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# Do consumers want reconditioned electric vehicle batteries? – A discrete choice experiment

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ABSTRACT

Reconditioning electric vehicle (EV) batteries for reuse as spare parts could extend the lifespan of EVs and reduce the environmental impact of battery production. However, this circular option's viability depends on consumer acceptance of reconditioned batteries. This study presents a discrete choice experiment among German residents to address this issue. A mixed logit behavioral model and Hierarchical Bayes estimation are used to evaluate the choice experiment. The experiment was conducted online and surveyed 1152 participants, with 837 providing sufficient data for analysis. The results indicate that there might be acceptance of reconditioned EV batteries as spare parts. A considerable number of respondents opted for this option when presented with the hypothetical choice of replacing a defective battery in their EV with a new or reconditioned spare battery, or scrapping the EV and purchasing a working vehicle. The study finds that the choice is primarily influenced by the expected battery lifetime and the associated costs. Ecological factors play a minimal role and are more of a bonus. The study also reveals that younger respondents and non-EV owners exhibit greater concern regarding the lifetime losses of reconditioned batteries compared to older respondents and EV owners. A self-assessment of the respondents concerning the most and least decisive battery characteristics shows a connection between stated importance of the attributes and the actual choice, but the connection is relatively weak. The results lead to the conclusion that industry and academic institutes should see EV battery reconditioning as an emerging research field that requests solutions for prolonging reconditioned batteries' lifetime while ensuring economical pricing to satisfy the demands of the consumers.

## Nomenclature

### Symbols

| | |
|---|---|
| $asc_{it}$ | Alternative-specific constant of option $i$ in choice situation $t$ |
| $b$ | Superscript denoting battery characteristics, $b \in$ {cost savings compared to a new battery; battery life losses compared to a new battery; greenhouse gas savings compared to a new battery} |
| $\beta$ | Vector of all coefficients (population level) |
| $\beta_n$ | Vector of all coefficients for decision maker $n$ |
| $\beta_y^{bv}$ | Vector of coefficients for $y$ regarding $bv \in$ {battery characteristics $b$; vehicle characteristics $v$} |
| $\beta_y^{bv,c}$ | Vector of coefficients for $y$ regarding $bv \in$ {battery characteristics $b$; vehicle characteristics $v$} *and* consumer characteristics $c$ |
| $c$ | Superscript denoting consumer characteristics, $c \in$ {age; income; education; residence; EV ownership; self-assessed importance of battery attributes $b$} |
| $\varepsilon_{nit}$ | Independent and identically distributed extreme value type I error term of decision maker $n$ for choice option $i$ in choice situation $t$ |

(*continued on next column*)

(*continued*)

| | |
|---|---|
| $f(\beta)$ | Density function of $\beta$ |
| $i$ | Subscript denoting choice option, $i \in$ {new spare battery, reconditioned spare battery; none option} |
| $j$ | Number of alternative utility functions |
| $L_{nij}(\beta)$ | Logit probability of decision maker $n$ for choice option $i$ in choice situation $t$ evaluated at $\beta$ |
| $n$ | Subscript denoting decision maker, $n \in \{1, \dots, N\}$ |
| $N$ | Number of decision makers $n$ |
| $P_{ni}$ | Choice probability of decision maker $n$ for choice option $i$ |
| $t$ | Choice situation, $t \in$ {1, …, T} |
| $T$ | Number of choice situations $t$ |
| $U_{nit}$ | Utility of decision maker $n$ from option $i$ in choice situation $t$ |
| $U_{j,nit}$ | $j$ th version of utility function $U_{nit}$ |
| $v$ | Superscript denoting vehicle characteristics, $v \in$ {car price level} |
| $x_{yt}$ | Vector of all observable variables of $y$ in choice situation $t$ |
| $x_{yt}^{bvc}$ | Vector of observable variables of $y$ in choice situation $t$ regarding $bvc \in$ {battery characteristics $b$; vehicle characteristics $v$; consumer characteristics $c$} |
| $y$ | Subscript, $y \in$ {decision maker $n$; choice option $i$} |

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*Abbreviations*

| | |
|---|---|
| AIC | Akaike information criterion |
| ANOVA | Analysis of variance |
| BEV | Battery electric vehicle |
| BIC | Bayesian information criterion |
| $CO_2$ | Carbon dioxide |
| DCE | Discrete choice experiment |
| EV | Electric vehicle |
| EVB | Electric vehicle battery |
| GHG | Greenhouse gases |
| HB | Hierarchical Bayes |
| MCMC | Monte Carlo Markov Chain |
| OEM | Original equipment manufacturer |

## 1. Introduction

Considering the pressing issue of climate change, it is essential to reduce greenhouse gas (GHG) emissions. Transportation is a significant contributor to carbon emissions, accounting for approximately one-fifth of all such emissions globally in 2021 (Crippa et al., 2021). There is a particular focus on transitioning this sector from predominantly internal combustion technology to less carbon-intensive alternatives. Electric mobility, which has gained increasing acceptance among policymakers, companies, and consumers, could be part of a viable solution for individual transportation. Policy-wise, many countries worldwide have enacted legislation banning internal combustion engine passenger cars in the future, implemented incentives to purchase electric vehicles (EVs), or established targets for EV quotas or charging infrastructure (IEA, 2020). Company-wise, the product range for EVs has increased over the last years (IEA, 2020), and some car manufacturers have announced plans to cease the development of internal combustion engine cars by the end of the decade (Ewing, 2021). At the consumer end, there has been a remarkable increase in global EV sales from about 2 million EV sales in 2018 to >10 million in 2022 (IEA, 2023).

It is widely recognized by various studies that EVs have a lower carbon footprint than those powered by internal combustion engines (e.g., Girardi et al., 2015; Hill et al., 2020; Verma et al., 2022).This advantage is expected to increase as the proportion of renewable energy sources in electricity generation grows (Burchart-Korol et al., 2018). Nevertheless, the production of electric vehicle batteries (EVBs) presents a challenge to their environmental friendliness as it is an energy- and resource-intensive process that can cause other forms of pollution (Dai et al., 2019). In the long term, it is crucial to develop less environmentally harmful batteries (Murdock et al., 2021). However, in the short and medium term, maximizing the effective use of EVBs is essential.

The service life of batteries within vehicles is limited. However, due to the uneven aging of battery cells and modules, uninstalled batteries from EVs still contain numerous well-functioning cells or modules that could be reused (Kampker et al., 2020). The reconditioning process is schematically illustrated in Fig. 1. Original equipment manufacturers (OEMs) and independent remanufacturers have begun or plan to manufacture reconditioned batteries that could be used as cost-efficient spare parts for older EVs (Autocraft Solutions Group, 2023; Stellantis N.V., 2023). For example, in 2022, Stellantis has remanufactured approximately 46 % of all returning end-of-life batteries (1032 of 2261, Stellantis N.V., 2023), Mercedes Benz operates a remanufacturing plant without disclosing remanufacturing numbers (Mercedes-Benz Group, 2024), and Hyundai points out battery remanufacturing as a future path (Hyundai Motor Company, 2023). Such reusing endeavors could serve sustainability in three ways: First, the lifetime of existing vehicles can be extended since spare parts could be an economically viable solution for a longer time (Glöser-Chahoud et al., 2021). While electric cars are expected to last at least as long as internal combustion cars (Hoekstra and Steinbuch, 2020), which is approximately 14 years in Germany (Oguchi and Fuse, 2015), EVBs are expected to last for about 10 years (Schulz-Mönninghoff et al., 2021), so there is a potential lifespan mismatch. Second, fewer new spare batteries would be needed (Huster et al., 2022), resulting in a lower resource consumption for production. Third, the value induced by the manufacturing process for the battery cells is conserved, thus serving economic sustainability (Kampker et al., 2023).

However, remanufactured, reconditioned, and repaired products, with the differences between the terms lying mainly in the quality and warranty of the end product (Ijomah et al., 2004), serve a purpose only if product demand exists. This demand exists only when there are batteries that fail before the rest of the vehicle, necessitating spare parts for the host vehicle. Simulations suggest a growing number of such vehicles in the future (Glöser-Chahoud et al., 2021; Huster et al., 2022). Another prerequisite is that customers accept reconditioned batteries. For other products such as consumer electronics, some customers prefer new products, even if the used products are remanufactured to a state as good as new (Abbey et al., 2015a). However, the market for remanufactured

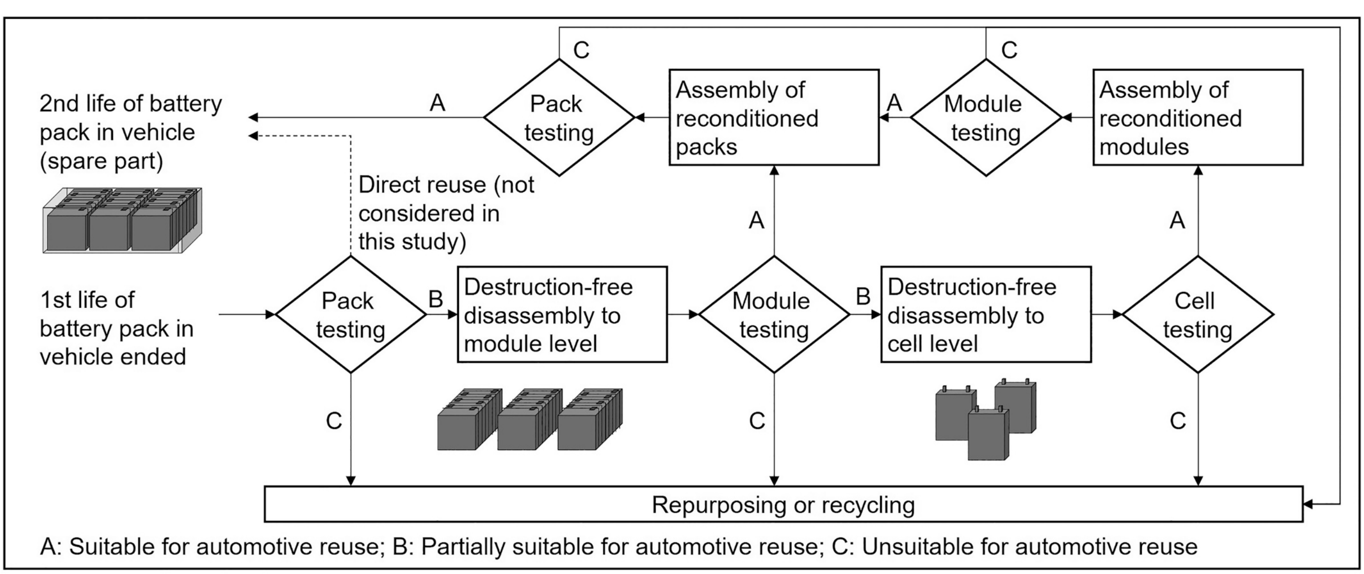


**Fig. 1.** Schematic representation of battery reconditioning.
(Based on Kampker et al. (2020), and Glöser-Chahoud et al. (2021).)

electronics is still expanding (Munde, 2024). Moreover, concerns regarding EVs and their batteries, such as price and performance, may also affect the acceptance of reconditioned EVBs (Stockkamp et al., 2021).

Research on reconditioned batteries is limited, as many publications have focused on recycling or repurposing EVBs for non-EV applications after their first use phase in an EV (Cong et al., 2021; Zhu et al., 2021). Consequently, consumer acceptance of reconditioned EVBs has not been extensively examined and fundamental questions remain unanswered. Specifically, the following research questions will be addressed:

- RQ1. Is there acceptance of reconditioned EVBs at all?
- RQ 2. What EVB attributes influence acceptance?
- RQ 3. Are there differences in acceptance among customers with distinct attributes, for example, regarding their demographics?

