Battery recycling policies for boosting electric vehicle adoption: evidence from a choice experimental survey

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Abstract

Electric vehicles must be widely accepted because of environmental concerns and carbon restrictions. Previous research has looked at consumer policy preferences and their influence on electric vehicle adoption. However, none have investigated the impact of policies linked to battery recycling on electric vehicle adoption. This study used a discrete choice model (the panel-data mixed logit model) to evaluate 552 actual consumer choice data from Southwest China collected via an online questionnaire. Our results indicate that (1) 75% of respondents feel that electric vehicles enhance the environment and are eager to embrace them. However, the lack of strong recycling policies may hinder their adoption of electric vehicles. Specifically, the four battery recycling policies significantly impact electric vehicle adoption. (2) Consumers appreciate producer-oriented incentives more than consumer-oriented incentives to a lesser extent, such as mandated battery recycling policies and electric vehicle battery flow tracing policies. (3) Consumers place a larger willingness to pay on charging station density than vehicle attributes. (4) Regarding consumer heterogeneity, the usual young group in higher-rated cities prefers electric vehicles, while customers who own a car are more inclined to buy electric vehicles. Finally, more management insights and policy recommendations are provided based on these findings to help government and producer policymakers.

Keywords: consumer preferences, electric vehicle adoption, discrete choice model, end-of-life battery recycling policies, policy incentives

1. Introduction

Fuel pollution and climate change have prompted governments worldwide to favor electric vehicles (EVs) (Stoffel et al., 2020; Valipour et al., 2020; Huang et al., 2021c). EV registrations grew by 41% in 2020, according to the International Energy Agency's "Global EV Outlook 2021," despite a 16 percent drop in global car sales due to the pandemic (IEA, 2021). Approximately 3 million EVs (4.6 percent of new auto sales) are sold worldwide, with 1.367 million sold in China, an increase of 10.9 percent annually (CAAM, 2021; IEA, 2021). By 2030, there are estimated to be 220 million EV owners worldwide, with China accounting for half of the global market by 2025 (Ding et al., 2020; Huang et al., 2022). EVs are becoming more popular, but the fact remains that their market share remains limited. For example, China had 4.92 million new energy vehicles in 2020, accounting for only 1.75 percent of the overall vehicle ownership (CBIN, 2021). Accelerating vehicle electrification will continue to be a priority in the future(Zhou et al., 2019c). However, consumers appear to be hesitant to embrace EVs due to their ineffective recycling system for spent batteries. Whether this product is ecologically benign is becoming a new source of concern.

According to the data, China's EV lithium battery sales in 2020 were 80 GWh, weighing approximately 640,000 tons, indicating a rapid expansion of the battery supply chain (GGII, 2021). EV batteries are typically lithium batteries with a lifespan of approximately 5-8 years and must be recycled at the end of their life cycle for recycling or disassembly usage (Mali and Tripathi, 2021). According to estimates, the total number of end-of-life EV batteries is expected to reach 780,000 tons by 2025, and as the EV market grows, the number of used batteries will be even larger (Li et al., 2020d; Yan and Sun, 2021). However, there is currently no recycling mechanism in place for end-of-life EV batteries in China, and firms lack the motivation to recycle spent batteries, which appears to be a new obstacle to the consumer adoption of EVs (Zhou et al., 2019a; Ding et al., 2020; Li et al., 2020d). For example, only 5,472 tons of EV batteries were recycled out of the 74,000 tons destroyed in 2018, representing a 7.4% recovery rate (Li et al., 2020d).

The waste battery recycling policy has been stated from the early stages of the promotion of EVs, but it is not the emphasis; after all, there are relatively few EVs in society, much alone waste batteries, so the impact of recycling is minimal. Another important reason is that these policies are not mandatory, and the roles and obligations of the parties involved in end-of-life battery recycling are unclear (Ding et al., 2020). The above two reasons have led to the neglect of waste battery recycling policies and poor implementation of the actual results. However, green preferences and environmental awareness have been critical antecedents of consumer adoption of EVs (Globisch et al., 2019; Wu et al., 2019; Zhou et al., 2019b). Existing studies have emphasized the impact of EV-related policies, such as subsidies, taxes, and free parking. They have neglected the effect of used batteries on consumer preferences. Moreover, existing studies fail to examine the impact of battery recycling policies on EV adoption from a full life-cycle perspective, as these policies can minimize vehicle aftermarket costs and environmental impacts. To the best of our knowledge, this study is the first to use discrete choice experiments to examine consumer preferences for these regulations and how they affect the uptake of EVs from a full life-cycle perspective.

