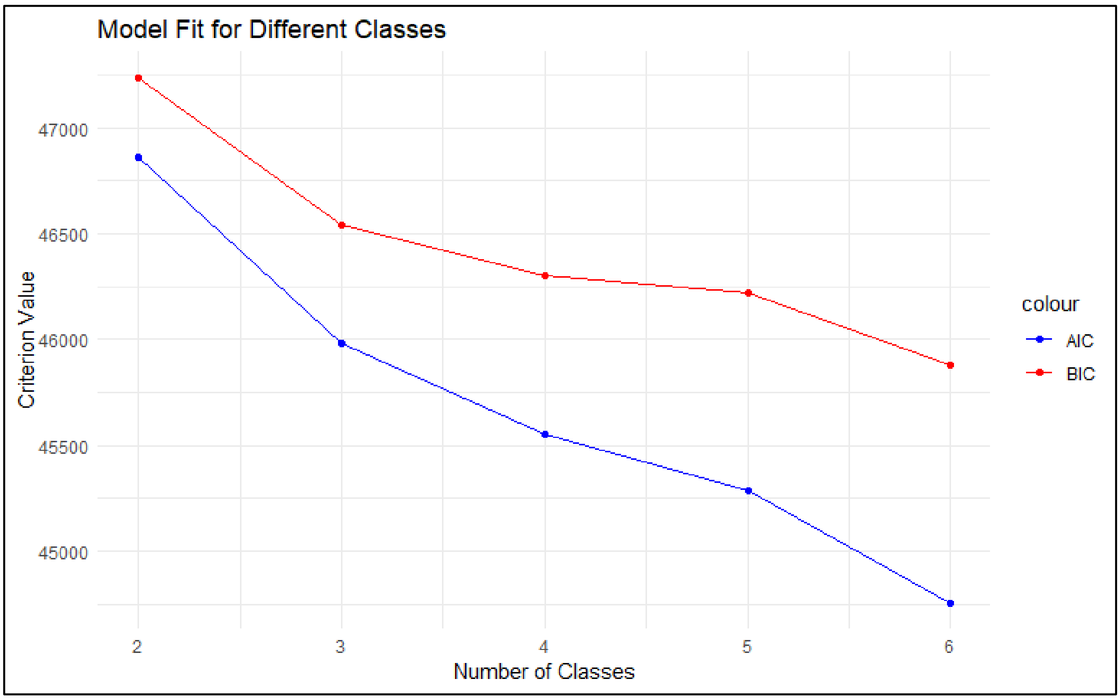


Figure 26. Model Criteria Values for Different Classes

So, AIC and BIC estimates of each model were initially calculated for 2 to 6 classes based on socio-demographic categorical variables and based on the elbow point found at 4; as shown in Figure 26, four classes were identified as optimal.

Further, the entropy of each defined class was calculated, where entropy is a statistic to diagnose the accuracy of model-defined classes. The model classification was validated as each class's entropy value was more than 1, as shown in Figure 27. Although there is no cut-off criterion on entropy considerations, any value above 0.8 is acceptable (Wang et al., 2017; Weller et al., 2020).

Additionally, posterior probabilities were calculated, defining the likelihood of each individual belonging to one class. Further, to understand class division percentages of individuals in identified classes, class population percentages were obtained; this was done to ensure that none of the classes accounted for a population of less than 5% to obtain a significant sample in each class and Class 1 accounted for 27.9%, Class 2 for 34%, Class 3 for 10,2% and Class 4 for 27.8% of the total population. Then, each individual was assigned to a particular class based on their highest posterior probability of belonging to a specific class.

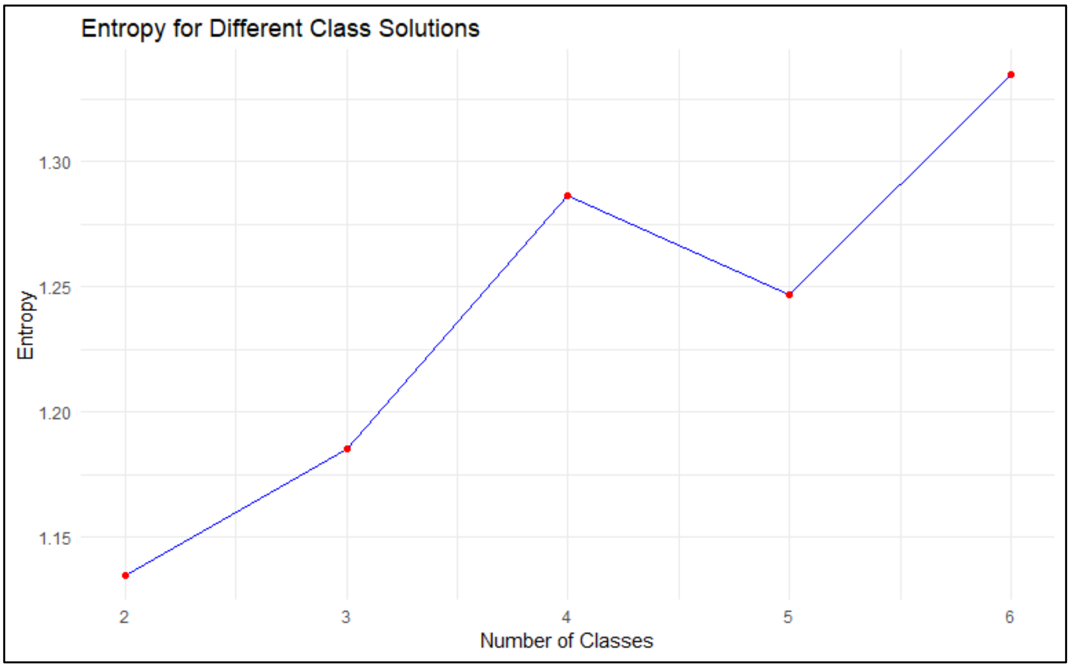


Figure 27. Entropy Values Across Defined Classes

Although individuals were assigned to a class based on maximum posterior probabilities, this assignment was biased as all the individuals could not be assigned to their true class. Also, each individual's maximum posterior probability was checked, and 160 individuals had less than 0.70, which might indicate poor classification. So, to account for this misclassification and to validate the classification, an error matrix is calculated to calculate misclassification probabilities.

So, the diagonal elements of this matrix account for true classification (Tompsett, n.d.). In the current analysis, all classes achieved almost true classification (>80%), showing high classification accuracy across all classes. With this validation, the classes identified were further analysed for their demographic distribution across their classes.

While keeping a minimum posterior probability of 0.4 as a threshold, each class was visualized to understand the class dynamics and to further identify their definition concerning the characteristics used to define them, as shown in Figures 28 and 29.

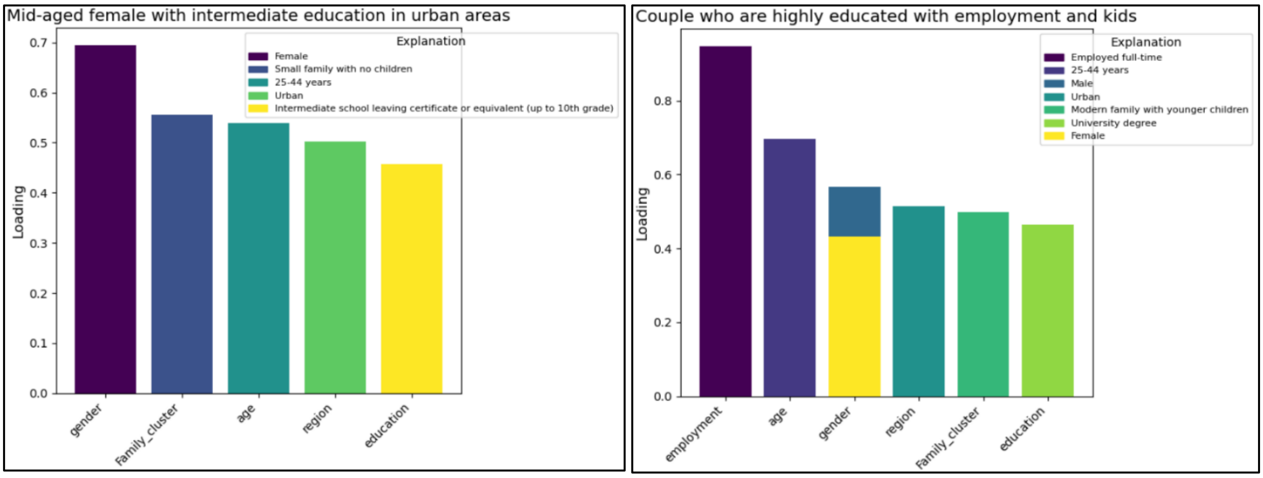


Figure 28. Characteristics Distribution Across Classes 1 and 2.

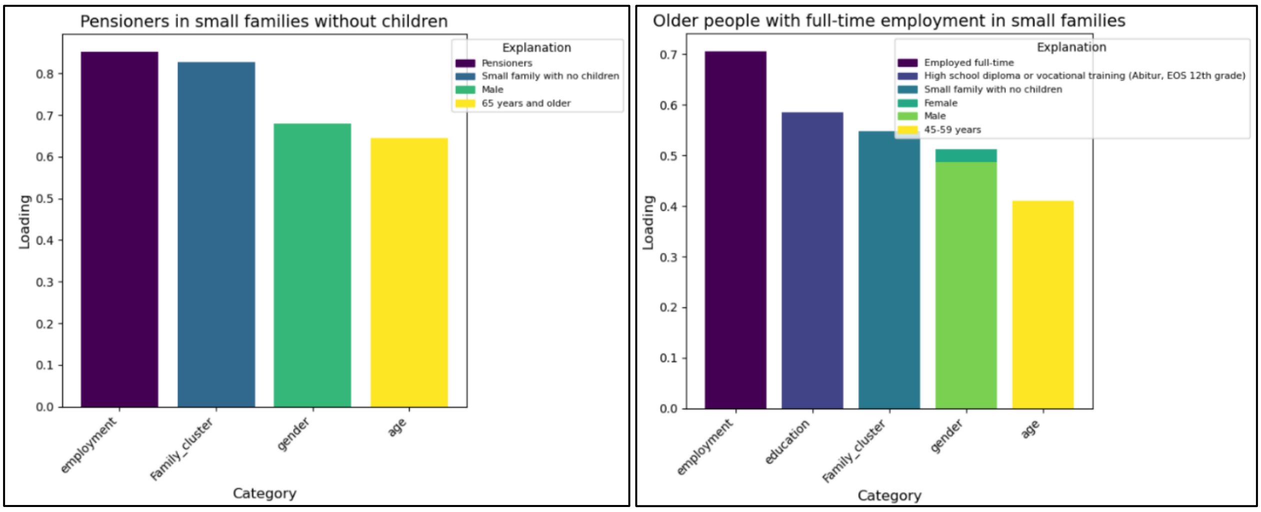


Figure 29. Characteristics Distribution Across Classes 3 and 4.

Class 1 showed high loadings for mid-aged females from small families with no children living in urban areas with intermediate education. So, they were named “Mid-aged females with intermediate education in urban areas”. Class 2 contained mid-aged individuals with university degrees and full-time employment in medium-sized families and urban areas, so it was depicted as a “Couple who are highly educated with employment and kids”. Class 3, which majorly had old, aged pensioners in small families, was named “Pensioners in small families without children”, and finally, Class 4, older people with full-time but no children, was named “Older people with full-time employment, in small families”.

Further, based on these understandings of classes, utilities for each class were developed, and the model was estimated in the next section, compared to a single class model.

5.1.4. Comparison of MNL and LCM

The MNL model with no alternative included was first estimated; MNL was estimated for all the choice attributes, derived latent variables, and additional variables considered, such as knowledge about microcars and nearby public transport availability. Further, all the variables were again used to estimate LCM with four classes defined. ASCs for alternatives across all models were significant, and all signs were as expected. All the utility functions considered during model development are shown in Appendix L.

Table 10 compares the two models and their estimations, including the t-test values of each estimate. Only significant coefficients at the 95% level were included in the Table. Additionally, model development was done with stepwise variable addition; once choice attributes were estimated, additional variables were included to improve the model further.

Further, LCM shows a better fit in terms of lowered AIC and higher log-likelihood when compared to single-class MNL, which depicts that LCM explains class-specific preference better and thus retains our Hypothesis 2 (Dividing individuals into classes improves the model performance compared to a single-model class).

Table 10.- Estimated Coefficients Across All Models: Comparing Single-Class MNL with Four-Class LCM

Estimated Utility Coefficient: Value [t-test value]; significant values are marked by *** (p-value<0.001), **(p-value<0.01) and *(p-value<0.05)											
		One Class (MNL)		Class 1 (LCM)		Class 2 (LCM)		Class 3 (LCM)		Class 4 (LCM)	
Coefficient	None of the above	Microcar	EV	Microcar	EV	Microcar	EV	Microcar	EV	Microcar	EV
ASC	Base case	0.80917 [2.2]*	3.86988 [12.0]***	0.60256 [0.0]*	3.21243 [6.8]***	1.70692 [3.4]***	2.69040 [7.1]***	-0.91439 [-1.1]	3.95362 [5.4]***	-0.91439 [-1.1]	3.95362 [5.4]***
Purchase Price	Base case	-0.31968 [3.5]***	-0.14655 [-4.7]***	-0.25531 [-1.7]*	-0.69976 [-5.5]***	-	-0.03391 [-3.0]**	-0.35684 [-3.5]*	-0.34298 [-3.8]***	-	-0.27013 [-4.5]***
I (Purchase Price × Safety)	-	-0.07361 [-3.8]***	-	-	-	-	-		-	-	-
I (Purchase Price × Speed)	-	-	0.39957 [2.8]**	-	-	-	-		0.10202 [2.8]**	-	0.08795 [3.5]**
I (Purchase Price × Range)	-	-	-	-	-	-	-	-0.4859 [-2.1]*	-	-	-
Charging Time	Base case	-	-	2.34355 [2.1]*	-	-	-	4.71646 [2.8]**	2.06362 [2.3]*	-	2.30446 [3.6]***
Battery Swapping	Base case	-0.15930 [-3.0]**	-	-	-	-	-	-	-	-	-
Car Usage Intensity	Base case	-0.26999 [-3.5]***	-	0.33627 [1.5]*	0.39016 [1.8]*	-0.46526 [-2.5]**	-	-	-	-0.46436 [-3.0]**	-
Environmental Concern	Base case	-	-	-	-	0.69569 [2.4]**	0.78232 [3.4]***	-	-	-	-
Knowledge About Microcar (reference = Fully Aware)	Base case	-	-	-	-	-	-	-	-	-	-
Not Aware	-	-0.77190 [-3.0]**	-1.00378 [-4.4]***	-	-0.39337 [-1.4].	-1.34389 [-2.3]*	-1.56219 [-3.3]**	-	-	-	-0.39950 [-1.4].
Nearby Public Transport (PuT) (reference = More than 5km)	Base case	-	-	-	-	-	-	-	-	-	-
Within 250m	-	-0.48545 [-1.7]*	-0.40877 [-1.7]*	-	-	-0.76836 [-1.6].	-0.64214 [-1.5].	-0.77404 [-1.4].	-	-	-
Within 2 to 5km	-	1.06150 [2.4]**	0.66231 [1.6]*	-	-	-	-	-	-	1.85681 [3.2]***	1.29739 [1.5]*
Model Parameters											
Sample Size	2664			2664							
Number of Estimated Parameters	14			35							
Initial log-likelihood	-2926.7			-2926.7							
Final log-likelihood	-2476.7			-2425.05							
AIC	4981.4			4920.1							

5.2. Model Co-efficient Estimation and Interpretation

5.2.1. MNL

MNL estimates coefficients considering all individuals have homogenous preferences across all alternatives, so the interpretation is considered a single class. ASCs for both alternatives were significant, and the estimate was significantly higher for EVs, indicating a stronger preference for EVs over microcars. Surprisingly, the purchase price for microcars had a positive coefficient, indicating that individuals might prefer higher-priced microcars for better quality. In contrast, the purchase price for EVs had negative sensitivity, showing price sensitivity (higher prices reduce the adoption).