Previous research in the field of consumer acceptance of remanufactured products often employed discrete choice experiments (DCEs) (Hidrue et al., 2011; Helveston et al., 2015; Liao et al., 2018), sometimes also referred to as choice-based conjoint experiments (Ben-Akiva et al., 2019). While some authors argue that the concepts of DCEs and conjoint analysis should be strictly separated since they are based on different theoretical foundations (Louviere et al., 2010a), others regard choice-based conjoint as an "umbrella term" for economic stated choice experiments (Ben-Akiva et al., 2019). DCEs involve potential customers selecting from multiple sets of options that vary in certain attributes (Raghavarao et al., 2010). These experiments are usually based on Random Utility Theory and can estimate the utility function and decisiveness of single attributes and their levels in a population (McFadden, 1974). It should be noted that there are choice situations that cannot be modeled with the Random Utility framework, as Hess et al. (2018) have pointed out. For some applications, other frameworks might fit the choice problem better, for instance the Random Regret Minimization Model (Chorus et al., 2014). DCEs were chosen as the research method for this study because of their suitability for investigating consumer preferences concerning electric vehicle battery reconditioning and their wide application. Additionally, discrete choice experiment have been found to be a good choice for obtaining information about future behavior considering the alternatives of conducting a costly pilot project or collect the opinion of experts who could be biased (Quaife et al., 2018). However, findings about the external validity of discrete choice experiments has been mixed (Telser and Zweifel, 2007; Rakotonarivo et al., 2016; Quaife et al., 2018). The experiments were carried out via an online survey in Germany. The questionnaire is provided in the supplementary information.

The contribution of this study is threefold. First, it complements existing literature about consumers' views on circular products by adding perspective on EVBs. As Section 2 will show, there is scarcity of research on consumer preferences for reconditioned EVBs, and this study seeks to overcome the limitations of existing literature, such as the lack of realistic choice options. Second, the findings of this study can support forecasting the demand for reconditioned batteries, which can assist OEMs and independent operators in determining the economic viability of building reconditioning capacity. Finally, by identifying the key battery attributes that most influence consumer perceptions of reconditioned batteries, this study can guide future research and development efforts aimed at improving the performance of reconditioned batteries. As such, this study can help to prioritize research budgets for both public and private entities.

The structure of the paper is as follows: In Section 2, an overview of consumer preferences regarding remanufactured products and EVs is given, as well as a summary of existing literature regarding consumer preferences for reconditioned electric vehicle batteries. In Section 3, theoretical foundation of discrete choice models is provided, followed by the specific implementation in this study. Additionally, the case study is described in Section 3. The results are presented and discussed in Sections 4 and 5, and the study is concluded in Section 6 with an outlook.

## 2. Literature review

When examining consumer behavior, the methods at hand to obtain data are manifold and include qualitative approaches like forming focus groups or observation, and quantitative procedures like surveys or experiments (Chrysochou, 2017). The theoretical foundations of analyzing the obtained data are equally diverse and encompass the theory of planned behavior, the theory of reasoned action, utility theory and others (Belbağ and Belbağ, 2023). With regard to consumer choice of circular products, DCEs and conjoint analyses have gained popularity. They belong to the class of stated preference methods and therefore to the family of surveys (Alamri et al., 2023). For example, Koide et al. (2023) examined the acceptance of buying or leasing circulated refrigerators in Japan with a DCE. They used a multinomial logit model and estimated it with a Hierarchical Bayes approach. Their findings indicate that there are customer segments that leaned towards certain alternatives, namely brand-new refrigerators or subscriptions offers respectively, and others who based their decision on all or some of the attributes of the options. Similarly, Lieder et al. (2018) applied DCEs to investigate the acceptance of renting washing machines or paying per wash as opposed to purchasing washing machines, to enable product remanufacturing. With their survey in Stockholm, they found that service levels were the most decisive attribute, followed by the price and payment scheme. Environmental friendliness was the least decisive item. Hunka et al. (2021) used DCEs and Hierarchical Bayes analysis to evaluate consumers choice of reused and remanufactured mobile phones and robot vacuum cleaners in the United Kingdom. The importance of the examined attributes varied between phones and vacuum cleaners, but the price was the most important one for both products. The importance differed the most for the attributes battery life, appearance and ease of fixing. Further studies about consumers' perspectives on remanufactured products can be found in the literature review by Belbağ and Belbağ (2023). They provide a summary of the theories employed, the countries and product types for which analyses have been conducted, and the methodologies applied. Belbağ and Belbağ (2023) found that, besides experiments like DCEs, structural equation modeling and regression analyses are popular methods for examining consumer preferences towards remanufactured products.

DCEs have been used to predict EV adoption. For example, Liao et al. (2018) conducted a DCE in the Netherlands to analyze which the effect new business models, namely EV leasing and EVB leasing, have on the adoption of battery electric vehicles and plug-in hybrid electric vehicles. The availability of both EV and EVB leasing barely changes the attractiveness of EVs on the aggregate level compared to the case where ownership is the only option. However, a latent class approach reveals that some groups, especially the EV-affine group, are affected by the availability of different business models (Liao et al., 2018). Han and Sun (2024) examined the willingness to pay for EV attributes in China by fitting a multinomial logit model and a latent class model. The attributes were the EV purchasing price, maintenance cost, range, charging facility coverage, fast charging time, replaceability of the battery and vehicle-to-grid capability. They found that all attributes they examined had a significant influence on the willingness to pay. Han and Sun (2024) found that the willingness to pay for the attributes differ between distinct regions in China. Bhat et al. (2024) conducted a similar DCE in India where they examined the effect of different vehicle attributes, service attributes, supporting schemes like toll tax exemption, socio-demographic factors and latent factors such as environmental awareness on the intention to adopt EVs. They found significantly negative effects for EV purchasing prices, operating costs and charging time, and a significantly positive influence of driving range and availability of charging facilities. Some socio-demographic characteristics, like age, and latent characteristics also influenced the adoption intention (Bhat et al., 2024).

Examinations of consumer preferences for reconditioned EVBs have been relatively limited. Tondolo et al. (2021) were among the first to investigate the purchasing likelihood of reconditioned EVBs dependent on the price and the service provided, and the perceived risk and value. They employed the experimental vignette methodology with purchasing likelihood as the dependent variable surveyed on a seven-point scale, and price and service varying between the vignettes. The participants were United States nationals. By regression analysis, Tondolo et al. (2021) found that price and service of reconditioned EVBs interacted with regard to the purchasing likelihood, and a higher perceived risk had a negative impact on purchasing likelihood. Furthermore, they observed that a higher willingness to pay was associated with the offer of services such as free upgrades or roadside assistance. Chinen et al. (2022) surveyed respondents in China on their perception of remanufactured EVBs and employed structural equation modeling for analysis. They found that consumers' price consciousness and perceived benefits affect their purchasing intention, which in turn affects their willingness to pay and acceptance. However, willingness to pay was not surveyed for certain battery characteristics but was based on general beliefs about remanufactured batteries.

It remains unclear whether the survey participants in the EVB studies above were aware of alternatives to remanufactured or reconditioned products, such as new replacement products or early scrapping of the vehicle. It is generally recommended to include realistic options in choice experiments, which may include opting-out or maintaining the status quo (Adamowicz and Boxall, 2001; Determann et al., 2019). Not including such alternative options when realistic, may influence the obtained part-worth utilities or estimated willingness to pay, and therefore overestimate demand (Ryan and Skåtun, 2004; Campbell and Erdem, 2019). However, depending on the choice situation and the intended analysis, omitting none options, i.e., opting-out or maintaining the status quo, can lead to equal relative importance of attributes as including them (Veldwijk et al., 2014). Tao et al. (2022) partially addressed the lack of realistic choices with regard to reconditioned EVBs by determining consumer preferences for the alternatives "new spare battery", which 57 % chose, "refurbished battery" [26 %], and "directly reused battery" [17 %]. They obtained this data via an online questionnaire in Japan and analyzed the data with a multinomial logit model. However, they did not consider the "none" option and assumed that all consumers would replace the EVB.

The authors are not aware of any other studies that have specifically addressed consumer acceptance or perception of reconditioned or remanufactured EV batteries. While previous studies have explored consumers' perspectives on other remanufactured or reconditioned products than EVBs, it is not possible to easily transfer these results. For instance, repulsion or disgust has been identified as a barrier to adopting remanufactured household and personal products (Abbey et al., 2015a; Lee and Kwak, 2020); however, this is not expected to apply to EVBs. All existing studies on EVBs present their findings across a sample of consumers without differentiating between consumer groups, such as demographic groups. As EV adoption rates vary across demographic groups (Yang and Tan, 2019; Shanmugavel et al., 2022), whether the same is true for the adoption of reconditioned EVBs remains an open research question. Additionally, it is unclear how consumer preferences are linked to specific battery characteristics, such as the cost of one unit of battery or the lifespan of one year.

## 3. Methods

First, this section presents background information on the application of discrete choice experiments in conjunction with behavioral models in the literature. Subsequently, the study design of the discrete choice experiment is introduced in this section, including the selection of items and the sample. The behavioral models for estimation and the focus of the analysis are then outlined.

### 3.1. Analysis of discrete choice experiments

Discrete choice experiments can be assessed using various behavioral models, which are generally divided into logit and probit models (Ziegler, 2005). One foundational evaluation model upon which other models are built is the multinomial logit model (Louviere et al., 2010b). This model allows the estimation of utility as a function of the attribute levels of an alternative, with the population weight of certain attribute levels expressed as coefficients, and an error term (Hauber et al., 2016). However, this multinomial logit behavioral model has certain limitations. The most relevant limitation to this study is that it does not consider taste variation within the population or the correlation of unobserved factors over time (Train, 2009). The lack of taste variation stems from the coefficients of the attribute levels being fixed values (Train, 2009), meaning that the entire examined population has the same valuation of an attribute level, such as one unit of cost savings. While this assumption may be a simplification in general, it seems overly simplistic for the case of EVB replacement evaluation and unsuitable for the research questions proposed in Section 1. The mixed logit model is an advanced logit model that addresses some of the limitations of the multinomial logit model. This model contains distributed coefficients, allowing for random taste variations within the population, and is robust to correlation in unobserved patterns over time (Louviere et al., 2010b; Hauber et al., 2016). In mixed logit models, the choice probability $P_{ni}$ of decision maker $n$ for choice option $i$ among a set of $I$ choices are denoted as

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta, \tag{1}$$

where $\beta$ is the parameter vector, $L_{ni}(\beta)$ the logit probability evaluated at $\beta$, and $f(\beta)$ a density function (Train, 2009). In case a decision maker faces a sequence of choice situations $t$, either over months or years in a panel study, or within one questionnaire, the logit probability $L_{nit}(\beta)$ is typically represented as

$$L_{nit}(\beta) = \frac{e^{\beta_n x_{nit}}}{\sum_{j=1}^{I} e^{\beta_n x_{njt}}} \tag{2}$$

with $\beta_n x_{nit}$ being the observed utility share (Revelt and Train, 1998). As per Hensher and Greene (2003), the utility $U_{nit}$ of decision maker $n$ from option $i$ in choice situation $t$ can be expressed as

$$U_{nit} = \beta_n x_{nit} + \varepsilon_{nit}. \tag{3}$$

$x_{nit}$ refers to the observable variables of $i$ and $n$, such as the price attribute of option $i$ or the age of decision maker $n$, in choice situation $t$. The vector of coefficients for individual $n$ is denoted by $\beta_n$. Within the population, these coefficients are distributed according to the density function $f(\beta)$, which distinguishes mixed logit from multinomial logit. In the latter, $\beta_n$ equals $\beta_m$ for all individuals $m$ and $n$ of the population (Train, 2009). $\varepsilon_{nit}$ represents an independent and identically distributed extreme value type I error term. While the decision maker is assumed to be aware of their coefficients $\beta_n$ and error term $\varepsilon_{nit}$, the researcher knows only the values of $x_{nit}$. Furthermore, the researcher assumes certain distributions for the coefficients, often normal or lognormal distributions (Louviere et al., 2010b). By utilizing the knowledge of the observable variables, assumptions about the coefficient distributions, and integration of Eq. (1), the coefficients can be estimated, for example, through simulation techniques (Hensher and Greene, 2003).