Based on the above logic, we may be curious whether the policy on used batteries would impact the consumer uptake of EVs. If so, which recycling policies should be treated seriously from the standpoint of consumers, and how much of a quantitative influence do they have on EV adoption? To the best of our knowledge, there has been no research on these topics in the existing literature. We categorized the policies linked to EV battery recycling in Figure 1 by classifying them as subsidized programs, punitive policies, and retroactive measures. Referring to Figure 1's policy map, four policies were extracted: mandatory recycling battery policy (Policy_MRB), battery trade-in policy (Policy_BTI), battery flow traceability policy (Policy_BFT), and consumer recycling subsidy policy (Policy_CRS). In addition, we designed a discrete choice experiment survey to empirically investigate the influence of these policies on EV adoption to address the issues above. We gathered 552 consumer preference data from respondents in Southwest China who were potential EV buyers because they had experience with EVs or wanted to buy one in the future. Our study's results and managerial insights provide additional practical recommendations for businesses and governments.

The remainder of this paper is organized as follows. Section 2 examines the relevant literature. Section 3 introduces the method, including the choice experiment design, model specifications, and data collection. The sample description, model estimation, and willingness to pay are examined in Section 4. Section 5 discusses the theoretical and managerial implications of this study. Finally, Section 6 closes the research.

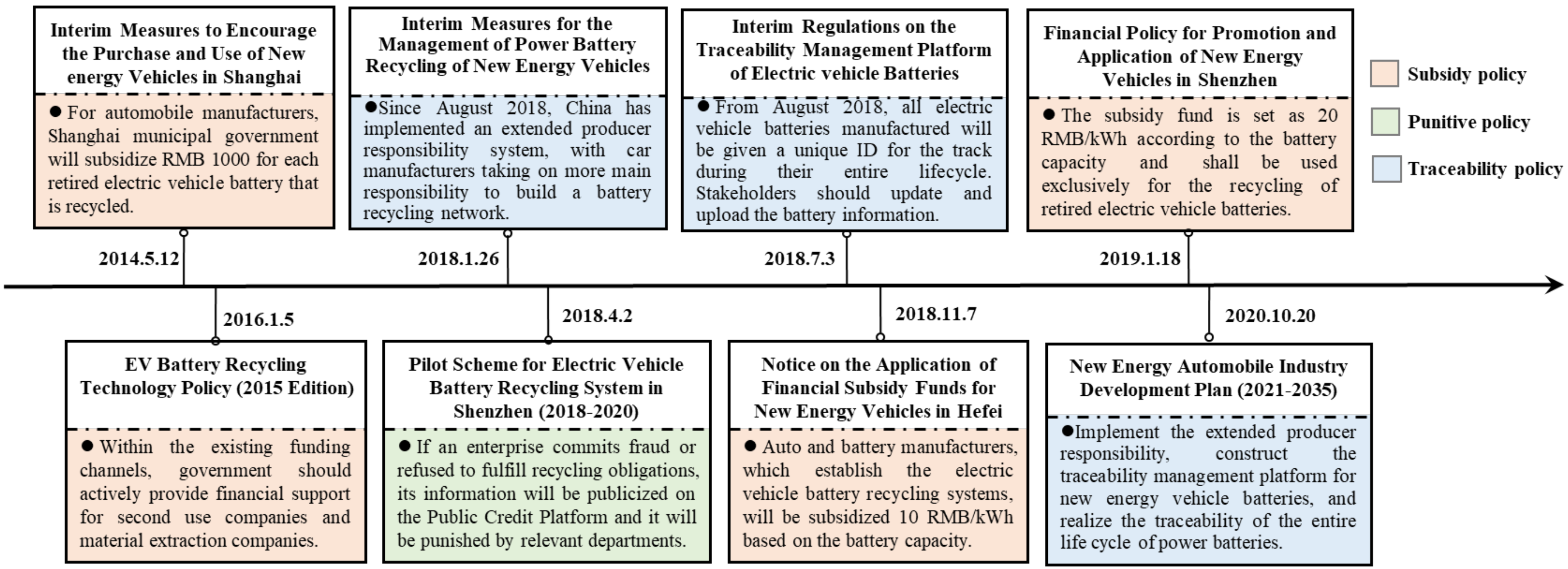

Figure 1. China's key policy for recycling end-of-life electric vehicle batteries (modified from Tang et al. (2019)).

2. Literature review

Choice behavior is influenced by "market conditions and constraints" as well as "preferences," which include perceptual indicators, attitude indicators, socio-demographic traits, and product attributes, among others (Swait, 1994). These indicators are the main explanatory factors for consumer decisions and impact actual consumer behavior. Consumer choice of EVs is a dynamic subject of research (Huang et al., 2021b; Li et al., 2021a; Mandys, 2021). Although the issue is still relatively young, there is already a substantial body of literature, including several typical literature reviews, such as Liao et al. (2017), Hardman (2019) and Kumar and Alok (2020). Our study is based on two lines of research: consumer policy preferences and the EV waste battery policy effect.