The interaction between the purchase price and safety had a negligible negative impact yet was significant, reflecting that respondents are less likely to choose microcars when safety improvement is tied up with increased purchase price. However, another interaction term between purchase price and speed for EVs showed a positive impact, indicating individuals prefer EVs with increased speed and price. Additionally, battery swapping was only significant in single-class and indicated that preference for microcar increases if there is wide battery swapping availability.

Additional variables considered, such as car usage intensity, less awareness about microcars and public transport availability within 250m, had a significant impact, indicating that higher car usage among individuals reduces the preference for microcars and individuals with less awareness about microcars and ones who have nearby public transport are less likely to choose microcar as an option. In contrast, individuals with public transport availability within 2 to 5km are likelier to adopt a microcar, indicating that microcars could bridge the gap in public transport accessibility.

5.2.2. LCM Class 1

Class 1 accounts for people who are mid-aged, females with intermediate education from small families in urban areas. They are less sensitive when choosing a microcar when compared to all individuals in one class, but a strong preference for EVs over microcars remains the same. Unlike MNL, these groups of people are sensitive to both microcars and EVs, with EVs holding the higher price sensitivity, likely due to the limited budget of class people due to intermediate education or perceived value of microcars. So, this group of people most likely prefer EVs, although they accept microcars.

Charging time has a significant positive effect on microcar adoption; the positive might be because the charging times of microcars are moderately correlated to the range and their top speed, so people of this class prefer higher ranges with a top speed while adopting a microcar. As car usage intensity increases, they are more likely to choose EVs over microcars as they provide a higher range that meets their urban travel patterns. Also, limited awareness among the class reduces the adoption of microcars, which might be related to the intermediate education levels of the class individuals. So, Class 1 individuals are price sensitive but prefer other convenience factors while adopting a microcar.

5.2.3. LCM Class 2

Class 2 consists of couples who are highly educated, have full-time employment, and are most likely with younger kids in the household who live in urban areas. This class significantly prefers microcar adoption, which is most likely associated with their environmental concerns and car usage intensity.

They still have strong loadings on EV adoption, but compared to MNL, they have better adaptability towards microcars with very strong loadings. They are comparatively less sensitive to the purchase price, likely due to their full-time employment and willingness to pay more for environmentally friendly technologies, which also comes with their high education qualification. Both microcar and EV preferences are positively affected by their environmental concerns, which likely explains the strong loadings of microcar adoption compared to other classes.

However, as car usage intensity increases, likely due to family car usage, long-distance travel, and a limited range of microcars, they are less likely to adopt a microcar. As for all classes and MNL, not being aware of the technology reduces the potential for adoption. Additionally, public transport within 250m negatively affects the adoption, indicating that individuals with greater accessibility are less likely to choose a microcar.

So, Class 2 individuals are less sensitive to price and more likely to adopt environmentally friendly options like microcars, but their increased car usage intensity limits this fact.

5.2.4. LCM Class 3

Class 3 includes pensioners who are 65 and older in small families without children, and they have a strong preference for EVs and have negative loading for microcars, which might be due to perceptions of microcar size and lack of awareness about microcars among older age groups. They are sensitive to purchase prices, indicating the financial contents of being a pensioner. Interaction terms for purchase price and range had a negative impact, which shows that these individuals are less sensitive to range increases when tied to purchase price increases, most likely due to fewer travel needs.

They are more sensitive to charging times; positive loading is most likely due to the moderate correlation of charging time with top speed. This indicates they prefer EVs with higher top speed and go as well with microcars. This is confirmed by the positive loading of another interaction term between the purchase price and speed. Additionally, they are less sensitive to adopting a microcar if public transport exists within 250m.

So, Class 3 individuals prefer EVs primarily because of their advantages over microcars. They are sensitive to the purchase price and public transport proximity, yet look for speed and convenience.

5.2.5. LCM Class 4

This class includes older people with mid-level education but are employed full-time in small families without children. They show weak adoption of microcars but very positive and strong loadings on EV adoption. They are moderately sensitive to price compared to other classes. Nevertheless, charging time has a positive adoption impact, indicating range and top speed preferences among individuals, possibly due to increased travel needs.

The greater the car usage intensity, the less likely to adopt microcars due to their disadvantages with increased travel needs might be due to work. Lack of awareness has the same impact as the rest of all classes, i.e. less awareness reduces the potential of adoption for microcars. However, these groups of individuals exhibit adoption of a microcar with greater significance if public transport availability is within 2 to 5km; yet again, this might be due to travel needs fulfilment across public transport availability.

So, again, like all classes, class 4 individuals are more likely to adopt an EV over a microcar, mainly due to high car usage intensity. Also, microcars can be a solution for last-mile problems with public transport. They might see microcars as options to fill the current mobility gaps, especially with improved awareness among the class.

5.2.6. Model Comparisons

Although MNL provides insights into the entire data set, it does not account for the class or segment-specific heterogeneity that LCM captures. Thus, this retains Hypothesis 1 (The multiple-class model from LCM can provide greater insights into the data than single-class estimation in MNL). LCM helped identify class-specific preferences and behaviours related to microcar adoption.

Further, to conclude, Class 1 individuals in urban families prefer convenience when choosing microcars and are sensitive to price and car usage intensity. Class 2, highly educated, environmentally conscious couples with kids avoid microcars due to high car usage and rely on public transport if available nearby. Class 3 pensioners prefer EVs and show price sensitivity towards adoption; finally, Class 4 older employed individuals seek convenience regarding speed and range. They also have the potential to adopt microcars for last-mile public transport connections, given that they are aware of the technologies.

5.3. Model Validation

Further, model evaluation metrics were determined to understand how well the model predicts output based on class utilities. The comparison of predicted and observed probabilities across all defined classes was plotted to understand how well the model predicts, as shown in Figure 30. As the model performs well on class 3 compared to others, further evaluation metrics were considered to better analyse the output and to understand performance across other classes.

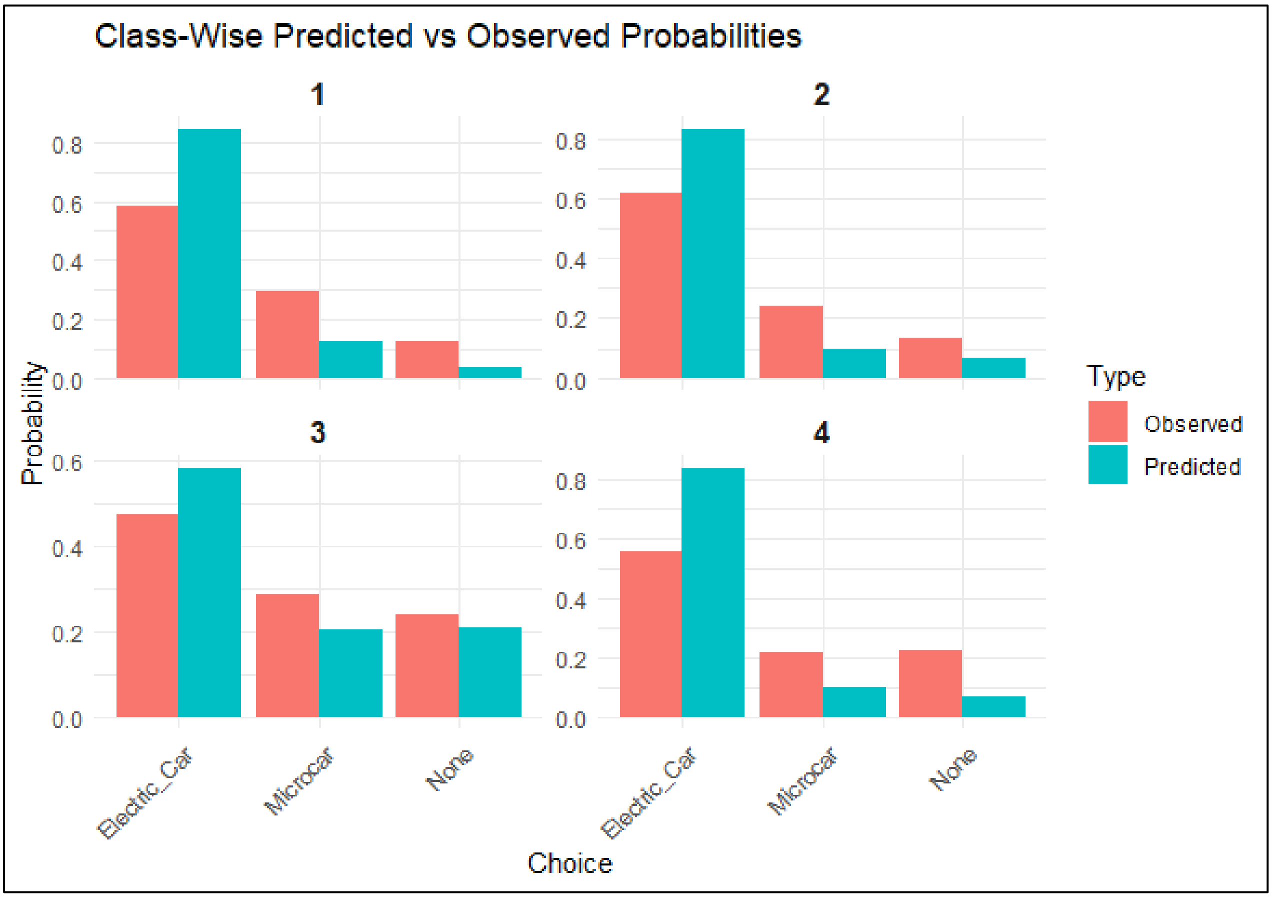


Figure 30. Predicted vs Observed Probabilities

So, further, ROC curves were used to evaluate AUC, and model evaluation metrics like recall, precision, accuracy, and F1 scores were estimated. The ROC curve is shown in Figure 31 for overall model performance concerning sensitivity and specificity for each alternative predicted. As it shows, model performance is moderate across all the alternative predictions, but the model seemed to underperform while predicting microcar. So, individual alternative-specific ROC curves were plotted to check for AUC (attached in **Appendix M**).

Class-wise ROC curves depicted that, also confirmed with choice probabilities distribution across class, the model predicts and classifies well on class 3, mostly likely due to less sample as it accounts for only 10.5% of the sample. However, It was mostly seen that, except for class 3, microcar predictions consistently showed lower AUC, indicating that the model found distinguishing between microcars and other alternatives challenging.

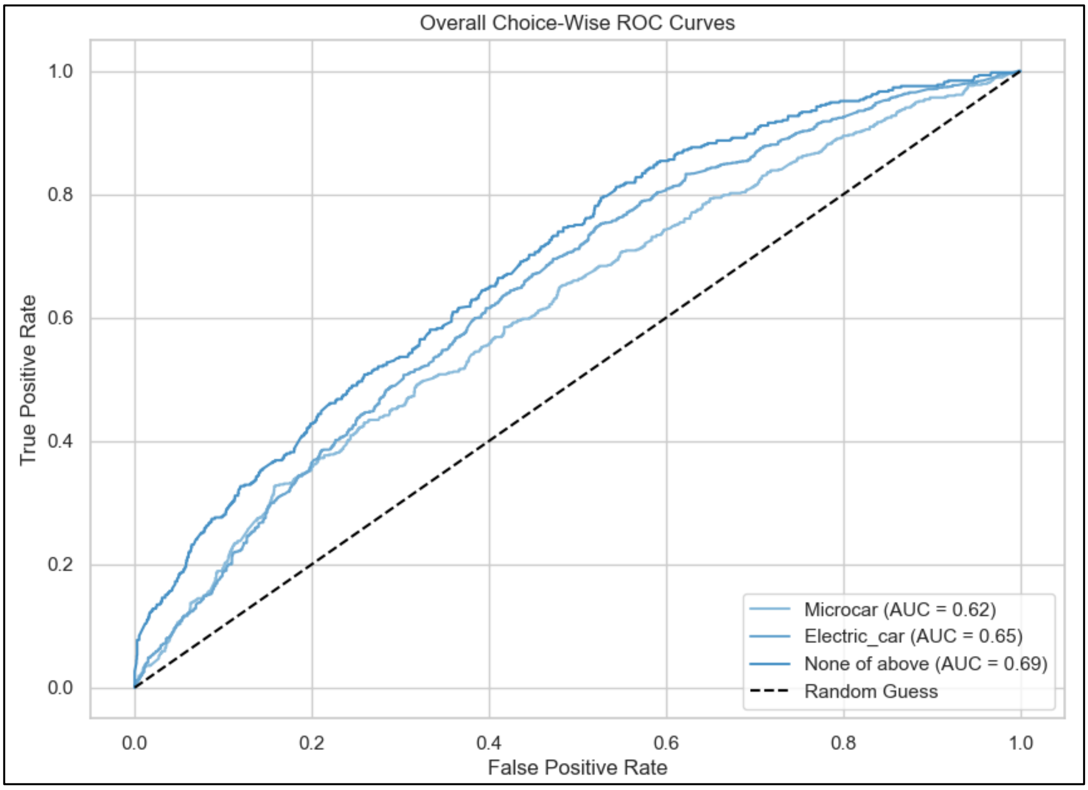


Figure 31. Overall Receiver Operating Characteristic Curve Across Alternatives

Although there might be several reasons for these false predictions, particularly for microcars, in the current study, a few predicted and understood reasons were found to be: 1. Under-sampled microcars compared to other alternatives, as shown in Figure 12 from section 4.2, where individuals prefer not to own any electric car over microcars. 2. A high correlation between the choice attributes and total attributes defined for microcars alone might not have been sufficient for the model to differentiate it across alternatives. 3. Another assumption is that the utility values of microcars might not have been distinct compared to other alternative utilities. The coefficient values determined for a single attribute across alternatives were close enough, as shown in Table 10 in section 5.1.4, making it difficult for a model to identify the difference even while quantifying utility. Furthermore, the limitations and possible future work are discussed in Chapter 7.