To gain more insight into the preferences of individual decision makers or groups of decision makers, such as those with similar age or educational backgrounds, one could apply a latent class approach. However, this method requires specifying the number of groups prior to estimation, and is not suitable for analyses in which individuals may belong to multiple classes (Hauber et al., 2016). Considering this study's objective of examining different preferences for reconditioned batteries among demographic groups and the presence of overlapping demographic markers, such as age and income, the Hierarchical Bayes (HB) approach appears to be a more appropriate choice. HB is an estimation method that has gained popularity in recent years. Instead of estimating the coefficients for the entire population, it estimates individual-level parameters which can be aggregated at the population level (Lenk, 2014). HB estimation can be applied to various behavioral models, such as multinomial or mixed logit models (Huber and Train, 2001). Bayesian methods require making assumptions about the parameters and their relative weights before estimation, which are referred to as *prior distributions* (Bolstad and Curran, 2016). These priors are then updated with observed data and normalized to ensure integration to one, resulting in *posterior distributions* that are the focus of estimation (Lenk, 2014). As it is unlikely that the posterior distribution for the entire parameter vector will have a simple form that can be easily drawn from, it is necessary to use sampling methods. In particular, Monte Carlo Markov Chain (MCMC) methods have been employed for HB sampling, such as Gibbs sampling and the Metropolis-Hastings algorithm (Train, 2009). With MCMC methods, draws from the posterior distribution can be taken for one parameter at the time. The means of these draws converge to be the posterior parameter estimates (Qian et al., 2003).

### 3.2. Study design of the discrete choice experiment

To address the research questions presented in Section 1 through the use of a discrete choice experiment, it is first necessary to establish a setting in which potential customers can choose a reconditioned battery. As reconditioned products are typically utilized as spare parts, the scenario must involve the respondents owning an EV whose battery has failed. Given that battery exchanges are typically covered under warranty for a period of 8 years or 160,000 km (ADAC, 2022), the customer will only find themselves in a choice situation if their battery fails beyond repair after the warranty expires, meaning that their vehicle is at least 8 years old or has accumulated a mileage of 160,000 km or more. In this instance, the customer has three viable alternatives: first, to replace the faulty battery with a new spare battery to restore the car's functionality; second, to replace the battery with a reconditioned spare battery to restore the car's functionality; or third, to scrap the car and purchase a new or used vehicle that is in working order. Of course, the option of not replacing the car and simply discarding it would also be available. Given that the aim of this study is not to examine preferences for transportation modes, the option of switching to an alternative mode of transportation will not be included in the experiment.

In order to gain a deeper understanding of the factors that influence decisions beyond general beliefs about the available options, it is important to determine the attributes and their respective levels of the battery to be tested in the experiment. Consumers often consider the price, quality, and environmental friendliness of reconditioned products when making decisions (Abbey et al., 2015a; Wang et al., 2018; Aydin and Mansour, 2023). Additionally, concerns about the price and performance of new EVs and EV batteries (Li et al., 2017) and the environmental impact of EV batteries (Hall and Lutsey, 2018; Dai et al., 2019; Zhang et al., 2023) may indicate that these factors are also relevant for reconditioned batteries. As a result, the battery's price, its environmental sustainability, represented by GHG emissions, and its expected lifespan have been chosen as the battery attributes for this study. The lifespan is assumed to incorporate concerns about performance and quality, as the definition of lifespan used is that of most warranty schemes, which consider a battery State-Of-Health (SOH) of 70 % as a threshold (ADAC, 2022). Thus, an expected lifespan of six years implies that the SOH is expected to be above 70 % for six years. Additionally, the price of a new EV is taken into account in the analysis in order to determine whether the cost of acquiring a vehicle impacts the preference for or against reconditioned spare parts.

In determining the price levels for new EVs, the approximate basis prices of the Renault Twingo Electric, the VW ID.3 Pro, and the Mercedes EQA were utilized, which amounted to approximately 25,000 €, 35,000 €, and 45,000 €, respectively. Within one choice set, the car price is the same for all options.

The cost of a new battery was set at 10,000 € (corresponding to the approximate cost of 161 € per kWh of battery for large car manufacturers in 2022, BloombergNEF, 2023). The prices of reconditioned batteries were examined at different discount levels of 25 %, 50 %, and 75 %, resulting in prices of 7500 €, 5000 €, and 2500 €, respectively. The study looked at battery life expectancies of 10 years for new batteries (Chen et al., 2019; Bruno and Fiore, 2023), and 8, 6, 4, and 2 years for reconditioned batteries. The environmental impact of the batteries was assessed in terms of the GHG emissions, with levels of 4350, 2900, and 1450 kg $CO_2$ equivalents, corresponding to the GHG emissions associated with production (approx. 75 kg $CO_2$ equivalents/kWh, Hoekstra and Steinbuch, 2020), and assumed reductions of one-third and two-thirds for reconditioned batteries. The emission reduction levels are within the range found for remanufactured products (Sundin and Lee, 2012). For example, roeren GmbH (2023) report 66 % GHG savings for a remanufactured 4-cylinder combustion engine. The reduction levels might be conservative for battery reconditioning, since LKQ Europe (2022) assume more than 80 % reductions in GHGs for business models including battery remanufacturing. The attributes and their levels are summarized in Table 1. The characteristics and their levels of the battery were redefined to facilitate more comprehensive analysis. For instance, the price of the battery was transformed into the attribute "cost savings compared to a new battery [10 %]", which allows for the evaluation of the utility gain for each unit of cost savings, i.e., 10 % of the cost savings. Similarly, the environmental criterion of GHG emissions was transformed into "GHG savings compared to a new battery [10 %]" to easily assess the influence of GHG savings of 10 % on the utility of a reconditioned battery. The battery life expectancy is measured in "Battery life losses compared to a new battery [years]" so that the loss of one year in life expectancy compared to a new battery can be evaluated. The vehicle price was translated into an ordinal scale of "low", "medium", and "high", which was further transformed into "0", "1", and "2". This means that a cheap vehicle is always the reference point (0), and the results show the difference between the cheapest and the medium-priced vehicle as well as the difference between the medium-priced and the highest examined price level. The level transformations are not expected to change the results compared to using the original levels, as the transformations are linear, and the utility will be specified linearly as well (cf. Section 3.3). Therefore, the transformations could have been performed either at this stage or later on when interpreting the results. The transformations are summarized in Table 1.

As one aim of the study is to determine whether there could be acceptance of reconditioned EVBs, it is necessary to label the options.

**Table 1**
Attribute levels of the discrete choice experiment before and after transformation.

| Attribute | Levels | Transformation for analysis | Levels after transformation |
|---|---|---|---|
| Battery price [€] | 2500; 5000; 7500; 10,000 | Cost savings compared to a new battery [10 %] | 0; 2.5; 5; 7.5 |
| Battery life expectancy [years] | 2; 4; 6; 8; 10 | Battery life losses compared to a new battery [years] | 0; 2; 4; 6; 8 |
| Greenhouse gas emissions [kg $CO_2$ equivalents] | 1450; 2900; 4350 | GHG savings compared to a new battery [10 %] | 0; 3.3; 6.6 |
| Car price [€] | 25,000; 35,000; 45,000 | Car price level [ordinal scale] | Low (0); medium (1); high (2) |

The labels are "New battery", "Reconditioned battery", and "Vehicle disposal" as the none option, in which no spare battery is installed, but the whole vehicle is replaced instead.

The number of attributes and levels shown in Table 1 lead to many possible combinations per option. However, the number of feasible combinations is reduced due to some particularities of the examined product laid out above, for example, the limitation that reconditioned batteries will always have lower GHG emissions, a lower price, and a lower expected lifespan than the new counterpart, or that all options within one choice set should have the same car price. Still, not all remaining combinations can be examined, as the number of choice sets would become overwhelmingly large. There is no definitive answer when determining the optimal number of questions and, consequently, the maximum number of attribute combinations one can include in a survey. For example, Caussade et al. (2005) find nine to ten choice situations to be optimal, but their results also depend on the number of alternatives and levels presented. Chung et al. (2011) consider six choice sets with five options optimal concerning variance, while Bech et al. (2011) observe no significant change in variance for up to 17 choice situations in a three-alternative DCE with six attributes. Johnson and Orme (1996) analyzed 21 existing datasets from DCEs with eight to 20 choice tasks and three to six attributes and could not find a decline in reliability. A review by Bekker-Grob et al. (2015) discovered that four to six attributes and nine to 16 choice sets per respondent were common. However, some of these studies do not reveal whether the respondents were paid or otherwise incentivized. Reliability of the results is probably the main concern for incentivized studies, while unincentivized studies may additionally face a greater risk of participants exiting the survey early. To minimize the risk of early dropouts, a comparatively low number of 14 choice sets was chosen for this study. Ten test subjects pretested the survey, and they needed approximately ten minutes to complete the survey with 14 choice sets, which they subjectively rated as appropriate.

An efficient design of choice sets would fulfill the criteria of "level balance", "orthogonality", "minimal overlap", and "utility balance" (Huber and Zwerina, 1996). "Level balance" means that all attribute levels should appear equally frequently (Rose and Bliemer, 2009). "Orthogonality" describes the independence of the attributes (Mariel et al., 2021). "Utility balance" ensures that all options within a set are equally attractive, minimizing obvious preferences (Huber and Zwerina, 1996). However, simultaneously achieving these criteria can be challenging, and an orthogonal design may lead to unrealistic combinations (Mariel et al., 2021). Because of the particularities of EVBs, independence of the attributes is not given, which inevitably leads to a design violating orthogonality. Efficient designs could still be obtained by measures derived from the asymptotic covariance matrix of parameter estimates (Mariel et al., 2021). However, designs obtained this way are only optimized for a certain DCE model formulation (Rose and Bliemer, 2009). As will be shown in Section 3.3, several utility functions encompassing different parameters and coefficients will be tested. Therefore, instead of optimizing the design for one of the utility formulations, the efficiency criteria of level and utility balance and minimal overlap were utilized to manually create a universal design, incorporating knowledge about the product. However, it is not ensured that the design is optimal for any or all of the utility functions tested with regard to measures as D-efficiency or others. The initial design was presented to ten test subjects in a small pilot study to ensure utility balance.

An example of a choice set is depicted in Fig. 2. The full questionnaire is provided in the supplementary information.

The choice experiment was carried out as an online survey from November 2021 to January 2022 using the Sawtooth software. The survey link was distributed via German EV forums and a German YouTuber with a channel focused on battery-related topics (approximately 300,000 subscribers). Therefore, the regional focus of the study was Germany. Participation was voluntary and not incentivized. A total of 1152 individuals participated in the survey, with 914 completing it. Of the 914 completed questionnaires, 837 respondents provided complete demographic information, including gender, age, education, household income, residence, and EV ownership to enable analysis by population characteristics. To enable best-worst scaling, respondents were additionally asked to rank the battery attributes (price, expected lifetime, GHG emissions) by indicating the most and least important attribute. A summary of the respondents' characteristics is provided in Table 2, which includes information on the attribute class sizes, as well as numerical class names assigned to the attribute classes thought to have a linear relationship to the coefficients. These numerical class names are used as the $x_{nit}$'s in Eq. (3) for later analysis. From Table 2 it becomes clear that the sample is not representative of the German population, for instance with regard to gender. There may be a selection bias due to the distribution channels mentioned above, which will further be discussed in Section 5.