To conclude, the overall and class-wise performance of the model in terms of metrics are shown in a radar chart in Figure 32. The metrics vary among the classes, showing that Class 3 performs the best, followed by Class 2, 1 and 4. Overall performance was consistent across metrics, but none of the classes reached the maximum values, indicating room for improvement, which, in turn, was also supported and identified in the above discussions.

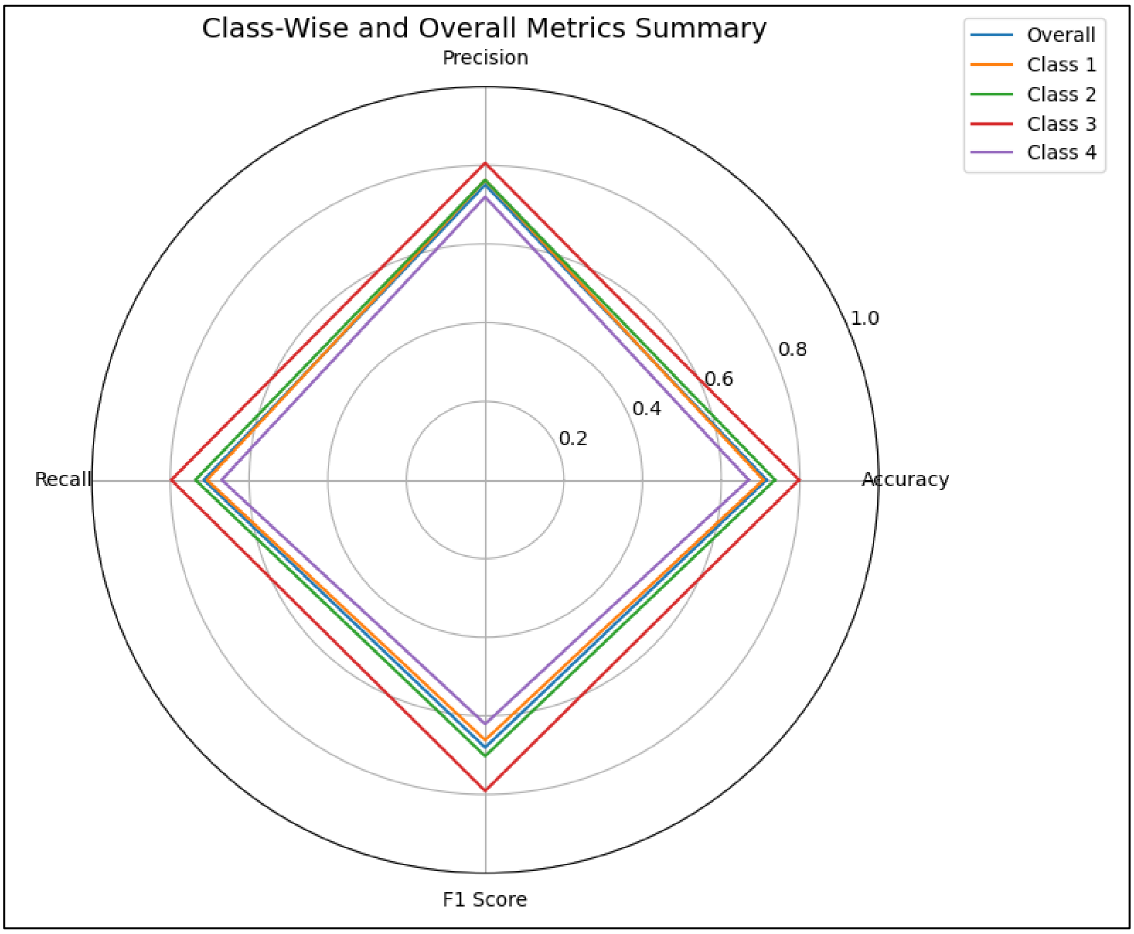


Figure 32. Model Performance Metrics Summary

6. Discussion

This chapter discusses the impact of choice attributes and how well-identified attributes were defined in the model, the possibility of adopting a microcar as a second car across defined clusters and classes, stated reasons by individuals for not adopting a microcar and final policy implications on the current research.

6.1. Discussion on Vehicle Attributes

As identified from the literature shown in Figure 4 Section 3.1.1, purchase price, charging time, range, and top speed were the significant factors affecting the adoption of EVs. At the same time, safety and comfort were considered in terms of microcars.

The model revealed a greater dependency and sensitivity towards purchase price across single-class MNL models and all classes in call models with high significance, depicting that purchase price could be a crucial factor in deciding any given vehicle adoption. Although the range and top speed were not directly involved as variables in models due to their correlation with the purchase price, interaction terms defined identified that few individuals and classes were sensitive towards speed and range.

In contradiction, since charging time was moderately correlated with range, top speed and purchase price, a positive coefficient on charging time revealed consumer preference for convenience towards adoption. Comfort was not interpreted in the current study as comfort levels had zero variance throughout, as defined levels were constant. However, safety was not directly interpreted in the model. It significantly impacted one of the classes when evaluated through an interaction term with the purchase price.

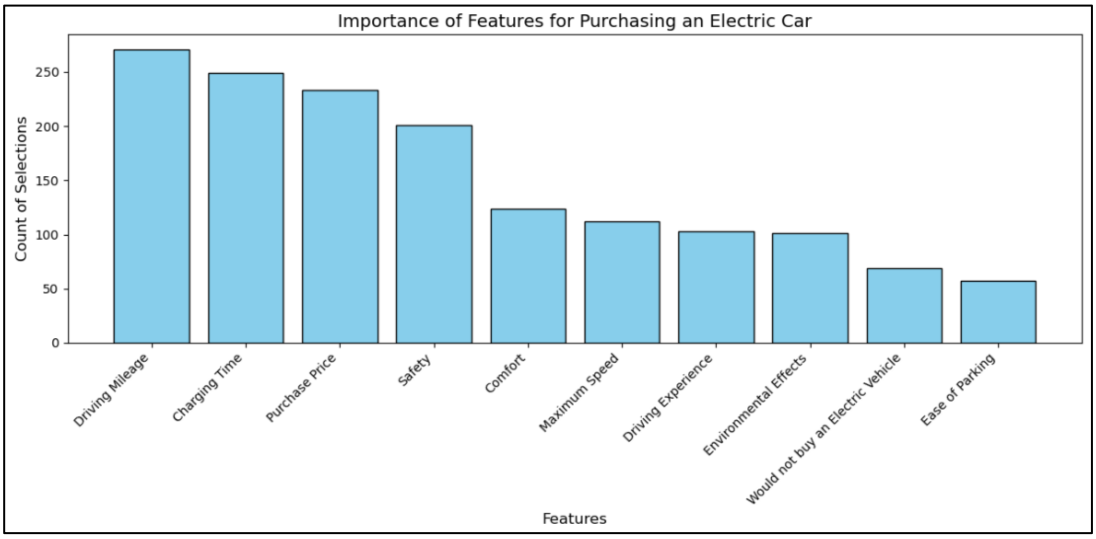


Figure 33. Important Features While Selecting an Electric Car

Figure 33 above shows the list of important features identified among survey respondents while purchasing an electric car, which was further used as evidence to confirm the interpretations described above as the most important features selected were identified from the literature and were found to be significant in model results, as shown in Table 10.

Although driving experience and ease of parking was not involved in the current study, environmental effects, which were analysed regarding respondents' concerns towards the environment, positively impacted adoption. Further details of attributes and their impact on individuals were discussed in section 5.2, and further implications will be discussed in section 6.4.

6.2. Primary and Secondary Adoption of Vehicles

To understand the possibility of adopting a microcar as a secondary car in a household, respondents who entered the choice sets and selected an alternative were asked for the type of adoption they would make. Further, these selections were grouped for Family Clusters identified in section 4.4 and classes identified from LCA in section 5.1.3.

So, the analysis revealed that Family Cluster 0, as shown in Figure 34, which comprises large families with older children, is more likely to adopt a microcar as a secondary vehicle in addition to an existing vehicle. Although family cluster 0 was not directly involved in models to compare the adoption possibility, this interpretation reveals the necessity of an additional small vehicle for households with older children, which can be considered an insight for future work and implications.

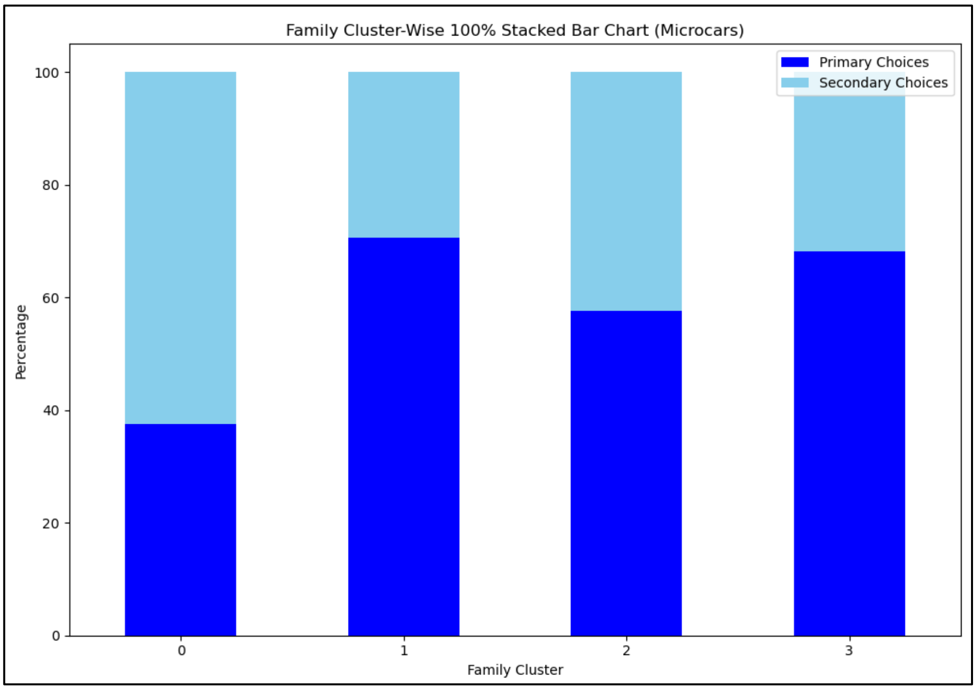


Figure 34. Secondary Adoption Possibility of Microcars Among Family Clusters

Further, Class 4 individuals, comprised of older people with full employment in small families, tend to adopt microcars as a secondary vehicle. This interpretation can be explained according to the results found in LCM, although class 4 individuals are more likely to adopt an EV due to high car usage intensity. Still, they are also more likely to adopt a microcar to serve as a last-mile public transport connectivity (explained in section 5.2.5), which explains the reasons for secondary adoption as shown in Figure 35.

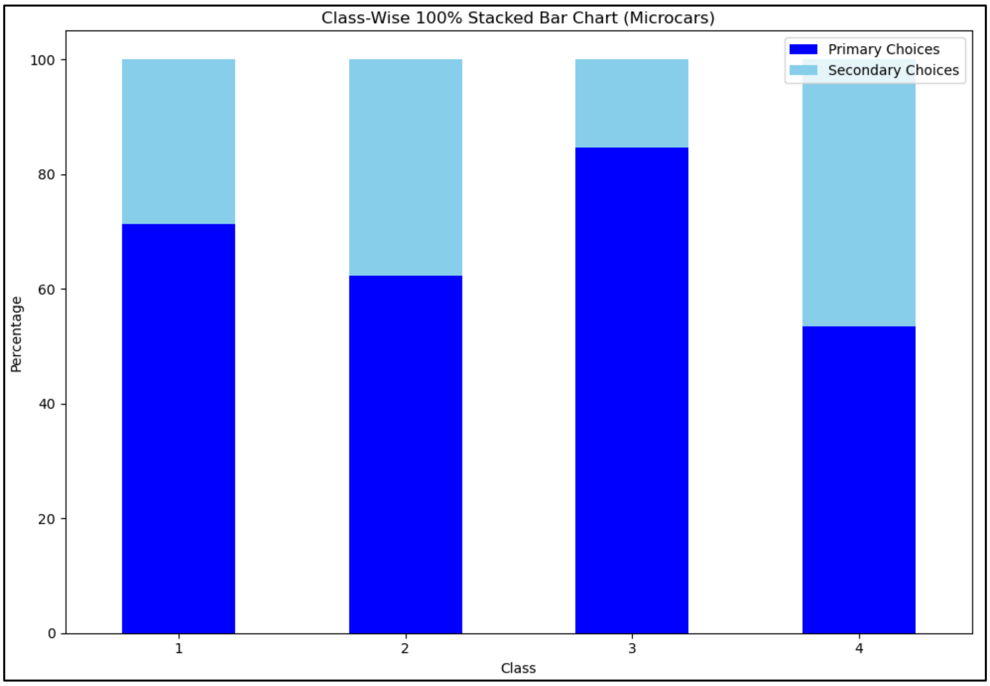


Figure 35. Secondary Adoption Possibility of Microcars Among Classes

6.3. Discussion on Adoption Reasons

To understand possible constraints in adopting a microcar among the respondents, they were asked to select a reason for not adopting it today. The results revealed a few significant attributes, such as smaller size and unsuitability for long distances, which were the primary concerns, as shown in Figure 36. This observation aligns with the findings of both MNL and LCM models, where individuals and classes with high car usage intensity had less priority in choosing a microcar due to long-distance travel. For classes 3 and 4, which exhibit similar preferences for microcars and EVs, the lower adoption of microcars may be influenced by their smaller size. This could be accounted for by the perception among older individuals that microcars are too small and compact to meet their needs. Other reasons explained by respondents are grouped together and attached in Appendix N.

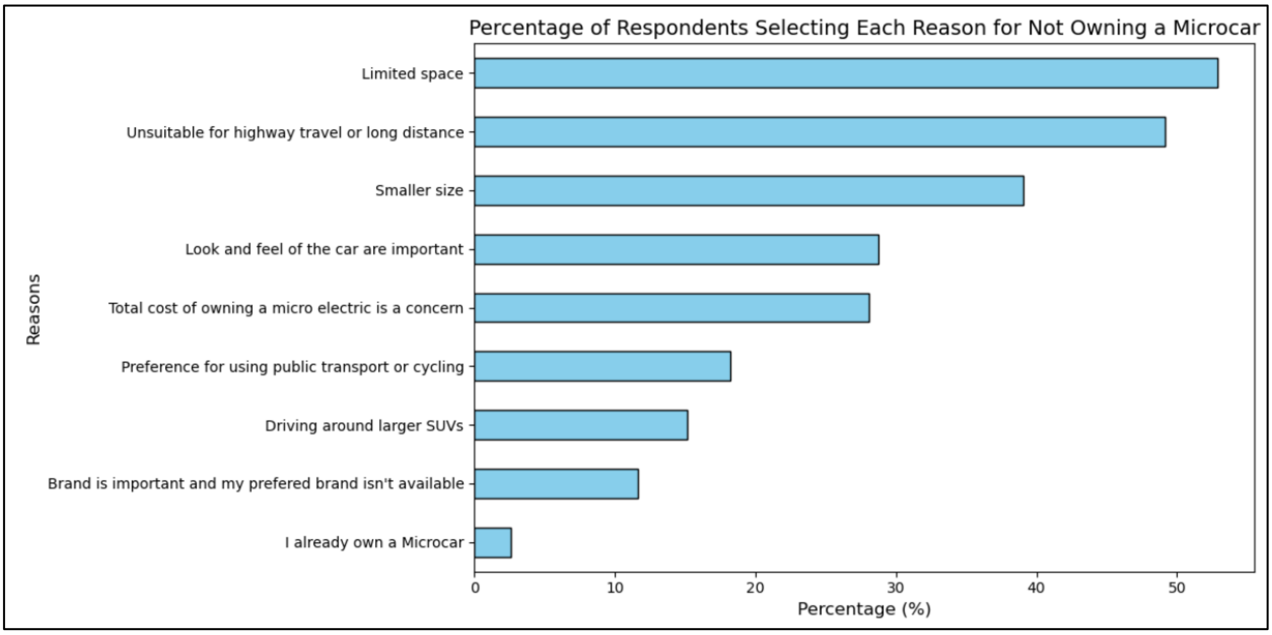


Figure 36. Reasons for Not Adopting a Microcar Today

6.4. Discussions on Hypotheses

This section includes the findings and discussions on microcar preference among different classes of individuals defined based on their socio-demographic characteristics and their policy implications (This section is based on explanations made in section 5.2).

The vehicle attributes defined, such as charging time, top speed, range and battery swapping, were found to be significant across the defined models, either directly or as an interaction term. This confirms that Hypothesis 6 (Charging time significantly affects microcar adoption), Hypothesis 7 (Top speed significantly affects microcar adoption), Hypothesis 8 (Range of vehicles significantly affects microcar adoption), and Hypothesis 9 (Possibility of swapping the battery significantly affects microcar adoption) can be retained.

Environmental concerns latent variable positively affected the adoption possibility among highly educated couples in class 2, confirming our Hypothesis 4 (A defined latent variable, “Environmental Concerns”, positively impacts microcar adoption). Also, higher car usage intensity decreased the possibility of adopting a microcar across all defined classes, confirming our Hypothesis 3 (A defined latent variable, “Car usage intensity”, negatively impacts microcar adoption.)

Similarly, the availability of public transport influenced the adoption behavior, reducing the possibility of adopting a microcar If the availability was within 250m. In contrast, it increased the possibility of microcar adoption if availability was farther away, i.e., from 2 to 5km. Based on this, our Hypothesis 11 (The presence of public transport nearby significantly affects microcar adoption) can be retained.

Not being aware of the technology affected and reduced the adoption rates of microcars across all the defined classes except for class 3, which confirms our Hypothesis 10 (Knowledge about electric vehicles significantly affects microcar adoption). In contrast, Class 2 individuals with the highest education showed the most positive possibility towards microcar adoption compared to all other classes. Hence, our Hypothesis 13 (Class of individuals with higher education is more likely to adopt a microcar) was retained.

Overall, the single-class analysis positively responded to adopting a microcar as the purchase price increases. However, when estimated according to classes, they were price-sensitive. Low-income individuals were highly sensitive towards the purchase price and, in turn, towards microcar adoption, which helps retain sour Hypothesis 5 (Purchase price significantly affects microcar adoption). Higher-income people were not directly defined by a class division, as the information contained only the employment status of individuals across the classes. However, full-time employed individuals were likelier to adopt a microcar, which might represent high income. So, Hypothesis 14 (Class of individuals with higher income is more likely to adopt a microcar) was partially retained.

Finally, classes 1 and 2, with young couples and with females, were more likely to adopt a microcar than old-aged people and pensioners. This partially supports Hypothesis 16 (Young individuals are likelier to adopt a microcar). So, it was neither retained nor rejected. Class 2 couples, most likely with younger children, were highly favourable in adopting a microcar that retains Hypothesis 12 (The presence of younger children in a family affects microcar adoption significantly) and classes with individuals in urban were indeed affected by their car usage intensity which helps us to partially retain Hypothesis 15 (Urban dwellers are more likely to adopt a microcar).

To conclude, the study supports almost all the hypotheses defined and demonstrates that LCM offers deeper insights into the data than single-class MNL by identifying segment-specific attributes. These findings further enhance the adoption and implementation of any policies that influence future behaviour towards sustainable goals by identifying the barriers among specified segments of individuals.

7. Conclusion

This chapter discusses the limitations of the current study on time and analysis, and future recommendations and works to further proceed in this research are proposed, which is finally followed by an overall conclusion on the entire study conducted.

7.1. Limitations and Recommendations

7.1.1. Survey Design

Even though random design methods were simple, using random design during the DCE might have introduced imbalanced combinations, unlike orthogonal, even though stratified design was adopted. Optimized designs like D-efficient or Bayesian might yield better estimates of utility equations.

Although real-world attributes and their levels specific for each alternative were considered, how respondents perceive the attribute based on the images shown might have introduced bias while answering choice sets, where respondents might have just seen the images instead of the choice attributes presented. So, adopting more real choice set representation might reduce the introduced biases.

Furthermore, the set of attributes included in analysing the adoption of microcars was limited. As shown in Figure 37 below, respondents found the most appealing design to them based on the images shown to them from one of the questions. Since respondents find bigger microcars (Smart Fortwo and Axiam City) appealing compared to small microcars (Microlino), these factors might help better understand the utility in future work. The correlation plot for the same further confirmed that respondents who chose Axiam city were more likely to adopt similar-sized microcars in order Smart Fortwo, XEV and Silence S04 and least likely to select Microlino and Fiat Topolino which is most likely because the latter are compact, that the former. Shown in Appendix O.

In addition to the above, additional attributes found from the literature (see Table 1) that were not included in the current study, like charging time, policy incentives, make and model of the existing vehicle, and others, could help quantify the utility in a better and differential way.

7.1.2. Sample Collection

Although a survey collection platform was used to get a representative sample across Germany, people who chose microcar as an option are undersampled in the data set for the model to build robust and reliable estimations. So, efforts to collect an increased sample size in future work might yield better model predictions while reducing the bias. Also, collecting more samples might help during segment analysis as it increases the class sample for more robust predictions.

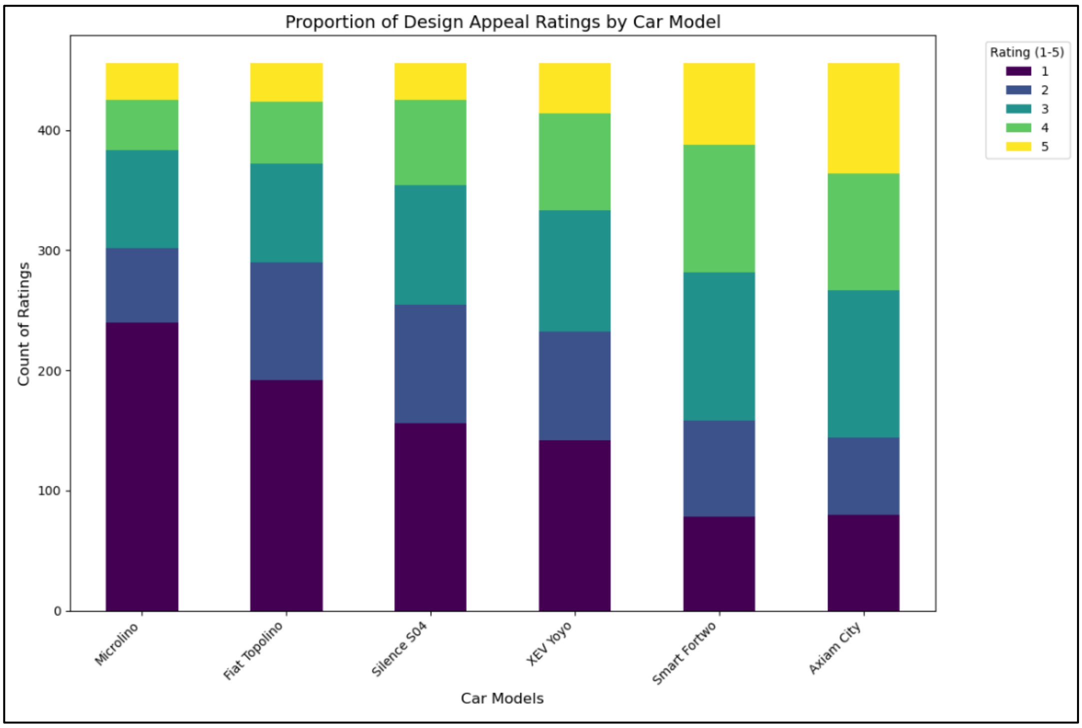


Figure 37. Most Appealing Design According to Respondents

7.1.3. Modelling

Modelling accounted for understanding four class LCM model; although results were moderately predicting the actual outcome, the class division could not account for most of the defined variables during the data preparation process, which might have led to the fact that the model was not able to capture all the observations while predicting. This, combined with the undersampling of microcar respondents, might have contributed to a similar estimation of utilities across alternatives, as most of the estimate values were close. So, accounting for these and improvising the techniques might help better understand the real-world scenario of microcar adoption.

Another limitation was that even though research saw the potential for emission reduction, it was not validated in the current study due to time limitations. So, this potential can further be quantified to understand environmental benefits based on real-life adoption behaviors.

7.2. Future Research

7.2.1. MiD Implementation

MiD offers a well-sampled survey that might be utilised to analyse adoption and emission reduction potential across Germany. Integrating the existing utility model while defining additional variables considered in the current study through SEM or Random Foster models might help improvise the potential realisations based on a large data set.

7.2.2. Emission Reduction Potential

The derived utility models from the current study can be incorporated into the existing Vector 21 agent-based model at DLR to realise and simulate adoption scenarios. Further, this method can be incorporated into other utility models and help realise the potential emission reduction from adopting a microcar.

7.2.3. Alternative Methods

Although the current study compares MNL with LCM, incorporating additional methods like mixed logit and nested logit while adding conventional vehicles as an alternative to the current study might help achieve the most robust results. Results and interpretations can then be further compared to obtain the best estimation method. Additionally, this study can validate revealed preference (RP) in microcar adoption for future RP or stated preference (SP) studies.

7.3. Conclusion

Space restrictions in urban travel environments have increased the demand for innovative solutions, making it possible to explore microcars as an option to meet the travel demand. Considering Germany as a case study, this research incorporated HCM methodology to evaluate independent variables affecting the adoption behaviour of microcars and identified potential population groups that are likely to adopt.

Considering further derived objectives to design an effective DCE and learn primary vehicle and individual attributes influencing choice behaviour and model performance, the study was initiated by conducting a robust DCE SP survey on microcar adoption versus EVs in September 2024, and 456 valid responses were collected. An online survey platform was utilized to obtain a representative sample for Germany.

Further, a simple discrete choice model like MNL was evaluated as a single-class model to compare with the LCM, where individuals were divided into classes based on identical characteristics. The interpreted results mainly comprised identifying groups more willing to adopt a microcar.

So, the results based on this case study suggested that this group of individuals have more significant potential in adopting a microcar while considering their limitations on adoption:

Mid-aged females in urban areas prefer the convenience of range and top speed when choosing a microcar. However, they are limited by their sensitivity to the purchase price and high car usage intensity.

Highly educated, full-time employed couples who are environmentally more conscious and less sensitive to the purchase price are more likely to adopt. However, they are hindered by high car usage intensity.

Pensioners who live in small family households without children are very sensitive to purchase prices, so they have the potential to adopt microcars over EVs with awareness.

Older people with full-time employment seek speed and range convenience but are likelier to adopt a microcar for their last-mile public transport connection.

Although the model revealed the preference of subgroups across the study, the limitations regarding adoption were majorly seen across all groups. So, considering these limitations and developing further robust modelling techniques, considering all the available variables to identify the adoption behaviour might yield better results.

Despite these limitations and potential biases, the current model results provide a preliminary understanding of real-world preferences and limitations of microcar adoptions and identify important vehicles, individuals, and other attributes of interest while adopting a microcar.