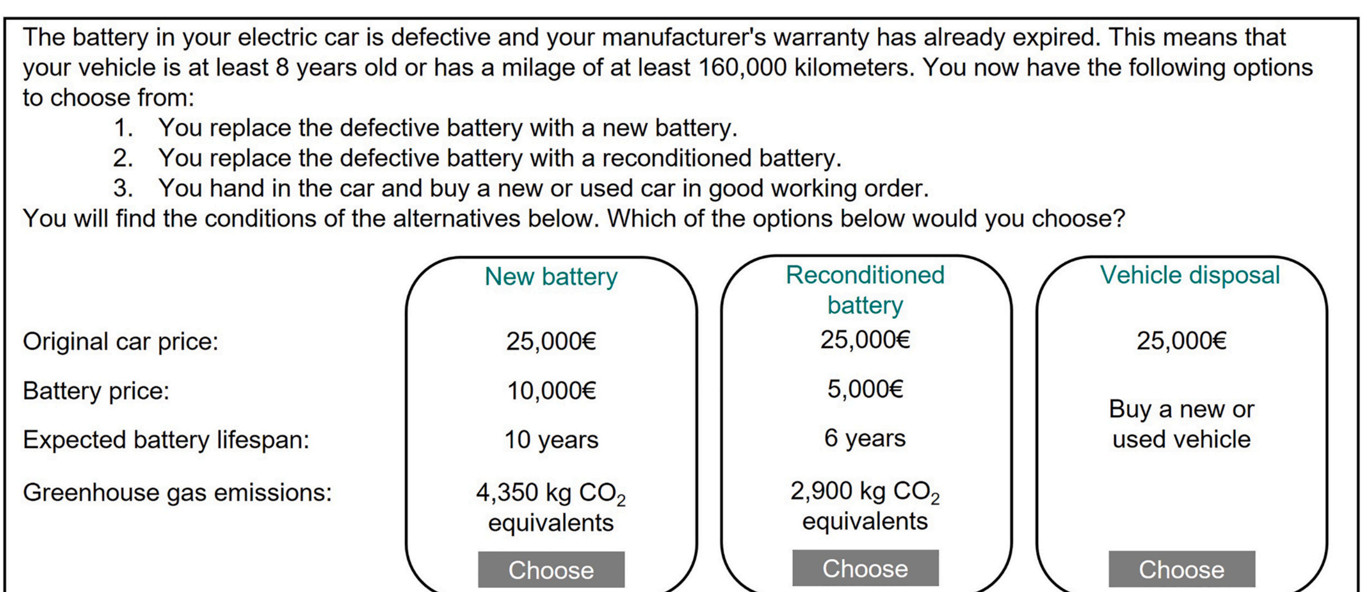


**Fig. 2.** Example choice set.

**Table 2**
Respondents' characteristics.

| Attribute | Attribute class | Class size | Numerical class name |
|---|---|---|---|
| Age[a] [years] | ≤29 | 64 [7.6 %] | – |
| | 30–39 | 165 [19.7 %] | – |
| | 40–49 | 198 [23.7 %] | – |
| | 50–59 | 265 [31.7 %] | – |
| | 60–69 | 129 [15.4 %] | – |
| | ≥70 | 16 [1.9 %] | – |
| Gender[b,c] | Male | 827 [98.8 %] | – |
| | Female | 10 [1.2 %] | – |
| Income [€] | ≤999 | 23 [2.7 %] | 0 |
| | 1000–1999 | 88 [10.5 %] | 1 |
| | 2000–2999 | 187 [22.3 %] | 2 |
| | 3000–3999 | 181 [21.6 %] | 3 |
| | 4000–4999 | 179 [21.4 %] | 4 |
| | ≥5000 | 179 [21.4 %] | 5 |
| Education | Basic (secondary school for grades five to nine or ten) | 217 [25.9 %] | 0 |
| | Intermediate (A-levels or comparable) | 189 [22.6 %] | 1 |
| | Advanced (academic) | 431 [51.5 %] | 2 |
| Residence | Rural area | 376 [44.9 %] | 0 |
| | Small or medium town | 211 [25.2 %] | 1 |
| | Suburb of a metropolis | 142 [17.0 %] | 2 |
| | Metropolis | 108 [12.9 %] | 3 |
| EV ownership | No | 427 [51.0 %] | 0 |
| | Yes | 410[49 %] | 1 |
| Most important attribute[a] (self-assessment) | Battery price | 358 [42.8 %] | – |
| | Battery life expectancy | 377 [45.0 %] | – |
| | Greenhouse gas emissions | 102 [12.2 %] | – |
| Least important attribute[a] (self-assessment) | Battery price | 147 [17.6 %] | – |
| | Battery life expectancy | 96 [11.5 %] | – |
| | Greenhouse gas emissions | 594[71 %] | – |

[a] No numerical class name because no linear change of coefficients is assumed.
[b] No completed survey forms for non-binary people.
[c] Insufficient data for non-male persons, therefore no analysis by gender is performed.

### 3.3. *Estimation of the behavioral model*

Eq. (3) is specified for the described use case to estimate the mixed logit behavioral model. In the first instance, two fundamental formulations for the utility, $U_{1,nit}$ and $U_{2,nit}$, are contrasted, where $n$ represents the decision-maker and $i$ represents the option, i.e., a remanufactured, new, or no spare battery, and $t$ the choice situation:

$$U_{1,nit} = asc_{it} + \sum_{\substack{\text{Battery} \\ \text{characteristics } b}} \beta_n^b \cdot x_{it}^b + \varepsilon_{nit}, \text{ and} \tag{4}$$

$$U_{2,nit} = asc_{it} + \sum_{\substack{\text{Battery} \\ \text{characteristics } b}} \beta_n^b \cdot x_{it}^b + \beta_{in}^v \cdot x_{it}^v + \varepsilon_{nit}. \tag{5}$$

$asc_{it}$ denotes alternative-specific constants that account for non-included attributes (Tardiff, 1978) and can be interpreted as the population-wide preference for or against one option, for example, remanufactured spare batteries, independent of the option attributes. The alternative-specific constant for new batteries, $asc_{new\ battery}$, is kept at zero as a baseline. The attributes of a battery $b$ include its price, the battery longevity, and the battery GHG emissions. $v$ represents the vehicle characteristics, i.e., the vehicle price. The vehicles' coefficients $\beta_{in}^v$ depend on the option $i$, and thus there are separate coefficients for reconditioned batteries, new batteries, and the none option. With this information, one can determine how a change in car size affects the overall preference for a particular option. As a reminder, a low-priced car serves as the reference point, with $x_{it}^v$ set to zero for this category (cf. Table 1).

The *asc*'s and the vehicle cost-specific coefficients are assumed to follow a normal distribution, while the battery coefficients presumably follow a lognormal distribution ("Cost savings compared to a new battery" and "GHG savings compared to a new battery") or negative lognormal distribution ("Battery life losses compared to a new battery"). In this way, all decision makers have a positive valuation of savings and a negative valuation of losses.

With the utility functions $U_{1,nit}$ and $U_{2,nit}$, one can evaluate which model best represents the data. As $U_{1,nit}$ does not include coefficients for vehicles, and $U_{2,nit}$ does, a better fit of $U_{2,nit}$ would mean that explicitly separating the effect induced by the vehicle size adds value to the model. Therefore, the comparison of $U_{1,nit}$ and $U_{2,nit}$ helps determine the relevance of the vehicle price in estimating the demand for remanufactured batteries. The actual significance of the influence would be determined when analyzing the model results. There are numerous methods for selecting the most appropriate model from a range of alternatives. Two widely used measures from the class of penalized model selection criteria are the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) (Kuha, 2004). These measures are based on the log likelihood of the model and weigh it against its complexity (Kuha, 2004). Consequently, if two models have the same explanatory power but one model uses more attributes, making it more complex, the simpler model with fewer attributes will have a better BIC and AIC. This approach of penalizing complexity aims to prevent overfitting. Lower values for AIC and BIC are considered preferable as they represent a smaller information loss (Mariel et al., 2021).

The superior model is utilized to analyze statistically significant differences within the population based on age, income, and other characteristics by examining the coefficient means of subgroups using a one-sided (Welch) Analysis of Variance (ANOVA), following the approach Paetz (2020) applied. This technique is feasible since HB estimates coefficients at the individual respondent level. In essence, each characteristic that is being examined (cf. Table 2) is treated as a categorical factor, and each respondent's coefficient estimates are considered as one realization of an experiment. To determine whether the mean of a specific coefficient, such as $\beta^{cost\ saving}$, differs between respondents belonging to different groups, for example, income groups 0 to 5, the variances of the betas within and between the income groups are compared with those of all other income groups. The results of an

ANOVA indicate if the means of all groups are equal, or if at least one pair of means is unequal (Shingala and Rajyaguru, 2015). Prior to conducting the ANOVA, the normality and homoscedasticity assumptions are assessed using the Shapiro-Wilk test and the Levene statistic, respectively, at a significance level of 0.05. IBM's SPSS software is used to perform these tests and the ANOVA. In the event that the ANOVA reveals disparities among any of the classes, post hoc Games-Howell tests are conducted at a significance level of 0.05 for further examination. The Games-Howell test is a multiple comparisons test that enables the identification of which group means differ from each other, even in the absence of homoscedasticity (Lee and Lee, 2018).

In addition to conducting an ANOVA to test for differences in the coefficients based on one of the basic utility models, a third method for estimating utility, $U_{3,ni}$, is employed. This approach takes into account the individual respondents' characteristics $c$ for the battery attributes. If the model based on utility function $U_{2,ni}$ outperforms the one that utilizes $U_{1,ni}$, the vehicle attributes are also included in the analysis.

$$U_{3,nit} = asc_{it} + \sum_{\substack{\text{Battery} \\ \text{characteristics } b}} \left(\beta_{\mathrm{n}}^{b} + \beta_{n}^{b,c} \cdot x_{nt}^{c}\right) \cdot x_{it}^{b} \left[ + \left(\beta_{in}^{v} + \beta_{i\,n}^{v,c} \cdot x_{nt}^{c}\right) \cdot x_{it}^{v} \right] + \varepsilon_{nit}, . \tag{6}$$

In $U_{3,ni}t$, there are two coefficients, $\beta_n^{b(v)}$ and $\beta_n^{b(v),c}$, which are used to describe the valuations placed on battery and vehicle attributes by the entire population, as well as the deviations of certain subpopulations from the population mean and their normal distribution. For instance, the population's $\beta^{cost\ savings}$ could follow a lognormal distribution with a mean of 2 and a standard deviation of 0.5. This indicates that a 10 % reduction in battery costs would result in an average increase in utility of 2 utility units. However, for respondents in the age group of 20–30 years, the utility increase might be 0.7 units higher on average. This would be represented by $\beta^{cost\ savings, age\ 20-30}$ having a mean of 0.7 and $x_{nt}^{age\ 20-30} = 1$.

From Eq. (6) and Table 2 it becomes clear that, except for age, all customer characteristics are considered to add to utility linearly. For example, with regard to education that means $\beta_n^{b,education}$ is multiplied by zero for the basic education group, by one for the intermediate group, and by two for the advanced group (cf. Table 2). There are other ways to specify utility, for example higher-order polynomials or semi-log transformations, which could accommodate for rising or decreasing influence of coefficients' levels (Han et al., 2022). However, only the simple linear specification was used, since other forms of interactions could also be uncovered by descriptive statistics obtained from utility functions $U_1$ and $U_2$.

The reason for conducting a double evaluation of the influence of respondent characteristics, once using ANOVA and once with a dedicated model, is to address the issue of HB estimation causing individual coefficients to shrink towards the population mean (Crabbe and Vandebroek, 2012). Consequential, differences between subgroups might be reduced. By introducing covariates for respondent characteristics, there are more potentially relevant subgroups to whose mean the covariates can shrink. The third behavioral model is then compared to those estimated using Eqs. (4) and (5), with the AIC and BIC serving as evaluation criteria.

The mixed logit models with HB estimation technique are calculated using R, version 4.2.2, and the R-Package "Apollo" (Hess and Palma, 2019). All priors for normally distributed coefficients were set to zero. The means of those following lognormal or negative lognormal distributions were set to −3 and 3 respectively, to start close to zero as well. The models were simulated using 100,000 burn-in iterations and 50,000 valid iterations in a MCMC simulation. The estimates were found to converge within the burn-in iterations upon visual inspection.

## 4. Results

Reconditioned batteries have been chosen by the participants of the survey in about half of the choice situations. A new spare battery and no spare battery, i.e., a replacement of the vehicle, were selected with approximately equal share (24 % each). Fig. 3 reveals that this distribution of 52 % choice of reconditioned batteries and 24 % for both new batteries and the none option is not valid for all respondents. There is a small proportion of survey participants who never selected the reconditioned battery (4 %), while 7 % selected them in all or almost all cases (13 to 14 of 14 times). 5 % would replace their car in (almost) all cases, while 40 % would never choose that option. The new battery option was chosen zero times by 31 % of the respondents, and 13 to 14 times by 1 % of the respondents. Many participants made choices between one and twelve times for each option, indicating that the options' attribute levels (as shown in Table 1) influenced their decision. Overall, research question 1 can be answered positively: It appears that there is acceptance of reconditioned batteries, albeit subject to specific conditions that require further investigation and clarification.

### 4.1. Results concerning battery and vehicle characteristics

In Section 3, two initial models were developed to evaluate whether vehicle attributes should be considered in the analysis, based on the utility functions outlined in Eqs. (4) and (5). The model based on $U_{1,nit}$, which did not include vehicle attributes, resulted in an AIC of 15,359 (BIC: 15,506), while model $U_{2,nit}$, which included the attributes, yielded

**Table 3**
Posteriors of the mixed logit model with utility function $U_{2,ni}$ (Eq. (5)).

| | Mean | Standard deviation |
|---|---|---|
| $asc_{new\ battery}$ [a] | 0.00 | 0.00 |
| $asc_{reconditioned\ battery}$ | 3.34 | 2.47 |
| $asc_{none\ option}$ | 0.89 | 4.24 |
| $\beta^{car\ price}_{new\ battery}$ | 1.50 | 0.52 |
| $\beta^{car\ price}_{reconditioned\ battery}$ | 1.13 | 0.46 |
| $\beta^{car\ price}_{none\ option}$ | −0.14 | 1.05 |
| $\beta^{battery\ cost\ savings}$ | 1.18 | 0.86 |
| $\beta^{battery\ life\ losses}$ | −1.53 | 1.03 |
| $\beta^{battery\ GHG\ savings}$ | 0.26 | 0.29 |

[a] $asc_{new\ battery}$ is a non-random coefficient with the fixed value "0" as a baseline for the other asc's.