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Appendix A: Real-world Vehicles and Their Original Levels

Micro-Electric Vehicles	1. SmartForTwo	21k, 4hrs, 130kmph, 100km, 4stars
	2. Microlino	21k, 4hrs, 90kmph, 230km, 4stars
	3. Renault Twizy	17k,3:30hrs,80kmph, 120km, 4 stars
	4. Varaneo	13k,6hrs,45kmph and 80kmph, 110km, 3stars
	5. Citroen Ami	8k,4hrs,45kmph,75km, 3stars
	6. Eli Zero	12k,3hrs, 45kmph, 100km, 4 stars
Electric Vehicles	1. Dacia Spring Electric 45	17k,4hrs,130kmph,170km, 5stars
	2.Hyundai INSTER Long Range	27k,5hrs,150kmph,300km, 5stars
	3. Renault 5 E-Tech 40kWh 95hp	25k,5hrs,140kmph,260km, 5stars
	4. Mini Cooper S	32k,4hrs, 160kmph, 230km, 4stars
	5. MG ZS EV Standard	34k, 8hrs, 180kmph, 270km, 5 stars
	6.Smart #1 Pure	35k, 7hrs, 180kmph, 250km, 5 stars

Appendix B: LCA Calculations of Vehicles while Defining Environmental Attribute Levels

Model	Battery Capacity (kWh)	Weight excl. Battery (kg)	Weight of Battery (kg)	Energy Consumption (kWh/100km)	Lifetime Mileage (km)
1. Smart EQ ForTwo	17.6	1095	~250	10.4	160,000 - 200,000
2. Microlino 2.0	5.5 / 10.5 / 14	496	N/A	5.5	Up to 200,000
3. Renault Twizy	6.1	474	~100	6.3	50,000 - 80,000
4. Varaneo Samsa 45	7.2 (Lead-acid battery)	680	N/A	6	100 - 150 per charge
5. Citroën Ami	5.5	471	N/A	6	~75 km per charge
6. Eli Zero	8 or 12	350	N/A	8	60 - 90 miles per charge
7. Dacia Spring Electric 45	27.4 (usable: 26.8)	1020	N/A	10.9	230 (WLTP)
8. Hyundai INSTER Long Range	49	1450	N/A	15.6	355 (WLTP)
9. Renault 5 E-Tech 40kWh 95hp	40	1400	N/A	15.7	255 - 300 (WLTP)
10. Mini Cooper SE	32.6	1440	N/A	16.1	180 - 234 (WLTP)
11. MG ZS EV Standard	49	1645	N/A	17.3	320 (WLTP)
12. Smart #1 Pure	49	1863	N/A	18.1	310 (WLTP)

Appendix B1: Models Considered and Their Properties

Smart EQ ForTwo	Microlino 2.0	Renault Twizy	Varaneo Samsa 45	Citroën Ami	Eli Zero	Dacia Spring Electric 45	Hyundai INSTER Long Range	Renault 5 E-Tech 40kWh 95hp	Mini Cooper SE	MG ZS EV Standard	Smart #1 Pure
17.6	5.5	6.1	7.2	5.5	8	27.4	49	40	32.6	49	49
1095	496	474	680	471	350	1020	1450	1400	1440	1645	1863
10.40	5.50	6.30	6.00	6.00	8.00	10.90	15.60	15.70	16.10	17.30	18.10
150000	150000	70000	150000	150000	150000	200000	200000	200000	200000	200000	200000
18.9	10.0	11.5	10.9	10.9	14.6	19.8	28.4	28.6	29.3	31.5	32.9
1627	508	564	666	508	740	2533	4530	3698	3014	4530	4530
10.8	3.4	8.1	4.4	3.4	4.9	12.7	22.7	18.5	15.1	22.7	22.7
4921	2324	2188	3199	2196	1482	4162	5532	5621	6109	6528	7642
33	15	31	21	15	10	21	28	28	31	33	38
6548	**2832**	**2752**	**3865**	**2704**	**2222**	**6695**	**10062**	**9319**	**9123**	**11058**	**12172**
44	**19**	**39**	**26**	**18**	**15**	**33**	**50**	**47**	**46**	**55**	**61**
63	**29**	**51**	**37**	**29**	**29**	**53**	**79**	**75**	**75**	**87**	**94**
60.14	**81.60**	**67.65**	**76.63**	**81.56**	**81.29**	**66.04**	**49.87**	**52.12**	**52.28**	**44.73**	**40.25**

Appendix B2: All the Vehicles and Their Emissions Reduction Potential Compared to Conventional Cars (Shown in Green)

Appendix C: Safety Levels Considerations of Vehicles

Micro-Electric Vehicles	1. SmartForTwo	AO 80%, CO 83%, SA 60%, 4 stars
	2. Microlino	AO 80%, CO 83%, SA 60%, 4 stars
	3. Renault Twizy	AO 80%, CO 83%, SA 60%, 4 stars
	4. Varaneo	AO 73%, CO 70%, SA 55%, 3stars
	5. Citroen Ami	AO 73%, CO 70%, SA 55%, 3stars
	6. Eli Zero	AO 80%, CO 83%, SA 60% , 4 stars
Electric Vehicles	1. Dacia Spring Electric 45	AO 94%, CO 89%, SA 82%, 5stars
	2.Hyundai INSTER Long Range	AO 94%, CO 89%, SA 82%, 5 stars
	3. Renault 5 E-Tech 40kWh 95hp	AO 94%, CO 89%, SA 82%, 5 stars
	4. Mini Cooper S	AO 80%, CO 83%, SA 60% , 4stars
	5. MG ZS EV Standard	AO 94%, CO 89%, SA 82%, 5 stars
	6.Smart #1 Pure	AO 94%, CO 89%, SA 82%, 5 stars

Where,

Driver safety: Adult occupant protection (AO)

Child's safety: Child occupant protection (CO)

Safety Assistance: Speed, lane and Car to Car assistance (SA)

Appendix D: Levels Adopted from MiD in for Survey

Attributes	Age	Gender	Education	Occupation	Income	Household Size	Household Type	Marital Status	City	Childern	Region
Measurement	Ordinal	Nominal	Nominal	Nominal	Ordinal	Ordinal	Nominal	Nominal	-	Metric	Nominal
Levels	18-24 years	Male	No qualification (yet)	Full-time employment	Under 500 euros	1 person	1-person home: person 18-29 years	Married	Text format	0 to 10	Urban region - metropolis
	25-44 years	Female	Primary or secondary school (POS 8th grade)	Part-time employment, i.e. 18 to less than 35 hours per week	500 to under 900 euros	2 person	1-person home: person 30-59 years	Widowed			Urban region - Regiopole and large city
	45-59 years	Not specified	Intermediate school leaving certificate, secondary school leaving certificate (POS 10th grade)	Marginally employed, i.e. 11 to less than 18 hours per week	900 to under 1,500 euros	3 person	1-person household: Person 60 years and older	Divorced			Urban region - medium-sized town, urban area
	60-64 years		University of Applied Sciences entrance qualification (Abitur, EOS 12th grade or vocational training with high school diploma)	Employed as a part-time job or in an internship	1,500 to under 2,000 euros	4 person	2-person household: youngest person 18-29 years	Seperated			Urban region - small town, village area
	65 years and older		University degree	Employed without specification of extent	2,000 to under 3,000 euros	5 person	2-person household: youngest person 30-59 years	Single			rural region - central city
			Other degree	Trainees	3,000 to under 4,000 euros	5 person and more	2-person household: youngest person 60 years and older	Prefer not to say			rural region - medium-sized town, urban area
			None of the above	Students	4,000 to under 5,000 euros		House hold with at least 3 adults				rural region - small town, village area
				Housewife/Househusband	5,000 to under 6,000 euros		Households with at least one child under 6 years				
				Pensioners	6,000 to 7,000 euros		Households with at least one child under 14 years				190, P29, B1
				Currently unemployed	More than 7,000 euros		Households with at least one child under 18 years				Metropolis
				None of the above			Single parents				Regiopole (big city)
							None of the above				Central city, medium sized
											Urban Space
											Small town, village area

Appendix D: Levels Adopted from MiD in for Survey (Continued)

Attributes/ Questions	Do you belong to the age group of 18 and above	Usage	Total daily travel distance	Usage for long distance travel? >2(	Car travel time to the nea	Annual mileage	Number of cars	PuT Availability
Measurement	Nominal	Ordinal	Ordinal	Ordinal	Ordinal	Ordinal	Ordinal	Ordinal
Levels	Yes	Daily or almost daily	Less than 5 km	Daily or almost daily	Under 10 min	Under 5,000 km	No car	Within 250 meter
	No	1-3 days per week	5 to less than 10 km	1-3 days per week	10 to less than 20 min	5,000 to less than 10,000 km	1 car	250 to less than 500 meter
		1-3 days per month	10 to less than 20 km	1-3 days per month	20 to less than 30 min	10,000 to less than 15,000 km	2 cars	500 meter to less than 1km
	Do you own a Car?	Less than monthly	20 to less than 30 km	Less than monthly	30 to under 40 min	15,000 to less than 20,000 km	3 cars and more	1 to under 2,5 km
	Nominal	Never or almost never	30 to less than 50 km	Never or almost never	40 min and more	20,000 to less than 25,000 km		2,5 to under 5 km
	Yes		50 to less than 100 km	None of the above		25,000 to less than 50,000 km	Company cars?	5 km and more
	No		100 to less than 200 km			50,000 km and more		
			200 to under 300 km					
	Do you own an electric Car?		300 km and more			or		
	Nominal					Metric		
	Yes					0 to 600,00		
	No							

Appendix E: Eight Choice Sets

Choice set 1		
Purchase Price	20,000 euros	22,000 euros
Charging Time (Home Charge)	4 hrs	8 hrs
Top Speed	80 km/hr	140 km/hr
Range	100 km	230 km
Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO2 reduction of 80% compared to electric-SUV	CO2 reduction of 60% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Available only at selected locations	Not Available
Choice set 2		
Purchase Price	8,000 euros	18,000 euros
Charging Time (Home Charge)	3 hrs	4 hrs
Top Speed	45 km/hr	140 km/hr
Range	75 km	200 km
Safety	3 Stars (50% safety assistance and 70% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO2 reduction of 80% compared to electric-SUV	CO2 reduction of 70% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Widely Available	Available only at selected locations
Choice set 3		
Purchase Price	17,000 euros	26,000 euros
Charging Time (Home Charge)	5 hrs	8 hrs
Top Speed	80 km/hr	140 km/hr
Range	100 km	230 km
Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO2 reduction of 70% compared to electric-SUV	CO2 reduction of 50% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Widely Available	Not Available

Choice set 4		
Purchase Price	8,000 euros	34,000 euros
Charging Time (Home Charging)	4hrs	8hrs
Top Speed	45km/hr	180km/hr
Range	75km	230km
Safety	3 Stars (50% safety assistance and 70% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO2 reduction of 80% compared to electric-SUV	CO2 reduction of 60% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Widely Available	Not Available
Choice set 5		
Purchase Price	13,000 euros	26,000 euros
Charging Time (Home Charging)	4 hrs	6 hrs
Top Speed	120 km/hr	160 km/hr
Range	100 km	270 km
Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO2 reduction of 80% compared to electric-SUV	CO2 reduction of 50% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Not Available	Widely Available
Choice set 6		
Purchase Price	17,000 euros	22,000 euros
Charging Time (Home Charging)	5 hrs	8 hrs
Top Speed	80 km/hr	140 km/hr
Range	120 km	300 km
Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO2 reduction of 70% compared to electric-SUV	CO2 reduction of 60% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Not Available	Available only at selected locations

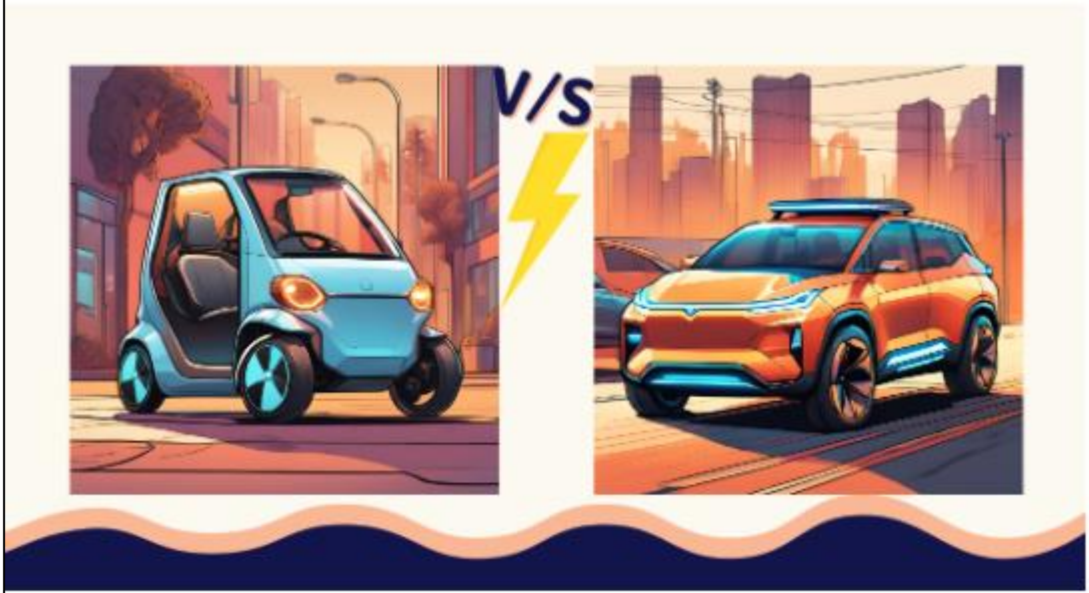
Appendix E: Eight Choice Sets (Continued)

Choice set 7		
Alternative	MEV	EV
PurchasePrice	10,000 euros	22,000 euros
ChargingTime	5hrs	6hrs
TopSpeed	120km/hr	160km/hr
Range	100km	300km
Safety	3 Stars (50% safety assistance and 70% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
EnvironmentalEffects	CO2 reduction of 80% compared to electric-SUV	CO2 reduction of 60% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
BatterySwapping	Available only at selected locations	Not Available
Choice set 8		
Alternative	MEV	EV
PurchasePrice	20,000 euros	34,000 euros
ChargingTime	4hrs	8hrs
TopSpeed	80km/hr	160km/hr
Range	120km	300km
Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
EnvironmentalEffects	CO2 reduction of 60% compared to electric-SUV	CO2 reduction of 40% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
BatterySwapping	Widely Available	Not Available

Appendix F: Survey Flow

Language: English - English Change the language

Light Electric Vehicle Adoption and its Potential in Carbon dioxide Reduction



Light electric vehicles (LEVs) have emerged as a promising solution to reduce greenhouse gas (GHG) emissions, especially in densely populated countries like Germany. Research indicates that LEVs have the potential to substantially reduce the carbon footprint of transportation in Germany by 2030.