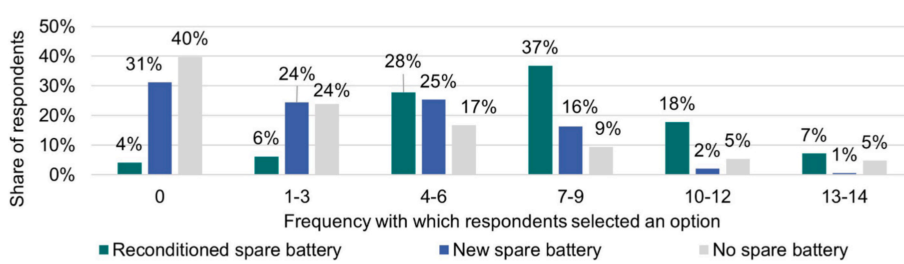


**Fig. 3.** Frequency of respondent selections of each option. Each respondent made 14 choices.

an AIC of 14,811 (BIC: 15,134). As smaller values indicate a better model fit, $U_{2,nit}$ is deemed superior to $U_{1,nit}$. In accordance with Section 3.3, a third mixed-logit model was estimated that incorporated coefficients for respondents' characteristics, based on utility function $U_{3,nit}$ as defined in Eq. (6). However, this model yielded much larger AIC and BIC values (21,176 and 42,170), making it less suitable than the previously mentioned models. Consequently, both models $U_{1,nit}$ and $U_{3,nit}$ are disregarded, and the analysis proceeds with the model based on $U_{2,nit}$.

Table 3 displays the coefficient posteriors of the mixed-logit model. The results indicate a positive alternative-specific constant for reconditioned batteries, which provides a base utility of 3.34 units relative to the "new battery" alternative. However, the standard deviation is relatively large at 2.47. Nonetheless, a normal distribution with a mean of 3.34 and a standard deviation of 2.47 still yields positive values in approximately 91 % of the draws $\left(1 - F_{X\sim N(3.34, 2.47^2)}(0) \approx 91\%\right)$. That means, in 91 % of the cases a higher utility stems from choosing reconditioned battery compared to choosing a new battery, before considering specific battery and vehicle attributes. The alternative-specific constant for the "none" option presents a different picture. Although the mean is positive, providing an average utility of 0.89 relative to the "new battery" option, the standard deviation of 4.24 indicates that only 58 % of the draws yield a positive part-worth utility $\left(1 - F_{X\sim N(0.89, 4.24^2)}(0) \approx 58\%\right)$. Consequently, 42 % of the draws are expected to produce a negative utility for the "none" option compared to the "new battery" option. A negative value means that the option is less favored than the baseline before considering specific option characteristics.

The cost of a vehicle can alter the appeal of various alternatives. As a reminder, the vehicle attributes contribute to the utility with the term $\beta^{v}_{i,n} \bullet x^{v}_{it}$ (cf. Eq. (5)), and $x^{v}_{it}$ is coded as 0, 1 and 2 for the low-cost, medium-cost and the high-cost vehicles (cf. Table 1). The car prices are the same for all options within one choice set. As automobile prices increase, the appeal of both new and reconditioned battery options also rises, with the mean beta coefficient for a new battery, $\beta^{car\ price}_{new\ battery}$, being approximately one-third higher than that of a reconditioned battery, $\beta^{car\ price}_{reconditioned\ battery}$. Specifically, a mean $\beta^{car\ price}_{new\ battery}$ of 1.5 means that the new battery option gains 1.5 utility units on average the higher the car price, and analogously, a mean $\beta^{car\ price}_{reconditioned\ battery}$ of 1.13 shows 1.13 utility unit gains on average the higher the car price. This indicates that the more expensive the vehicle, the more likely it is that the battery will be replaced with either a new or a reconditioned battery. Additionally, the more costly the car, the more respondents tend to favor new batteries. It is worth noting that the mean value of the car price attribute for the "none" option is close to zero, suggesting that the "none" option was not significantly impacted by the price of the vehicle.

The battery attributes also influence the utilities of the options ($\beta^{b}_{n} \bullet x^{b}_{it}$, cf. Eq. (5)). Among the various attributes of a battery, the loss of battery life compared to a new battery has the greatest impact on average utility. With a mean of −1.53, the coefficient of one unit of battery life loss (1 year or 10 %) is approximately 30 % higher than the beta mean for a 10 % cost savings compared to a new battery and nearly five times the beta mean for a 10 % GHG savings compared to a new battery. It should be noted that the coefficients of battery attributes follow lognormal distributions (as outlined in Section 3.3), thus ensuring that the valuation of cost savings and GHG savings is always positive, while the valuation of life losses is always negative.

### 4.2. Results concerning observable characteristics

The examination of coefficient means within subgroups to identify statistically significant differences in age, income, and other observable characteristics was conducted through a one-sided (Welch) ANOVA. The Shapiro-Wilk test and Levene's test at significance level 0.05 were utilized to assess the normality and homoscedasticity of the mean distributions (cf. Section 3.3). Only 20 % of the subgroups were found to follow normal distributions, with the remainder being classified as non-normal. One subgroup could be the means of $\beta^{battery\ cost\ savings}$ within the age group "30–39" (cf. Table 1). However, an ANOVA has shown to be robust for non-normal data (Blanca et al., 2017), so non-normality does not contradict the usage of a normal ANOVA. Homogeneity of variances can be assumed for 82 % of the attributes according to a Levene's test, i.e., there is no homoscedasticity for 18 % of the attributes. This rules out a classic ANOVA since it is not robust under the violation of homoscedasticity (Bishop and Dudewicz, 1981). In this case, it is often recommended to use a Welch ANOVA instead (Jan and Shieh, 2014), which was done here. However, the classic ANOVA and the more robust Welch approximation lead to the same results concerning equality of means at the significance level of 0.05.

The results indicate that there are no discernible differences among participants with varying educational backgrounds. With regard to income and residence classes, only one coefficient stands out as significantly different. Specifically, for the income classes, it is the alternative-specific constant for the "none" option, and for the residence classes, it is the $\beta^{car\ price}_{reconditioned\ battery}$ that varies.

The most notable disparities between the coefficients' means are primarily evident in relation to the demographic characteristic of age (4 out of 8 coefficients, as demonstrated in Table 4). $\beta^{car\ price}_{new\ battery}$ decreases with higher age, so that older respondents differentiate slightly less

**Table 4**
Welch ANOVA for the respondents' attribute "age" and means of the coefficients within the age subgroups.

| | Welch ANOVA[a] | Means for subgroup age [years] | | | | | |
|---|---|---|---|---|---|---|---|
| | Statistic[b] | ≤29 | 30–39 | 40–49 | 50–59 | 60–69 | ≥70 |
| $asc_{reconditioned\ battery}$ | 0.776 | 3.413 | 3.105 | 3.405 | 3.380 | 3.371 | 3.472 |
| $asc_{none\ option}$ | 1.563 | 0.133 | 0.768 | 1.062 | 1.219 | 0.426 | −0.006 |
| $\beta^{car\ price}_{new\ battery}$ | 3.978*** | 1.554 | 1.506 | 1.491 | 1.507 | 1.466 | 1.456 |
| $\beta^{car\ price}_{reconditioned\ battery}$ | 1.548 | 1.143 | 1.127 | 1.134 | 1.128 | 1.151 | 1.155 |
| $\beta^{car\ price}_{none\ option}$ | 2.752** | −0.381 | −0.162 | −0.100 | −0.136 | −0.088 | −0.122 |
| $\beta^{battery\ cost\ savings}$ | 3.942*** | 1.303 | 1.227 | 1.155 | 1.190 | 1.082 | 0.841 |
| $\beta^{battery\ life\ losses}$ | 6.731*** | −1.858 | −1.600 | −1.460 | −1.505 | −1.436 | −1.079 |
| $\beta^{battery\ GHG\ savings}$ | 1.435 | 0.308 | 0.255 | 0.241 | 0.254 | 0.277 | 0.289 |

[a]Analysis of variance.
[b]Asymptotically F distributed.
*Significant at the level of 0.1.
**Significant at the level of 0.05.
***Significant at the level of 0.01.

**Table 5**
Welch ANOVA for the respondents' attribute "EV ownership" and means of the coefficients within the subgroups.

| | Welch ANOVA[a] | Means for subgroup electric vehicle ownership | |
|---|---|---|---|
| | Statistic[b] | No | Yes |
| $asc_{reconditioned\ battery}$ | 0.488 | 3.295 | 3.375 |
| $asc_{none\ option}$ | 16.409*** | 0.345 | 1.405 |
| $\beta^{car\ price}_{new\ battery}$ | 0.019 | 1.499 | 1.500 |
| $\beta^{car\ price}_{reconditioned\ battery}$ | 2.391 | 1.139 | 1.129 |
| $\beta^{car\ price}_{none\ option}$ | 3.132* | −0.182 | −0.104 |
| $\beta^{battery\ cost\ savings}$ | 3.798* | 1.209 | 1.138 |
| $\beta^{battery\ life\ losses}$ | 12.756*** | −1.604 | −1.435 |
| $\beta^{battery\ GHG\ savings}$ | 9.938*** | 0.280 | 0.238 |

[a]Analysis of variance.
[b]Asymptotically F distributed.
*Significant at the level of 0.1.
**Significant at the level of 0.05.
***Significant at the level of 0.01.

between the vehicle price classes when opting for a new spare battery. However, the decrease is not linear with age, and not all subgroups differ from all other subgroups in a statistically significant manner. A Games-Howell post hoc test reveals that the means of the youngest group ("≤29") deviate from those of the "40–49", "60–69" and "≥70" year old groups, while other deviations are not significant at the 0.05 level. A similar pattern is observed for $\beta^{car\ price}_{none\ option}$. Once again, significant differences occur between the youngest group ("≤29") and older groups, particularly the three groups between 30 and 69 years. The older groups base their decision for or against the none option less on the car price than the youngest group does. The mean values of the coefficients $\beta^{battery\ cost\ savings}$ and $\beta^{battery\ life\ losses}$ also differ between the age groups according to the Welch ANOVA. However, for the $\beta^{battery\ cost\ savings}$'s, that only applies to the two youngest groups ("≤29" and "30-39") compared to the oldest group ("≥70") in a statistically significant manner, as demonstrated by a Games-Howell post hoc test at the 0.05 significance level. With regard to the $\beta^{battery\ life\ losses}$'s, the youngest group's means are distinguishable from almost all other age groups' means ("40–49", "50–59", "60–69", "≥70"), and additionally significant differences occur between the age groups "30–39" and "≥70", and "50–59" and "≥70". Thus, in terms of age, the strongest influence is observed for the battery lifetime reductions, that younger respondents punished to a greater extent than older respondents.

Table 5 indicates notable variations between EV owners and non-EV owners with respect to three coefficients. First, EV owners have a stronger preference for the "none" option compared to the "new" option than non-EV owners ($asc_{none\ option}$). Second and third, non-EV owners view each year of battery life losses from a reconditioned battery compared to a new battery as worse than EV owners, and they also derive slightly greater utility from less GHG-intensive options. As there are only two groups involved, i.e., EV owners and non-EV owners, post hoc tests are not applicable. Any statistically significant deviation in the coefficient means detected by the Welch ANOVA by default is indicative of differences between the two groups.

### 4.3. Results concerning self-assessment of the respondents

The study participants were asked to identify the most and least important battery attributes regarding their decision, which are non-observable and depend on their self-assessment. A Welch ANOVA was applied, revealing statistically significant differences in the coefficients' means of battery cost savings, battery life losses, and GHG savings between the groups who rated the attributes most, second-most, and least important (cf. Table 6). The results indicate that respondents who rated battery price as the most important attribute derive greater utility from each 10 % of cost savings compared to those who rated it least important. Similarly, those who considered battery life expectancy as the most important attribute place a higher value on each year of battery life loss than those who ranked it least important. Additionally, those who ranked environmental friendliness as the most important attribute place a higher value on every 10 % of GHG savings compared to those who ranked it least important. However, the effect is smaller than expected, measured by the Marginal Rates of Substitution, i.e., the rates at which respondents are willing to trade one level of one attribute for a level of another one (Lancsar and Louviere, 2008; Mott et al., 2020). Even those who ranked environmental friendliness as the most important attribute, require 41 % of GHG savings to compensate for one year (=10 %) of battery life loss $\left(\left|{-1.367}/{0.335}\right| \approx 4.1\right)$. For those who rated battery price as the most important attribute, the intersection is at 66 % GHG savings $\left(\left|{-1.466}/{0.221}\right| \approx 6.6\right)$, and 59 % $\left(\left|{-1.615}/{0.276}\right| \approx 5.9\right)$ GHG savings for those who ranked battery life the most important attribute.

Similarly, the statement that battery price is the most important attribute does not imply that a 10 % reduction in price is equivalent to a 10 % loss in battery life. The respondents who ranked the battery price as the top priority actually place a 10 % decline in battery life on par with a 11.7 % price reduction $\left(\left|{-1.466}/{1.253}\right| \approx 1.17\right)$. Those who selected life expectancy as their primary concern require an average

**Table 6**
Influence of self-assessment on coefficients' means.

| Self-assessment concerning importance of attributes | | $\beta^{battery\ cost\ savings}$ | $\beta^{battery\ life\ losses}$ | $\beta^{battery\ GHG\ savings}$ |
|---|---|---|---|---|
| Battery price | most important | 1.253 | -1.466 | 0.221 |
| | 2nd most important | 1.188 | -1.608 | 0.265 |
| | least important | 0.953 | -1.460 | 0.341 |
| Battery life expectancy | most important | 1.168 | -1.615 | 0.276 |
| | 2nd most important | 1.205 | -1.469 | 0.244 |
| | least important | 1.082 | -1.350 | 0.256 |
| Environmental friendliness | most important | 0.922 | -1.367 | 0.335 |
| | 2nd most important | 1.063 | -1.452 | 0.288 |
| | least important | 1.244 | -1.564 | 0.240 |
| Shaded values indicate the corresponding coefficients and attributes | | | | |

Shaded values indicate the corresponding coefficients and attributes.

price reduction of 13.8 % $\left(\left|-1.615/1.168\right| \approx 1.38\right)$ to gain equal utility.

## 5. Discussion

The discrete choice experiment addressed the three research questions presented in Section 1. Firstly, the study revealed that there could be acceptance of reconditioned EV batteries as spare parts. A considerable number of respondents opted for this option when presented with the hypothetical choice of replacing a faulty battery in their EV, outside of the warranty period, with a new or reconditioned spare battery, or scrapping the EV and purchasing a working vehicle. Secondly, the study found that the choice is primarily influenced by the expected battery lifetime and the associated costs. Ecological factors play a minimal role and are more of a bonus. Moreover, the study identified that general beliefs about the options, expressed as alternative specific constants, play a role and are partially dependent on the EV's original price. Thirdly, differences between potential customer groups with regard to observable factors are mainly related to the age of the respondents, and to respondents actually owning an EV or not. EV owners, who may face a less hypothetical choice situation than non-EV owners, were found to slightly prefer the "none" option, i.e., scrapping the vehicle and replacing it, over the "new" option. Additionally, they were less punitive towards reductions in the life expectancy of reconditioned batteries compared to new ones. This finding aligns with research that suggests that the fear of a limited range of EVs, which is closely associated with the expected battery lifetime, is more pronounced in individuals without EV experience (Rauh et al., 2020). The self-assessment of the respondents concerning the most and least decisive battery characteristics showed a connection between stated choice and stated importance of the attributes, however, the connection was relatively weak.

### 5.1. Comparison with other studies' findings

The results mainly support the findings of other studies. The importance of price attributes has been found for EVBs (Tondolo et al., 2021), EVs (Bhat et al., 2024; Han and Sun, 2024) and non-EV related products (Klemm and Kaufman, 2024). Also the decisiveness of battery life has been pointed out before by Hunka et al. (2021) for remanufactured mobile phones, or the quality of circular products in the technology, household and personal care sector by Abbey et al. (2015a). The study found that the environmental attribute had a low influence, which aligns with Aydin and Mansour (2023), who determined the relative importance of $CO_2$ emissions compared to the other examined factors to be 3.4 % only. Concerning the influence of socio-demographic factors, results in the literature have been mixed. Bhat et al. (2024) examined the adoption of EVs and found age and EV ownership to have significant effects, which is in line with the findings of this study. The results of Abbey et al. (2015b) indicate significant influence of age and number of children on the attractiveness of remanufactured products of the technology, household, and personal care segments. Some of the segments were also influence by other socio-demographic factors. For technological products, education and income did not show significant effects (Abbey et al., 2015b). Kim et al. (2014) identified significant influences of socio-demographics on the intention to purchase an EV for gender and education, and no significances for age and income.

### 5.2. Limitations

While the findings regarding the examined attributes are mostly in line with the literature, the attributes were limited to the vehicle price, the battery price, the battery life expectancy and the battery GHG intensity. There may be other attributes that also influence the decision making of consumers. For example, Tondolo et al. (2021) found the purchasing likelihood of EVBs to be higher when service was included. On the other hand, Liao et al. (2018) report only minor effects on EV attractiveness when leasing options were present. The effect of service offers or alternative business models in combination with the examined attributes remains an open question. The same holds for other potential attributes like policy interventions, that were examined for example by Li et al. (2022) or Wang et al. (2017) with regard to EV adoption.

Further potential limitations may exist concerning the method of the survey and the analysis. This study employed a mixed logit behavioral model and Hierarchical Bayes estimation based on a stated choice study. The data basis may be enhanced by combining it with data about revealed preferences, i.e., observing peoples' choice behavior, as for example Brownstone et al. (2000) did. As the offers for reconditioned EVBs are rare right now, the data basis would also be limited, but that could change in the future. Additionally, applying a mixed logit model requires making assumptions about the form of the density functions of coefficients. In this study, all coefficients related to costs and quality losses were defined to follow a negative lognormal distribution, all coefficients relating to GHG saving were assumed to follow a lognormal distribution, and all other coefficients were modeled as normal distributions. While those are common distributions (Hensher and Greene, 2003; Train, 2009), it has not been investigated if others fit the use case better. Moreover, there is no standard way on how to define utility functions. Here, three forms were tested and the selection criteria BIC and AIC were used to choose the best one of the three. However, there are many more ways utility could be defined, potentially affecting the results. Furthermore, different approaches to reveal heterogeneity could be applied. In this study, socio-demographic markers and the self-assessment of respondents were used for a priori segmentation. A latent class approach could be used to find segments instead (Eggers et al., 2022).

One fundamental question remains regarding the scope of the results. The study utilized a discrete choice survey, which was completed by 1152 participants, of whom 837 provided complete information for further analysis. While this sample size is reasonable, as Johnson et al. (2013) found that the precision of studies typically does not increase significantly beyond 300 observations, it is important to note that the analysis entailed sub-groups of much lower size (cf. Table 2). Consequently, the results for these smaller groups must be interpreted with caution. Additionally, the sample is not representative of the German population. Probably due to the distribution channels of the survey link, i.e., EV forums and a YouTube channel for battery related topics, and its target group, about half of the respondents own an EV, and about 98 % are male. However, one could argue that this technically interested group that networks in EV forums and watches technical battery videos could be the early adopters of reconditioned batteries, who may be influential in shaping the opinions of other car owners. Nonetheless, further research is necessary to validate the findings with a more diverse and representative sample. Moreover, such further research could be a panel and uncover whether there are developments in customers' preferences over time, since this study only covers a single survey.

### 5.3. Impact of stakeholders

It should be noted that the success of reconditioned batteries as spare parts does not only depend on customer acceptance. It is essential that workshops are aware of the option of reconditioned batteries, endorse it, and present it to customers. This option is contingent upon the availability of reconditioned batteries in the market, which relies on OEMs and potentially other market players such as independent third-party refurbishing companies in the future. Currently, recycling is the default battery End-of-Life option in the EU, as it is required by law, and recycling an EV battery costs more than selling the regained raw materials yield (Gernant et al., 2022). OEMs are legally obligated to take back used EV batteries and cover the costs for recycling (European Parliament and European Council, 2023). Consequently, as long as recycling remains unprofitable, third parties are likely to accept the enforced offer and return used batteries to the OEMs, who then decide whether to recycle them directly or to recondition or repurpose them first. Therefore, OEMs are currently the key players in deciding for or against reconditioning. They also control their service network of workshops and can influence whether or not their workshops offer reconditioned spare parts. When recycling becomes profitable, control over End-of-Life batteries may shift. If a third-party firm reconditions or repurposes an EV battery, it assumes responsibility for the final treatment, i.e., recycling, according to the new EU battery regulation (European Parliament and European Council, 2023). Thus, the profitability of recycling could enable other second-life strategies. On the other hand, when recycling becomes profitable, it could be a strong alternative to second-life concepts due to the lower economic risk. Furthermore, the introduction of EU quotas for secondary raw materials in battery production, which will take effect in 2031 (European Parliament and European Council, 2023), may favor recycling over reconditioning. It is evident that political will, as demonstrated through the enactment of legislation, plays a significant role in determining the End-of-Life pathways for EV batteries.

### 5.4. Implications for stakeholders

This study indicates that there may be demand from the customer side when the batteries are durable and competitively priced. In case policy makers want to foster the spread of reconditioned EVBs, these are the starting points for action. Quality could be promoted by funding research projects dealing with developing EVB reconditioning processes. Another step for quality promotion has already been done by the EU battery regulation by defining the term “remanufacturing” so that remanufactured batteries must have a capacity of at least 90 % of the original battery. In this way, customers can be certain about the quality if the EVB is labelled “remanufactured”. Other terms, like reconditioning or refurbishment, are not protected. The price of reconditioned EVBs can be impacted by governments by various means. For example, they can provide subsidies for end customers in the form of a circularity premium or financially support reconditioning activities within the industry. Additionally, governments can invest in research and development to improve cost-efficient processes. Instead of lowering the costs and improving the quality of reconditioned EVBs, policy makers can also focus on changing customer perception of reconditioned batteries. For example, they could support business models that rent out reconditioned spare batteries, which could reduce the importance of battery longevity and overall costs. Governments could, for instance, tax those circular products less, create suitable legislative frameworks, or make use of circular battery options in public vehicle fleets.

OEMs and reconditioners could also promote reconditioned batteries without government support. To successfully introduce reconditioned batteries to the market on a large scale, this study suggests they concentrate their research and development efforts on the aspects of battery longevity and cost competitiveness, and on batteries for more expensive cars. The results of this study can also be used to target advertising to different demographics, particularly younger consumers who place a high value on battery life expectancy.

Lastly, end customers could evaluate their decision making based on the study results. Although it may seem intuitive that a longer EVB lifespan is always preferable, it could be argued that for vehicles aged eight years or more, an EVB with a like-new lifespan may not always be essential. By taking a step back and reflecting on their decision-making process, end users may gain a different perspective and potentially alter the outcome.

## 6. Conclusion

The findings of the study indicate that the durability of batteries is the primary concern for consumers when deciding on the replacement of defective EV batteries, followed closely by the batteries’ price. This is particularly true for respondents who are younger and those who do not own electric vehicles. The significance of ecological sustainability in the purchasing decision is relatively minor, even among those who consider environmental friendliness to be the most important attribute in their decision-making process. The vehicle price segment should also be taken into account, as the results show that the likelihood of replacing a battery with either a new or reconditioned battery is greater in more expensive vehicles. However, the more costly the car, the more respondents tend to favor new batteries.

Future research may supplement the outcomes of this study by implementing a more comprehensive and diverse survey sample, and by collecting data from additional countries for cross-cultural comparisons. Additionally, research could contribute to the topic of acceptance of reconditioned batteries by broadening the scope from consumers to other stakeholders in the battery value chain, like workshops.