To better understand and quantify this emission reduction potential, a utility model approach is used. Vector21, an agent-based model, simulates decision-making processes of individuals when choosing between different types of vehicles, taking into account economic, environmental, and practical considerations.

By implementing a Discrete Choice Experiment (DCE), this study aims to explore the real-world adoption potential of LEVs in Germany. The DCE will present participants with various scenarios involving different vehicle options, each with specific attributes such as price, range, charging time, and safety features. Participants' choices will provide valuable insights into their preferences and the trade-offs they are willing to make when selecting a vehicle.

The findings from this study will help to understand the factors that drive consumer decisions towards LEVs and identify the most effective incentives and policies to encourage their adoption. By aligning consumer preferences with sustainable transportation goals, this research will contribute to developing strategies that maximize the emission reduction potential of LEVs.

Image created using Canva:
Source: Canva (www.canva.com)

Estimated Time to Complete:

The survey will take approximately **12 to 15 minutes** to complete. Your honest responses are invaluable and will contribute significantly to our understanding of the factors that influence vehicle choices and the potential for LEVs to reduce emissions.

This survey is anonymous.

The record of your survey responses does not contain any identifying information about you, unless a specific survey question explicitly asked for it.

If you used an identifying access code to access this survey, please rest assured that this code will not be stored together with your responses. It is managed in a separate database and will only be updated to indicate whether you did (or did not) complete this survey. There is no way of matching identification access codes with survey responses.

Next

Current Car Usage

*Do you own a car?

- Yes
- No

*How far is the nearest public transport from your home?

Choose one of the following answers

- Within 250 meters (3 minutes walking)
- 250 to less than 500 meters (3-6 minutes walking)
- 500 meters to less than 1 km (6-12 minutes walking)
- 1 to under 2.5 km (12-30 minutes walking)
- 2.5 to under 5 km
- 5 km and more

*Do you own an electric car?

- Yes
- No

*Please select an option which best describes your current car usage

Choose one of the following answers

- Daily or almost daily
- 1-3 days per week
- Less than monthly
- Never or almost never

*What is your current total daily travel distance?

Choose one of the following answers

- Less than 5 km
- 5 to less than 10 km
- 10 to less than 20 km
- 20 to less than 30 km
- 30 to less than 50 km
- 50 to less than 100 km
- 100 to less than 200 km
- 200 km and more

*Please select an option that best describes your car usage for long distance travel (>200km)

Choose one of the following answers

- Daily or almost daily
- 1-3 days per week
- 1-3 days per month
- Less than monthly
- Never or almost never

*How many miles do you travel by car each year? Please select the option that best describes your annual car travel mileage.

Choose one of the following answers

- Under 5,000 km
- 5,000 to less than 10,000 km
- 10,000 to less than 15,000 km
- 15,000 to less than 20,000 km
- 20,000 to less than 25,000 km
- 25,000 to less than 50,000 km
- 50,000 km and more

*How many cars does your household have?

Choose one of the following answers

- 1 car
- 2 cars
- 3 cars and more

*How far is the nearest public transport from your home?

Choose one of the following answers

- Within 250 meters (3 minutes walking)
- 250 to less than 500 meters (3-6 minutes walking)
- 500 meters to less than 1 km (6-12 minutes walking)
- 1 to under 2.5 km (12-30 minutes walking)
- 2.5 to under 5 km
- 5 km and more

*What is the make and model of the car you currently own?

Instruction: Please specify the manufacturer (e.g., Toyota) and model (e.g., Corolla)

Attitude towards environment

*Please indicate your level of agreement with the following statements, with 1 being "**Strongly disagree**" and 5 being "**Strongly agree**".

	1	2	3	4	5
Continuing usage of conventional cars would have severe environmental effects in future	○	○	○	○	○
I will always choose to buy the most energy efficient home appliances (refrigerator, washing machine, etc.)	○	○	○	○	○
I have changed my lifestyle to help the environment	○	○	○	○	○
Environmental problems have been greatly exaggerated	○	○	○	○	○
Adapting electric vehicle would contribute to global emissions reduction	○	○	○	○	○

Attitude towards micro-electric car

*How aware are you of the technologies adopted by micro electric vehicles?

Choose one of the following answers

- Fully aware
- Aware
- Somewhat aware
- Not aware

*What is your perception of the range (the maximum distance the vehicle can go without recharging) of a micro-electric vehicle?

Choose one of the following answers

- <50 km
- 50-100 km
- 100-200 km
- >200km

*What is your perception of the time required to fully charge a micro-electric vehicle using a standard home charger?

Choose one of the following answers

- 1 hour
- 1 to 3 hours
- 3 to 6 hours
- 6 to 8 hours
- More than 9 hours

*If you were to buy an electric car tomorrow, what would be the most important thing when choosing an electric vehicle?

Select all that apply

- Driving Mileage/Range
- Drivability (Driving Experience)
- Purchase Price
- Charging Time
- Maximum Speed
- Safety
- Comfort
- Environmental and Climate Effects

Choice Set

Please assume that the vehicles described below are available for you. Carefully consider the attributes, including purchase price, charging time, speed, range, safety features, environmental impact, and additional features such as comfort and battery swapping and answer the total of **8 choice scenarios** represented for you.

We would like you to review the details for both vehicles presented in each choice set and select the option you would most likely choose for your personal use.

Next

*Please select an option from the choices given below:

Choice Set 1	Choice A	Choice B
		
Purchase Price	20,000 euros	22,000 euros
Charging Time (Home Charge)	4 hrs	8 hrs
Top Speed	80 km/hr	140 km/hr
Range	100 km	230 km
Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO_2 reduction of 80% compared to electric-SUV	CO_2 reduction of 60% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Available only at selected locations	Not Available

Choose one of the following answers

Choice A | Choice B | None of the above

*Please select an option from the choices given below:

Choice Set 2	Choice A	Choice B
		
Purchase Price	8,000 euros	18,000 euros
Charging Time (Home Charge)	3 hrs	4 hrs
Top Speed	45 km/hr	140 km/hr
Range	75 km	200 km
Safety	3 Stars (50% safety assistance and 70% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO_2 reduction of 80% compared to electric-SUV	CO_2 reduction of 70% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Widely Available	Available only at selected locations

Choose one of the following answers

Choice A | Choice B | None of the above

*Please select an option from the choices given below:

Choice Set 3	Choice A	Choice B
		
Purchase Price	17,000 euros	26,000 euros
Charging Time (Home Charge)	5 hrs	8 hrs
Top Speed	80 km/hr	140 km/hr
Range	100 km	230 km
Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO_2 reduction of 70% compared to electric-SUV	CO_2 reduction of 50% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Widely Available	Not Available

Choose one of the following answers

Choice A | Choice B | None of the above

*Please select an option from the given choices below:

Choice Set 4	Choice A	Choice B
		
Purchase Price	8,000 euros	34,000 euros
Charging Time (Home Charge)	4 hrs	8 hrs
Top Speed	45 km/hr	180 km/hr
Range	75 km	230 km
Safety	3 Stars (50% safety assistance and 70% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO_2 reduction of 80% compared to electric-SUV	CO_2 reduction of 60% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Widely Available	Not Available

Choose one of the following answers

Choice A | Choice B | None of the above

*Please select an option from the given choices below:

Choice Set 5	Choice A	Choice B
		
Purchase Price	13,000 euros	26,000 euros
Charging Time (Home Charge)	4 hrs	6 hrs
Top Speed	120 km/hr	160 km/hr
Range	100 km	270 km
Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO_2 reduction of 80% compared to electric-SUV	CO_2 reduction of 50% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Not Available	Widely Available

Choose one of the following answers

Choice A | Choice B | None of the above

*Please select an option from the given choices below:

Choice Set 6	Choice A	Choice B
		
Purchase Price	17,000 euros	22,000 euros
Charging Time (Home Charge)	5 hrs	8 hrs
Top Speed	80 km/hr	140 km/hr
Range	120 km	300 km
Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO_2 reduction of 70% compared to electric-SUV	CO_2 reduction of 60% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Not Available	Available only at selected locations

Choose one of the following answers

Choice A | Choice B | None of the above

*Would you be willing to adopt this vehicle as your primary car or second car?

Choose one of the following answers

- Primary Car (As a new car or by replacing the existing one)
- Second Car

*Please select an option from the choices given below:

Choice Set 7	Choice A	Choice B
		
Purchase Price	10,000 euros	22,000 euros
Charging Time (Home Charge)	5 hrs	6 hrs
Top Speed	120 km/hr	160 km/hr
Range	100 km	300 km
Safety	3 Stars (50% safety assistance and 70% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO_2 reduction of 80% compared to electric-SUV	CO_2 reduction of 60% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Available only at selected locations	Not Available

Choose one of the following answers

Choice A | Choice B | None of the above

*Please select an option from the choices given below:

Choice Set 8	Choice A	Choice B
		
Purchase Price	20,000 euros	34,000 euros
Charging Time (Home Charge)	4 hrs	8 hrs
Top Speed	80 km/hr	160 km/hr
Range	120 km	300 km
Safety	4 Stars (60% safety assistance and 80% driver safety)	5 Stars (80% safety assistance and 95% driver safety)
Environmental Effects	CO_2 reduction of 60% compared to electric-SUV	CO_2 reduction of 40% compared to electric-SUV
Comfort	Basic (Two seater)	Standard (Four seater)
Battery Swapping	Widely Available	Not Available

Choose one of the following answers

Choice A | Choice B | None of the above

Design Preference Choice

*Please rate the visual appeal of each vehicle based on its design. Assign a rating to each vehicle using a scale from 1 to 5, where **1 represents that the design does not appeal to you, and 5 represents that the design appeals to you.**

	1	2	3	4	5
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○

Reason for not buying / choosing a micro car today

What would be the main barriers preventing you from adopting a micro-electric (Microcar) car today?

Select all that apply

- [ ] Concerns about safety in traffic due to smaller size
- [ ] Unsuitable for highway travel or long distance trips
- [ ] Limited space or passenger capacity
- [ ] Preference for using public transport or cycling
- [ ] Look and feel of the car are important for me
- [ ] Brand is important and my prefered brand isn't available yet
- [ ] The total cost of owning a micro electric is a concern for me
- [ ] Concerns about driving around larger SUVs in traffic
- [ ] I already own a Microcar
- [ ] Other:

Small Car, Big Advantages: Discover the Benefits of Micro Electric Cars

Image created using Canva; Source: Canva (www.canva.com)

*With the advantages of micro-electric cars in mind, how willingly would you consider adopting a micro-electric vehicle as your next car?

Choose one of the following answers

- ○ Willing
- ○ Somewhat willing
- ○ Undecided
- ○ Not willing/Not convinced

Demographics

*How do you describe your gender?

Choose one of the following answers

- Male
- Female
- Others
- Prefer not to say

*Please select your age group

Choose one of the following answers

- 18-24 years
- 25-44 years
- 45-59 years
- 60-64 years
- 65 years and older

*Would you please indicate your marital status?

Choose one of the following answers

- Married/In a relationship
- Unmarried/Not in a relationship
- Other
- Prefer not to say

*What is the highest level of education?

Choose one of the following answers

- No formal qualification yet
- Primary or secondary school (up to 8th grade)
- Intermediate school leaving certificate or equivalent (up to 10th grade)
- High school diploma or vocational training (Abitur, EOS 12th grade)
- University degree
- Other degree

*What best describes your current employment status?

Choose one of the following answers

- Employed full-time
- Part-time job or internship (18 to less than 35 hours per week)
- Employed marginally (11 to less than 18 hours per week)
- Student
- Housewife/Househusband
- Pensioners
- Currently unemployed

*How many people, including yourself, are currently living in your household?

Choose one of the following answers

- 1 person
- 2 people
- 3 people
- 4 people
- 5 or more people

*How many children currently live with you?

Only numbers may be entered in this field.

*Which option best describes children in your household? Please select the category that includes the age of your youngest child.

Choose one of the following answers

- Households with at least one child under 6 years
- Households with at least one child under 14 years
- Households with at least one child under 18 years
- Not applicable

*In what type of region do you currently live?

Choose one of the following answers

- Metropolis
- Urban
- Sub-urban
- Rural

*Please select your State

Choose one of the following answers

- Baden-Württemberg
- Bayern
- Berlin
- Brandenburg
- Bremen
- Hamburg
- Hesse
- Lower Saxony
- Mecklenburg-Vorpommern
- North Rhine-Westphalia
- Rhineland-Palatinate
- Saarland
- Saxony
- Saxony-Anhalt
- Schleswig-Holstein
- Thuringia

*Please select your monthly household net income range from the options below.