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## CRediT authorship contribution statement

**Sandra Huster:** Writing – original draft, Formal analysis, Conceptualization. **Sonja Rosenberg:** Writing – review & editing. **Simon Hufnagel:** Investigation. **Andreas Rudi:** Writing – review & editing, Project administration. **Frank Schultmann:** Writing – review & editing, Supervision.

## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used the tool “Paperpal” in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

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## References

Abbey, J.D., Meloy, M.G., Blackburn, J., Guide, V.D.R., 2015a. Consumer markets for remanufactured and refurbished products. Calif. Manag. Rev. 57, 26–42.
Abbey, J.D., Meloy, M.G., Guide, V.D.R., Atalay, S., 2015b. Remanufactured products in closed-loop supply chains for consumer goods. Prod. Oper. Manag. 24, 488–503.
ADAC, 2022. Elektroauto-Batterie: Lebensdauer, Garantie, Reparatur. https://www.adac.de/rund-ums-fahrzeug/elektromobilitaet/info/elektroauto-batterie/. (Accessed 29 January 2024).
Adamowicz, V., Boxall, P., 2001. Future directions of stated choice methods for environment valuation. In: Choice Experiments: A New Approach to Environmental Valuation, pp. 1–6.

Alamri, A.S., Georgiou, S., Stylianou, S., 2023. Discrete choice experiments: an overview on constructing D-optimal and near-optimal choice sets. Heliyon 9, e18256.
Autocraft Solutions Group, 2023. What is EV battery remanufacturing and why it matters. https://autocraftsg.com/news/insights/what-is-ev-battery-remanufacturing-and-why-it-matters/. (Accessed 6 May 2024).
Aydin, R., Mansour, M., 2023. Investigating sustainable consumer preferences for remanufactured electronic products. J. Eng. Res. 11, 100008.
Bech, M., Kjaer, T., Lauridsen, J., 2011. Does the number of choice sets matter? Results from a web survey applying a discrete choice experiment. Health Econ. 20, 273–286.
Bekker-Grob, E.W. de, Donkers, B., Jonker, M.F., Stolk, E.A., 2015. Sample size requirements for discrete-choice experiments in healthcare: a practical guide. The Patient 8, 373–384.
Belbağ, A.G., Belbağ, S., 2023. Remanufactured products: a systematic review from the consumer perspective. Jnl Remanufactur 13, 207–241.
Ben-Akiva, M., McFadden, D., Train, K., 2019. Foundations of stated preference elicitation: consumer behavior and choice-based conjoint analysis. FNT in Econometrics 10, 1–144.
Bhat, F.A., Seth, Y., Verma, A., 2024. Motivators and barriers to the widespread adoption of electric four-wheelers in India – a discrete choice analysis of potential electric four-wheeler buyers. Travel Behav. Soc. 35, 100748.
Bishop, T.A., Dudewicz, E.J., 1981. Heteroscedastic Anova. Sankhyā: The Indian Journal of Statistics, Series B (1960-2002) 43, 40–57.
Blanca, M.J., Alarcón, R., Arnau, J., Bono, R., Bendayan, R., 2017. Non-normal data: is ANOVA still a valid option? Psicothema 29, 552–557.
BloombergNEF, 2023. Lithium-ion battery pack prices hit record low of $139/kWh. https://about.bnef.com/blog/lithium-ion-battery-pack-prices-hit-record-low-of-139-kwh/. (Accessed 2 February 2024).
Bolstad, W.M., Curran, J.M., 2016. Introduction to Bayesian Statistics, 3rd ed. John Wiley and Sons Ltd, [s.l.]. (624 pp.).
Brownstone, D., Bunch, D.S., Train, K., 2000. Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transp. Res. B Methodol. 34, 315–338.
Bruno, M., Fiore, S., 2023. Material flow analysis of lithium-ion battery recycling in Europe: environmental and economic implications. Batteries 9, 231.
Burchart-Korol, D., Jursova, S., Folęga, P., Korol, J., Pustejovska, P., Blaut, A., 2018. Environmental life cycle assessment of electric vehicles in Poland and the Czech Republic. J. Clean. Prod. 202, 476–487.
Campbell, D., Erdem, S., 2019. Including opt-out options in discrete choice experiments: issues to consider. The Patient 12, 1–14.
Caussade, S., Ortúzar, J.d.D., Rizzi, L.I., Hensher, D.A., 2005. Assessing the influence of design dimensions on stated choice experiment estimates. Transp. Res. B Methodol. 39, 621–640.
Chen, M., Ma, X., Chen, B., Arsenault, R., Karlson, P., Simon, N., Wang, Y., 2019. Recycling end-of-life electric vehicle lithium-ion batteries. Joule 3, 2622–2646.
Chinen, K., Matsumoto, M., Tong, P., Han, Y.S., Niu, K.-H.J., 2022. Electric vehicle owners' perception of remanufactured batteries: an empirical study in China. Sustainability 14, 10846.
Chorus, C., van Cranenburgh, S., Dekker, T., 2014. Random regret minimization for consumer choice modeling: assessment of empirical evidence. J. Bus. Res. 67, 2428–2436.
Chrysochou, P., 2017. Consumer behavior research methods. In: Emilien, G., Weitkunat, R., Lüdicke, F. (Eds.), Consumer Perception of Product Risks and Benefits. Springer International Publishing, Cham, pp. 409–428.
Chung, C., Boyer, T., Han, S., 2011. How many choice sets and alternatives are optimal? Consistency in choice experiments. Agribusiness 27, 114–125.
Cong, L., Liu, W., Kong, S., Li, H., Deng, Y., Ma, H., 2021. End-of-use management of spent lithium-ion batteries from sustainability perspective: a review. J. Manuf. Sci. Eng. 143.
Crabbe, M., Vandebroek, M., 2012. Improving the efficiency of individualized designs for the mixed logit choice model by including covariates. Computational Statistics & Data Analysis 56, 2059–2072.
Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Monforti-Ferrario, F., Banja, M., Olivier, J., Vignati, E., Solazzo, E., Grassi, G., Rossi, S., 2021. GHG Emissions of all World: 2021 Report. Publications Office of the European Union, Luxembourg (1 online resource).
Dai, Q., Kelly, J.C., Gaines, L., Wang, M., 2019. Life cycle analysis of lithium-ion batteries for automotive applications. Batteries 5, 48.
Determann, D., Gyrd-Hansen, D., Wit, G.A. de, Bekker-Grob, E.W. de, Steyerberg, E.W., Lambooij, M.S., Bjørnskov Pedersen, L., 2019. Designing unforced choice experiments to inform health care decision making: implications of using opt-out, neither, or status quo alternatives in discrete choice experiments. Medical Decision Making: An International Journal of the Society for Medical Decision Making 39, 681–692.
Eggers, F., Sattler, H., Teichert, T., Völckner, F., 2022. Choice-based conjoint analysis. In: Homburg, C., Klarmann, M., Vomberg, A. (Eds.), Handbook of Market Research. Springer International Publishing, Cham, pp. 781–819.
European Parliament and European Council, 2023. Regulation (EU) 2023/1542 of the European Parliament and of the Council of 12 July 2023 Concerning Batteries and Waste Batteries, Amending Directive 2008/98/EC and Regulation (EU) 2019/1020 and Repealing Directive 2006/66/EC.
Ewing, J., 2021. Volvo Plans to Sell Only Electric Cars by 2030. The New York Times.
Gernant, E., Seister, F., Duffner, F., Jambor, M., 2022. Understanding the Automotive Battery Life Cycle: a comprehensive analysis fo current challenges in the circular economy of automotive batteries, Porsche Consulting. https://www.porsche-consulting.com/sites/default/files/2023-04/battery-life-cycle-c-porsche-consulting-2022.pdf. (Accessed 18 December 2023).
Girardi, P., Gargiulo, A., Brambilla, P.C., 2015. A comparative LCA of an electric vehicle and an internal combustion engine vehicle using the appropriate power mix: the Italian case study. Int. J. Life Cycle Assess. 20, 1127–1142.
Glöser-Chahoud, S., Huster, S., Rosenberg, S., Baazouzi, S., Kiemel, S., Singh, S., Schneider, C., Weeber, M., Miehe, R., Schultmann, F., 2021. Industrial disassembling as a key enabler of circular economy solutions for obsolete electric vehicle battery systems. Resour. Conserv. Recycl. 174, 105735.
Hall, D., Lutsey, N., 2018. Effects of battery manufacturing on electric vehicle life-cycle greenhouse gas emissions. https://theicct.org/sites/default/files/publications/EV-life-cycle-GHG_ICCT-Briefing_09022018_vF.pdf. (Accessed 13 December 2019).
Han, H., Sun, S., 2024. Identifying heterogeneous willingness to pay for new energy vehicles attributes: a discrete choice experiment in China. Sustainability 16, 2949.
Han, Y., Pereira, F.C., Ben-Akiva, M., Zegras, C., 2022. A neural-embedded discrete choice model: learning taste representation with strengthened interpretability. Transp. Res. B Methodol. 163, 166–186.
Hauber, A.B., González, J.M., Groothuis-Oudshoorn, C.G.M., Prior, T., Marshall, D.A., Cunningham, C., IJzerman, M.J., Bridges, J.F.P., 2016. Statistical methods for the analysis of discrete choice experiments: a report of the ISPOR Conjoint Analysis Good Research Practices Task Force. Value in Health: The Journal of the International Society for Pharmacoeconomics and Outcomes Research 19, 300–315.
Helveston, J.P., Liu, Y., Feit, E.M., Fuchs, E., Klampfl, E., Michalek, J.J., 2015. Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U. S. and China. Transp. Res. A Policy Pract. 73, 96–112.
Hensher, D.A., Greene, W.H., 2003. The mixed logit model: the state of practice. Transportation 30, 133–176.
Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. J. Choice Model. 32, 100170.
Hess, S., Daly, A., Batley, R., 2018. Revisiting consistency with random utility maximisation: theory and implications for practical work. Theor. Decis. 84, 181–204.
Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resour. Energy Econ. 33, 686–705.
Hill, N., Amaral, S., Morgan-Price, S., Nokes, T., Bates, J., Helms, H., Fehrenbach, H., Biemann, K., Abdalla, N., Jöhrens, J., Cotton, E., German, L., Harris, A., Haye, S., Sim, C., Bauen, A., 2020. Determining the Environmental Impacts of Conventional and Alternatively Fuelled Vehicles Through LCA: Final Report. Publications Office of the European Union, Luxembourg (1 online resource).
Hoekstra, A., Steinbuch, M., 2020. Comparing the lifetime green house gas emissions of electric cars with the emissions of cars using gasoline or diesel, Eindhoven. https://static.arkku.datadesk.hs.fi/arkku/files/26649046englisch_StudieEAutoversusVerbrenner_CO2.pdf. (Accessed 26 January 2021).
Huber, J., Train, K., 2001. On the similarity of classical and Bayesian estimates of individual mean partworths. Mark. Lett. 12, 259–269.
Huber, J., Zwerina, K., 1996. The importance of utility balance in efficient choice designs. J. Mark. Res. 33, 307–317.
Hunka, A.D., Linder, M., Habibi, S., 2021. Determinants of consumer demand for circular economy products. A case for reuse and remanufacturing for sustainable development. Bus. Strateg. Environ. 30, 535–550.
Huster, S., Glöser-Chahoud, S., Rosenberg, S., Schultmann, F., 2022. A simulation model for assessing the potential of remanufacturing electric vehicle batteries as spare parts. J. Clean. Prod. 363, 132225.
Hyundai Motor Company, 2023. Road to sustainability: 2023 sustainability report, Seoul. https://www.hyundai.com/content/hyundai/ww/data/csr/data/0000000051/attach/english/hmc-2023-sustainability-report-en-v5.pdf. (Accessed 10 May 2024).
IEA, 2020. Global EV Outlook 2020: Entering the Decade of Electric Drive? IEA, Paris. https://www.iea.org/reports/global-ev-outlook-2020. (Accessed 7 July 2020).
IEA, 2023. Global EV Outlook 2023: Catching Up With Climate Ambitions. IEA, Paris. https://iea.blob.core.windows.net/assets/dacf14d2-eabc-498a-8263-9f97fd5dc327/GEVO2023.pdf. (Accessed 25 January 2024).
Ijomah, W.L., Childe, S., McMahon, C., 2004. Remanufacturing: a key strategy for sustainable development. In: Proceedings of the 3rd International Conference on Design and Manufacture for Sustainable Development. 1st - 2nd September 2004. International Conference on Design and Manufacture for Sustainable Development, Burleigh Court, Loughborough University, UK. 01.-02.09.2004. Cambridge University Press, Bury St. Edmunds.
Jan, S.-L., Shieh, G., 2014. Sample size determinations for Welch's test in one-way heteroscedastic ANOVA. Br. J. Math. Stat. Psychol. 67, 72–93.
Johnson, R.M., Orme, B.K., 1996. How many questions should you ask in choice-based conjoint studies?. In: Research Paper Series https://sawtoothsoftware.com/resources/technical-papers/how-many-questions-should-you-ask-in-choice-based-conjoint-studies. (Accessed 1 May 2022).
Johnson, F.R., Lancsar, E., Marshall, D., Kilambi, V., Mühlbacher, A., Regier, D.A., Bresnahan, B.W., Kanninen, B., Bridges, J.F., 2013. Constructing experimental designs for discrete-choice experiments: report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force. Value Health 16 (1), 3–13 the journal of the International Society for Pharmacoeconomics and Outcomes Research.
Kampker, A., Wessel, S., Fiedler, F., Maltoni, F., 2020. Battery pack remanufacturing process up to cell level with sorting and repurposing of battery cells. Jnl Remanufactur. https://doi.org/10.1007/s13243-020-00088-6.
Kampker, A., Heimes, H.H., Offermanns, C., Frieges, M.H., Graaf, M., Soldan Cattani, N., Späth, B., 2023. Cost-benefit analysis of downstream applications for retired electric vehicle batteries. WEVJ 14, 110.
Kim, J., Rasouli, S., Timmermans, H., 2014. Expanding scope of hybrid choice models allowing for mixture of social influences and latent attitudes: application to intended purchase of electric cars. Transp. Res. A Policy Pract. 69, 71–85.

Klemm, C., Kaufman, S., 2024. The importance of circular attributes for consumer choice of fashion and textile products in Australia. Sustainable Production and Consumption 45, 538–550.
Koide, R., Yamamoto, H., Kimita, K., Nishino, N., Murakami, S., 2023. Circular business cannibalization: a hierarchical Bayes conjoint analysis on reuse, refurbishment, and subscription of home appliances. J. Clean. Prod. 422, 138580.
Kuha, J., 2004. AIC and BIC. Sociol. Methods Res. 33, 188–229.
Lancsar, E., Louviere, J., 2008. Conducting discrete choice experiments to inform healthcare decision making: a user's guide. PharmacoEconomics 26, 661–677.
Lee, S., Kwak, M., 2020. Consumer valuation of remanufactured products: a comparative study of product categories and business models. Sustainability 12, 7581.
Lee, S., Lee, D.K., 2018. What is the proper way to apply the multiple comparison test? Korean J. Anesthesiol. 71, 353–360.
Lenk, P., 2014. Bayesian estimation of random utility models: 20. In: Hess, S., Daly, A. (Eds.), Handbook of Choice Modelling. Edward Elgar Publishing, pp. 457–497.
Li, W., Long, R., Chen, H., Geng, J., 2017. A review of factors influencing consumer intentions to adopt battery electric vehicles. Renew. Sust. Energ. Rev. 78, 318–328.
Li, L., Wang, Z., Xie, X., 2022. From government to market? A discrete choice analysis of policy instruments for electric vehicle adoption. Transp. Res. A Policy Pract. 160, 143–159.
Liao, F., Molin, E., Timmermans, H., van Wee, B., 2018. The impact of business models on electric vehicle adoption: a latent transition analysis approach. Transp. Res. A Policy Pract. 116, 531–546.
Lieder, M., Asif, F.M., Rashid, A., Mihelič, A., Kotnik, S., 2018. A conjoint analysis of circular economy value propositions for consumers: using "washing machines in Stockholm" as a case study. J. Clean. Prod. 172, 264–273.
LKQ Europe, 2022. LKQ expects major savings in cost and CO2 from traction battery repair and remanufacturing. https://www.lkqcorp.com/blog/news/lkq-expects-major-savings-in-cost-and-co2-from-traction-battery-repair-and-remanufacturing/. (Accessed 12 May 2024).
Louviere, J.J., Flynn, T.N., Carson, R.T., 2010a. Discrete choice experiments are not conjoint analysis. J. Choice Model. 3, 57–72.
Louviere, J.J., Hensher, D.A., Swait, J.D., Adamowicz, W., 2010b. Stated Choice Methods. Cambridge University Press.
Mariel, P., Hoyos, D., Meyerhoff, J., Czajkowski, M., Dekker, T., Glenk, K., Jacobsen, J.B., Liebe, U., Olsen, S.B., Sagebiel, J., Thiene, M., 2021. Environmental Valuation with Discrete Choice Experiments. Springer International Publishing, Cham.
McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (Ed.), Frontiers in Econometrics. Acad. Pr, New York u.a., pp. 105–142
Mercedes-Benz Group, 2024. Batteries are a key focus of the circular economy, Mercedes-Benz Group. https://group.mercedes-benz.com/responsibility/sustainability/resources/battery.html. (Accessed 10 May 2024).
Mott, D.J., Chami, N., Tervonen, T., 2020. Reporting quality of marginal rates of substitution in discrete choice experiments that elicit patient preferences. Value in Health: The Journal of the International Society for Pharmacoeconomics and Outcomes Research 23, 979–984.
Munde, S., 2024. Refurbished electronics market research report, Market Research Future. https://www.marketresearchfuture.com/reports/refurbished-electronics-market-12333. (Accessed 1 February 2024).
Murdock, B.E., Toghill, K.E., Tapia-Ruiz, N., 2021. A perspective on the sustainability of cathode materials used in lithium-ion batteries. Adv. Energy Mater. 11.
Oguchi, M., Fuse, M., 2015. Regional and longitudinal estimation of product lifespan distribution: a case study for automobiles and a simplified estimation method. Environ. Sci. Technol. 49, 1738–1743.
Paetz, F., 2020. Analyzing socio-demographic determinants for fair trade label's price premia: a practical approach. Archives of Data Science, Series A 7.
Qian, S.S., Stow, C.A., Borsuk, M.E., 2003. On Monte Carlo methods for Bayesian inference. Ecol. Model. 159, 269–277.
Quaife, M., Terris-Prestholt, F., Di Tanna, G.L., Vickerman, P., 2018. How well do discrete choice experiments predict health choices? A systematic review and meta-analysis of external validity. The European Journal of Health Economics: HEPAC: Health Economics in Prevention and Care 19, 1053–1066.
Raghavarao, D., Wiley, J.B., Chitturi, P., 2010. Choice-based Conjoint Analysis. Chapman and Hall/CRC.
Rakotonarivo, O.S., Schaafsma, M., Hockley, N., 2016. A systematic review of the reliability and validity of discrete choice experiments in valuing non-market environmental goods. J. Environ. Manag. 183, 98–109.
Rauh, N., Günther, M., Krems, J.F., 2020. Positive influence of practical electric vehicle driving experience and range related knowledge on drivers' experienced range stress. Transport. Res. F: Traffic Psychol. Behav. 71, 182–197.
Revelt, D., Train, K., 1998. Mixed logit with repeated choices: households' choices of appliance efficiency level. Rev. Econ. Stat. 80, 647–657.
roeren GmbH, 2023. CO2 savings through remanufacturing of spare parts using the example of combustion engines: remanufacturing as a building block of sustainability strategies in OEM aftersales, Landshut. https://www.roeren.eu/wp-content/uploads/20231218_Uebersetzung_Whitpaper_Motor_eng.pdf. (Accessed 12 May 2024).
Rose, J.M., Bliemer, M.C.J., 2009. Constructing efficient stated choice experimental designs. Transp. Rev. 29, 587–617.
Ryan, M., Skåtun, D., 2004. Modelling non-demanders in choice experiments. Health Econ. 13, 397–402.
Schulz-Mönninghoff, M., Bey, N., Nørregaard, P.U., Niero, M., 2021. Integration of energy flow modelling in life cycle assessment of electric vehicle battery repurposing: evaluation of multi-use cases and comparison of circular business models. Resour. Conserv. Recycl. 174, 105773.
Shanmugavel, N., Alagappan, C., Balakrishnan, J., 2022. Acceptance of electric vehicles: a dual-factor approach using social comparison theory and technology acceptance model. Res. Transp. Bus. Manag. 45, 100842.
Shingala, M.C., Rajyaguru, A., 2015. Comparison of post hoc tests for unequal variance. International Journal of New Technologies in Science and Engineering 2, 22–33.
Stellantis N.V, 2023. 2022 Corporate Social Responsibility Report, Hoofddorp. https://www.stellantis.com/content/dam/stellantis-corporate/sustainability/csr-disclosure/stellantis/2022/Stellantis-2022-CSR-Report.pdf. (Accessed 10 May 2024).
Stockkamp, C., Schäfer, J., Millemann, J.A., Heidenreich, S., 2021. Identifying factors associated with consumers' adoption of e-mobility—a systematic literature review. Sustainability 13, 10975.
Sundin, E., Lee, H.M., 2012. In what way is remanufacturing good for the environment? In: Matsumoto, M., Umeda, Y., Masui, K., Fukushige, S. (Eds.), Design for Innovative Value Towards a Sustainable Society. Springer, Netherlands, Dordrecht, pp. 552–557.
Tao, F., Kishita, Y., Scheller, C., Blömeke, S., Umeda, Y., 2022. Designing a sustainable circulation system of second-life traction batteries: a scenario-based simulation approach. Procedia CIRP 105, 733–738.
Tardiff, T.J., 1978. The Use of Alternative Specific Constants in Choice Modeling. Institute of Transportation Studies., Irvine, UC Irvine. https://escholarship.org/uc/item/5j43q8mj. (Accessed 5 June 2023).
Telser, H., Zweifel, P., 2007. Validity of discrete-choice experiments evidence for health risk reduction. Appl. Econ. 39, 69–78.
Tondolo, V.A.G., Paiva, E.L., Da Tondolo, R.R.P., Santos, J.B., 2021. Servitization as a Strategy for Remanufacturing: An Experimental Study. BAR, Braz, Adm. Rev, p. 18.
Train, K., 2009. Discrete Choice Methods With Simulation. Cambridge University Press, Cambridge (388 pp.).
Veldwijk, J., Lambooij, M.S., Bekker-Grob, E.W. de, Smit, H.A., Wit, G.A. de, 2014. The effect of including an opt-out option in discrete choice experiments. PLoS One 9, e111805.
Verma, S., Dwivedi, G., Verma, P., 2022. Life cycle assessment of electric vehicles in comparison to combustion engine vehicles: a review. Materials Today: Proceedings 49, 217–222.
Wang, N., Tang, L., Pan, H., 2017. Effectiveness of policy incentives on electric vehicle acceptance in China: a discrete choice analysis. Transp. Res. A Policy Pract. 105, 210–218.
Wang, Y., Yin, X., Du, Q., Jia, S., Xie, Y., He, S., 2018. Consumers' green preferences for remanufactured products. In: Wang, S., Price, M., Lim, M.K., Jin, Y., Luo, Y., Chen, R. (Eds.), Recent Advances in Intelligent Manufacturing, vol. 923. Springer Singapore, Singapore, pp. 332–342.
Yang, Y., Tan, Z., 2019. Investigating the influence of consumer behavior and governmental policy on the diffusion of electric vehicles in Beijing. China. Sustainability 11, 6967.
Zhang, H., Xue, B., Li, S., Yu, Y., Li, X., Chang, Z., Wu, H., Hu, Y., Huang, K., Liu, L., Chen, L., Su, Y., 2023. Life cycle environmental impact assessment for battery-powered electric vehicles at the global and regional levels. Sci. Rep. 13, 7952.
Zhu, J., Mathews, I., Ren, D., Li, W., Cogswell, D., Xing, B., Sedlatschek, T., Kantareddy, S.N.R., Yi, M., Gao, T., Xia, Y., Zhou, Q., Wierzbicki, T., Bazant, M.Z., 2021. End-of-life or second-life options for retired electric vehicle batteries. Cell Reports Physical Science 2, 100537.
Ziegler, A., 2005. A comparison between multinomial logit and probit models. In: Scarpa, R., Alberini, A. (Eds.), Applications of Simulation Methods in Environmental and Resource Economics, vol. 6. Springer-Verlag, Berlin/Heidelberg, pp. 97–116.