Choose one of the following answers

- Less than 500 euros
- 500 to less than 1,500 euros
- 1,500 to less than 2,000 euros
- 2,000 to less than 3,000 euros
- 3,000 to less than 4,000 euros
- 4,000 to less than 5,000 euros
- 5,000 to less than 6,000 euros
- 6,000 to less than 7,000 euros
- More than 7,000 euros

Appendix G: Information Card

Small Car, Big Advantages: Discover the Benefits of Micro Electric Cars

*

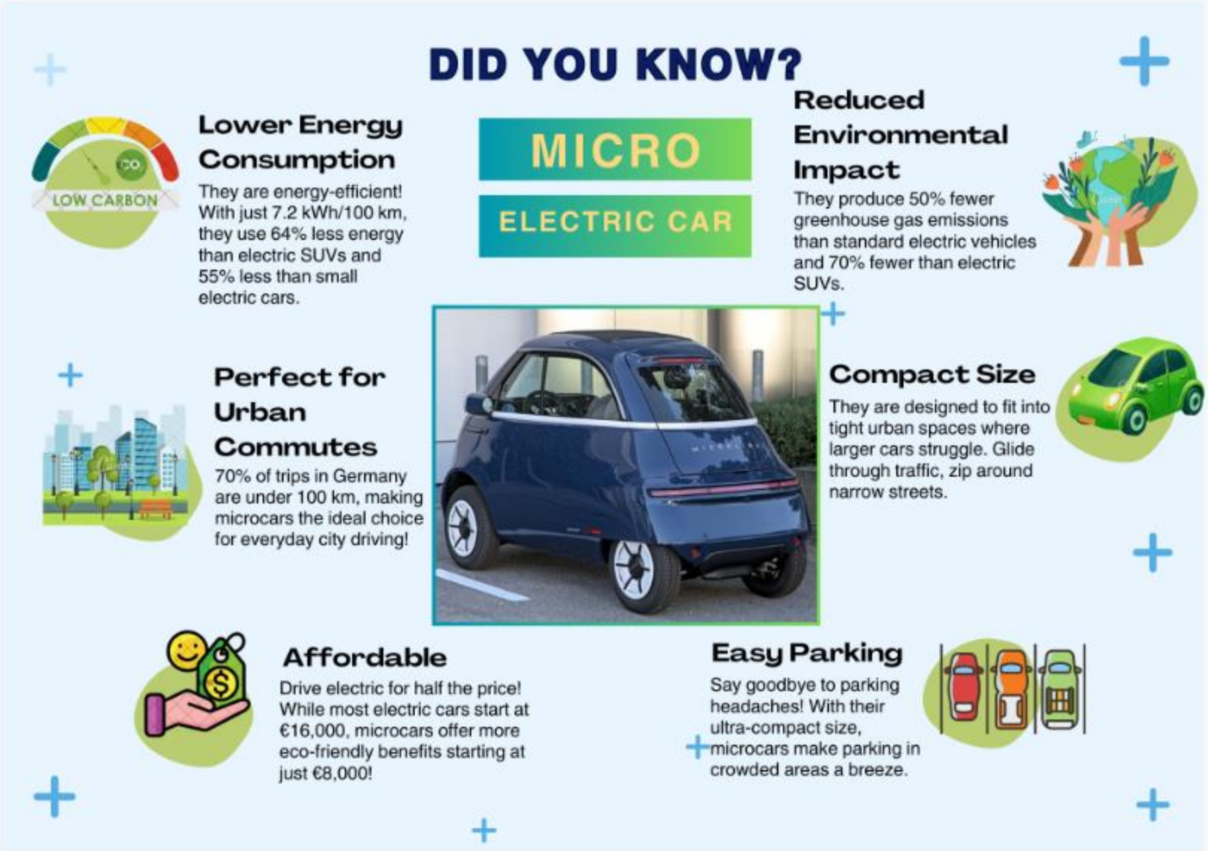
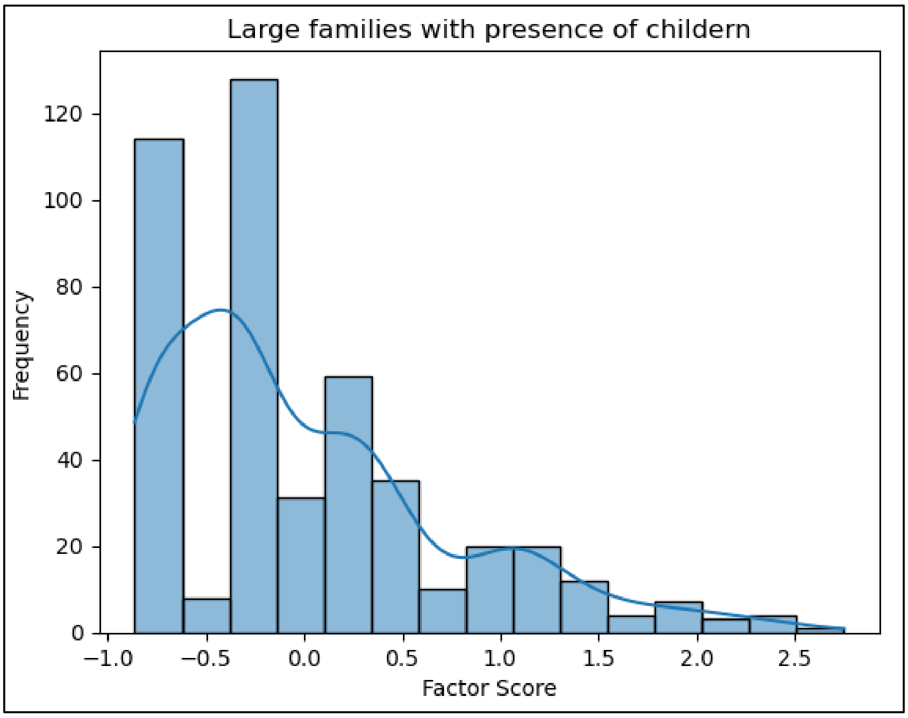


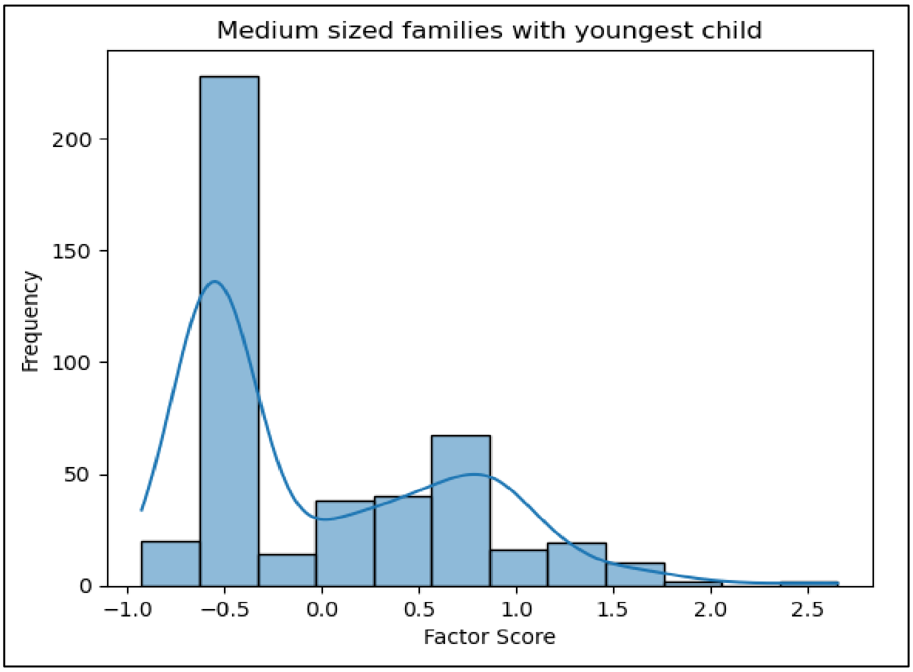
Image created using Canva: Source: Canva (www.canva.com)

*With the advantages of micro-electric cars in mind, would you consider adopting an electric or a micro-electric vehicle as your next car?

○ Yes ○ No

Appendix I: Factor Scores Distribution (EFA)





1. A smaller number of households have high factor scores (>1), indicating that fewer households have strong characteristics of being large and having children. Most families in the sample are moderately large.

2. A smaller tail exists toward higher scores (>1), indicating fewer households strongly exhibit the characteristics of having the youngest child in a medium-sized family.

3. Since our focus is on knowing if the presence of children and the youngest child in a family makes a difference in adoption, these results might be useful.

Appendix J: Utility Equation (CFA + SEM)

```
# Define the SEM
sem_model <- '
  # Latent variable definitions
  Environmental_Concern_FS =~ envi_concern1 + envi_concern2 + envi_concern3 + envi_concern5
  Car_Usage_Intensity_FS =~ car_usage + daily_ttd + car_usage_ld + yearly_ttd + no_cars

  # Correlated residuals for Environmental Concern
  envi_concern1 ~~ envi_concern5

  # Correlated residuals for Car Usage Intensity
  daily_ttd ~~ car_usage
  daily_ttd ~~ yearly_ttd
  car_usage_ld ~~ car_usage
  car_usage_ld ~~ yearly_ttd

  # Structural relationships
  Environmental_Concern_FS ~    education + region_Rural +region_Sub.urban

  Car_Usage_Intensity_FS ~ gender_Male+ Employed.full.time +
                               Employed.marginally..11.18.hr.w.+
                               Housewife.Househusband +
                               Employed_part.time +
                               Pensioners +
                               Students + region_Rural +region_Sub.urban +region_Urban+
                               age_45.59.years + age_60.64.years + age_65.years.and.more+
                               education_No.qualification+ education_Other.degree+
                               education_Primary.or.secondary+
                               income_2000.to.3000.euros+ income_2000.to.3000.euros+
                               income_3000.to.4000.euros+
                               income_4000.to.5000.euros+ income_5000.to.6000.euros
                               + income_500.to.1500.euros+ income_6000.to.7000.euros+
                               income_Less.than.500.euros
'
```

Appendix K: Covariance Matrix and Variance Matrix of CFA

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.envi_concern1 ~~						
.envi_concern5	0.147	0.026	5.656	0.000	0.147	0.217
.car_usage ~~						
.daily_ttd	-0.124	0.017	-7.220	0.000	-0.124	-0.342
.daily_ttd ~~						
.yearly_ttd	0.430	0.033	13.177	0.000	0.430	0.300
.car_usage ~~						
.car_usage_ld	-0.063	0.014	-4.496	0.000	-0.063	-0.203
.car_usage_ld ~~						
.yearly_ttd	0.277	0.025	11.143	0.000	0.277	0.225
.Environmental_Concern_FS ~~						
.Cr_Usg_Intn_FS	-0.135	0.016	-8.259	0.000	-0.164	-0.164

Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.envi_concern1	0.627	0.033	19.232	0.000	0.627	0.400
.envi_concern2	0.929	0.025	37.835	0.000	0.929	0.720
.envi_concern3	0.642	0.028	23.323	0.000	0.642	0.450
.envi_concern5	0.731	0.029	25.336	0.000	0.731	0.526
.car_usage	0.108	0.014	7.961	0.000	0.108	0.078
.daily_ttd	1.218	0.046	26.192	0.000	1.218	0.315
.car_usage_ld	0.901	0.030	30.112	0.000	0.901	0.385
.yearly_ttd	1.683	0.045	37.077	0.000	1.683	0.461
.no_cars	0.243	0.006	37.549	0.000	0.243	0.429
.Envrnmntl_C_FS	0.883	0.042	20.910	0.000	0.938	0.938
.Cr_Usg_Intn_FS	0.772	0.023	33.469	0.000	0.612	0.612

Appendix L: MNL and LCM Utility Equations

Appendix L1: MNL Utility

```
# Define utility functions
V <- list()
V[["Microcar"]] <- asc_Microcar +
  beta_price_MEV * PurchasePrice_MEV +
  beta_price_safety_MEV * Price_Safety_MEV +
  beta_swapping_MEV * BatterySwapping_MEV +
  beta_car_usage_MEV * Car_Usage_Intensity +
  beta_knowledge1_Not.aware_MEV * knowledge1_Not.aware+
  beta_PuT_2to5km_MEV * PuT_2to5km+
  beta_PuT_250m_MEV *PuT_250m

V[["Electric_car"]] <- asc_Electric_car +
  beta_price_EV * PurchasePrice_EV +
  beta_price_speed_EV * Price_speed_EV +
  beta_knowledge1_Not.aware_EV *  knowledge1_Not.aware+
  beta_PuT_2to5km_EV *  PuT_2to5km+
  beta_PuT_250m_EV *PuT_250m

V[["None of the above"]] <- asc_None
```

Where:

1. MEV: Microcar
2. EV: Electric Car
3. asc: Alternative specific constant
4. PuT: Public Transport
5. Knowledge1: Knowledge about electric vehicle technologies
6. Price_Safety = Interaction term between purchase price and safety

Note: In the utility functions of each alternative, the rest of all variables are written in complete form for better interpretability.

Appendix L2: LCM Utility

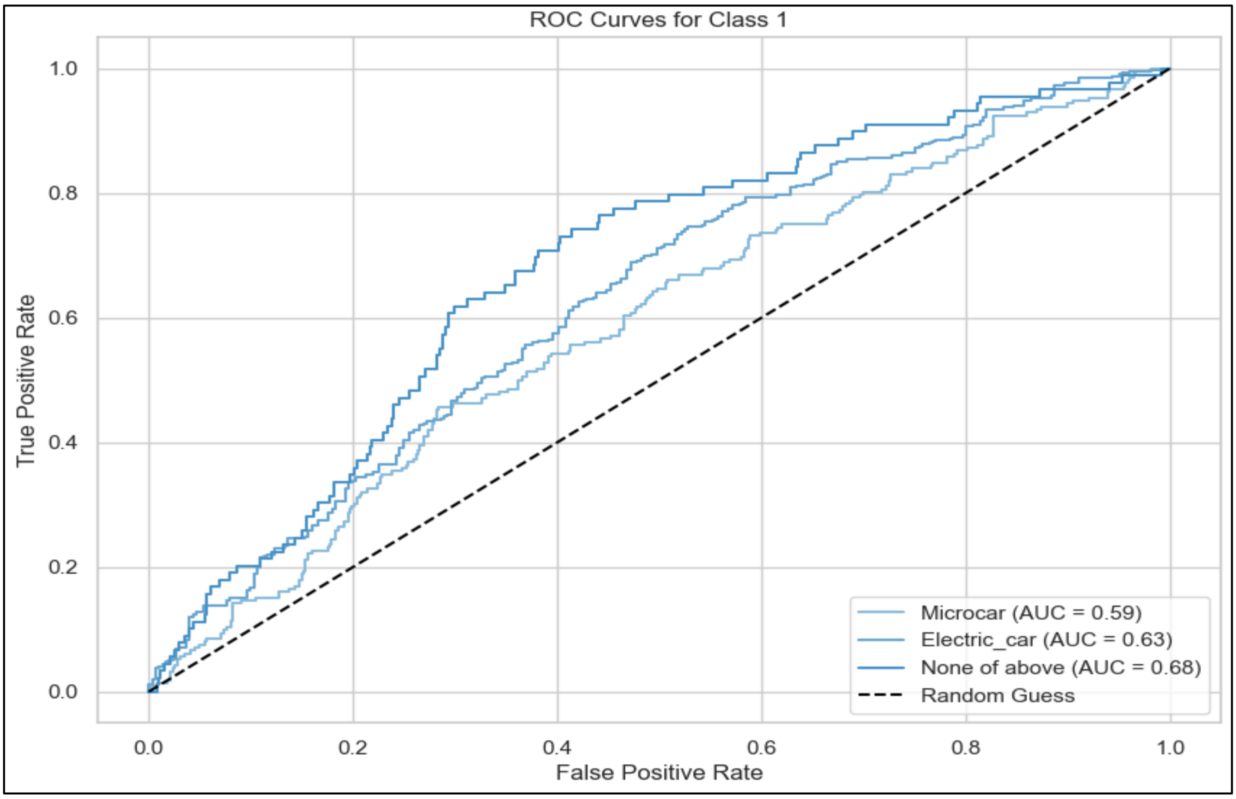
```
# Define Utility Functions for Each Class
V <- list(
  Microcar = ifelse(Class == 1,
                    asc_Microcar_class1 + beta_price_MEV_class1 * PurchasePrice_MEV +
                      beta_time_MEV_class1 * ChargingTime_MEV +
                      beta_Car_Usage_Intensity_MEV_class1 * Car_Usage_Intensity,
                    ifelse(Class == 2,
                           asc_Microcar_class2 +
                             beta_Environmental_Concern_MEV_class2 * Environmental_Concern +
                             beta_Car_Usage_Intensity_MEV_class2 * Car_Usage_Intensity +
                             beta_knowledge1_Not.aware_MEV_class2 * knowledge1_Not.aware +
                             beta_PuT_250m_MEV_class2 * PuT_250m,
                           ifelse(Class == 3,
                                  asc_Microcar_class3 + beta_time_MEV_class3 * ChargingTime_MEV +
                                    beta_Price_Range_MEV_class3 * Price_Range_MEV +
                                    beta_PuT_250m_MEV_class3 * PuT_250m,
                                  ifelse(Class == 4,
                                         asc_Microcar_class4 +
                                           beta_Car_Usage_Intensity_MEV_class4 * Car_Usage_Intensity+
                                           beta_PuT_2to5km_MEV_class4 * PuT_2to5km, 0)))),

  Electric_car = ifelse(Class == 1,
                        asc_Electric_car_class1 + beta_price_EV_class1 * PurchasePrice_EV +
                          beta_Car_Usage_Intensity_EV_class1 * Car_Usage_Intensity +
                          beta_knowledge1_Not.aware_EV_class1 * knowledge1_Not.aware,
                        ifelse(Class == 2,
                               asc_Electric_car_class2 + beta_price_EV_class2 * PurchasePrice_EV +
                                 beta_Environmental_Concern_EV_class2 * Environmental_Concern +
                                 beta_knowledge1_Not.aware_EV_class2 * knowledge1_Not.aware +
                                 beta_PuT_250m_EV_class2 * PuT_250m,
                               ifelse(Class == 3,
                                      asc_Electric_car_class3 + beta_price_EV_class3 * PurchasePrice_EV +
                                        beta_time_EV_class3 * ChargingTime_EV +
                                        beta_Price_speed_EV_class3 * Price_speed_EV,
                                      ifelse(Class == 4,
                                             asc_Electric_car_class4 + beta_price_EV_class4 * PurchasePrice_EV +
                                               beta_time_EV_class4 * ChargingTime_EV +
                                               beta_Price_speed_EV_class4 * Price_speed_EV +
                                               beta_knowledge1_Not.aware_EV_class4 * knowledge1_Not.aware+
                                               beta_PuT_2to5km_EV_class4 * PuT_2to5km, 0)))),

  None = asc_None  # Reference
```

Where:

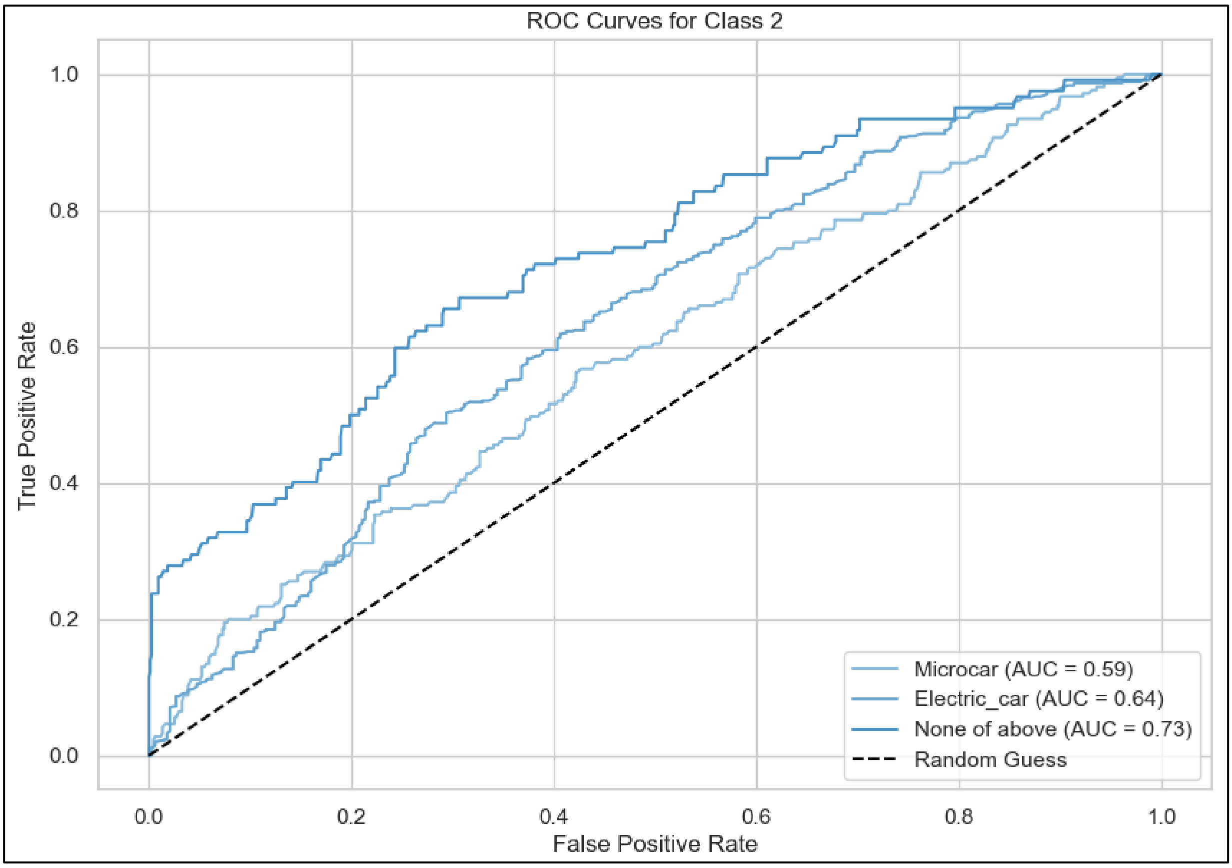
1. MEV: Microcar
2. EV: Electric Car
3. asc: Alternative specific constant
4. PuT: Public Transport
5. Knowledge1: Knowledge about electric vehicle technologies
6. Price_Safety = Interaction term between purchase price and safety
7. Price_Range = Interaction term between purchase price and range
8. Price_Speed = Interaction term between purchase price and top speed

Note: In the utility functions of each alternative and class, the rest of all variables are written in complete form for better interpretability.

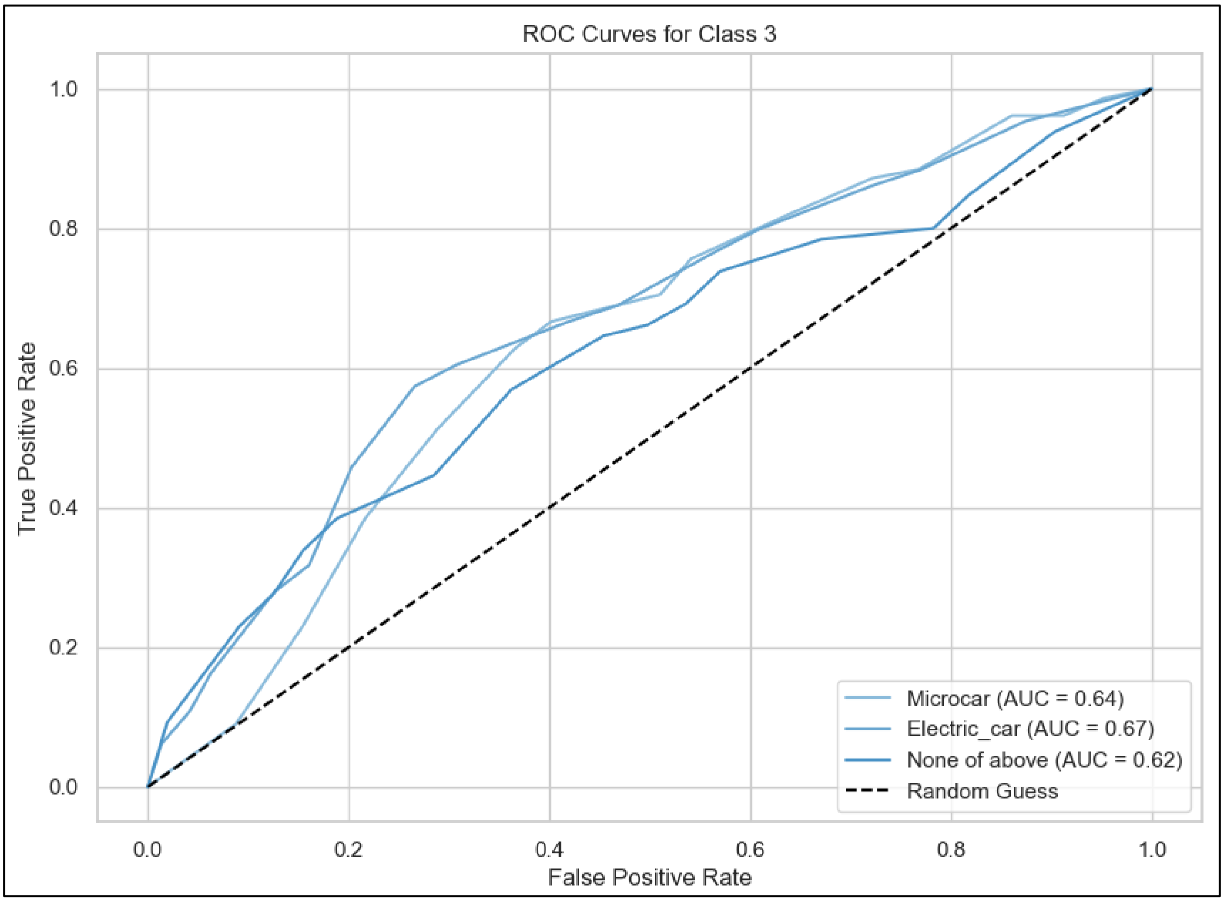
Appendix M: Class-Wise ROC Across Each Alternative



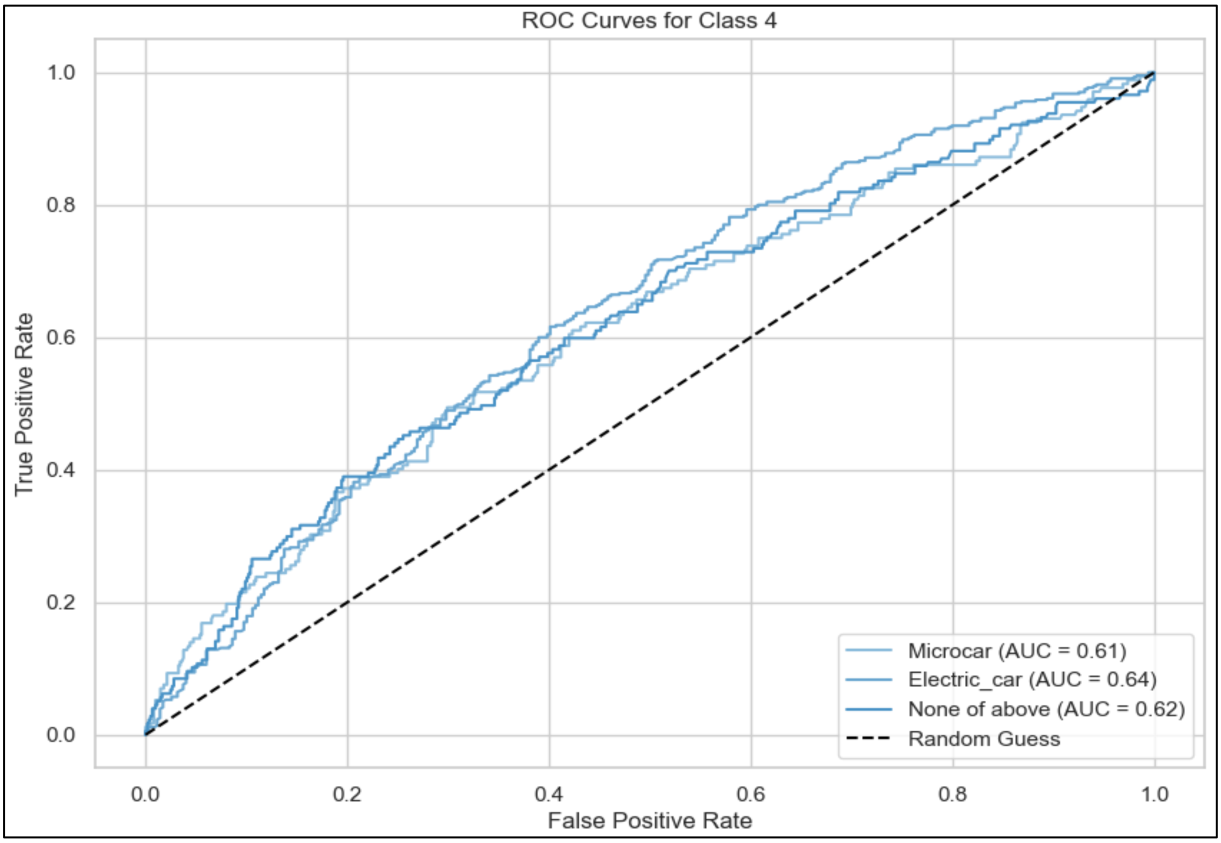
Appendix M1: ROC for Class 1



Appendix M2: ROC for Class 2



Appendix M3: ROC for Class 3



Appendix M4: ROC for Class 4

Appendix N: Other Reasons Stated by Respondents for Not Adopting a Microcar Toady

Cost-Related Issues:
- The price
- Price - performance is often
- No money
- Total cost of owning a microcar

Environmental/Efficiency Concerns:
- Lack of energy efficiency overall
- Is not as environmentally friendly as it is advertised

Safety Concerns:
- Fear of tipping over
- Completely flat in an accident
- I'm afraid of thunderstorms

Size/Space Issues:
- Smaller size
- Too small with a child!

Personal Reasons:
- I don't drive a car
- I have two children who I can't keep down
- An electric car is completely out of the question for me
- Pointless

Technology/Infrastructure Issues:
- The long loading time
- Charging infrastructure is not in place
- Other technology will come

Other:
- Appearance
- My preferred brand isn't available
- Only bought a new car in 2023
- Garbage

Note: “No money” had a frequency of three.

Appendix O: Correlation matrix Most Appealing Design Preference