Policy attributes refer to "market conditions and constraints" (Swait, 1994). This stream of the literature aims to determine the efficacy of policies and consumer policy preferences. Policy incentives can encourage people to choose EVs by lowering their prices or making them more convenient (Li et al., 2020b; Li et al., 2020c). Financial and non-financial incentives are two types of policy incentives that are commonly used, and their incentive effects on consumers vary. Many studies have demonstrated the significance of financial incentive schemes, such as subsidies or tax credits (Noori and Tatari (2016); Harrison and Thiel (2017); Qian et al. (2019)). However, the primary issue with financial incentives as a temporary policy is that they create a significant burden on government coffers and are inequitable, comparable to social assistance. They are only accessible when purchasing an EV. Consequently, a global trend toward lowering or removing financial incentives may emerge. For example, Denmark and Georgia in the United States have abolished tax exemptions, while China has been eliminating purchasing incentives since 2020 (Li et al., 2020b).

In the literature, scholars have begun to focus on non-financial incentives as alternatives to financial incentives. According to Huang et al. (2021d), the willingness to pay (WTP) for free and immediate issues of a driver's license is greater than that for the subsidy program. This finding is consistent with those reported by Qian et al. (2019). Wang et al. (2017) divided the policies into four categories: EV production, purchase, use, and infrastructure. They found that consumers favor rules that exclude them from buying limitations (such as a license plate control policy) and driving restrictions, followed by discounted/free charges and access to bus lanes. Moreover, the influence of the personal carbon trading program and transferable driving credit program on EV adoption was experimentally examined by (Li et al., 2020c; Li et al., 2022), who concluded that both policies might hypothetically replace purchase subsidies. However, these studies focus more on EV-related policies, do not examine the impact of used battery recycling-related policies, and lack a full life-cycle perspective on consumers' willingness to adopt EVs, as these policies minimize car aftermarket costs and environmental impact. To the best of our knowledge, this study is the first to use discrete choice experiments to examine consumer preferences for these regulations and how they affect the uptake of EVs.

Our research is also related to a growing body of literature on the impact of EV waste battery policies in recent years. Most of these studies concentrated on EV supply chain operations management and examined the environmental and economic advantages of reusing spent batteries. Gu et al. (2017), for example, examined the influence of government subsidies and battery recycling on the optimal EV production strategy and discovered that both policies help counterbalance the negative impact of loss aversion on the optimal production quantity and expected utility. Tang et al. (2019) examined the long-term effects of reward-penalty mechanisms in the EV battery recycling business. They discovered that the technique had a greater influence on recycling rates and social welfare. Ding et al. (2020) examined the impacts of collection and dismantling subsidies on businesses' optimum decisions and discovered optimal policy preferences for the various firm and government objectives. Li et al. (2021b) reviewed all the current policies for recycling EV batteries. Although these studies have examined the effects of battery policies, they have not empirically determined the effects of EV battery policies on consumer preferences and EV adoption intentions. To the best of our knowledge, only the work by Li et al. (2020a) is related to ours. They formed a policy set of used battery recycling policies with EV-related policies. They used a technology acceptance model to analyze the impact of the policy portfolios on EV adoption. However, they consider waste battery recycling policies as a policy and do not subdivide them. We present four types of waste battery recycling policies for analysis and use a discrete choice model for empirical analysis. Therefore, the more detailed setting and differences in research methods make our study significantly different from existing studies.

Regarding the modeling approach, our research is strongly connected to the discrete choice model (DCM), which allows us to separate the impact of decision characteristics and the trade-off between choice attributes via repeated selections (Liebe and Meyerhoff, 2021). The revealed preference (RP) and the stated preference (SP) are two types of study data (SP). RP denotes data generated in real-world circumstances, whereas SP denotes various customer options in a hypothetical scenario (Kroes and Sheldon, 1988; Hensher et al., 2015). Researchers typically prefer SP. On the one hand, SP outperforms RP in simulating the decision between existing and exotic possibilities (Hensher et al., 2015). However, this is due to the limited availability of EVs in the market, which means market data are scarce (Mandys, 2021). In summary, DCM is based on choice modeling, and in most situations, SP is employed. Section 3.2 delves into specific DCM modeling concepts. DCM has also been utilized in a variety of disciplines, including vote choice (de Vries, 2007), travel mode selection (Yang et al., 2018), social policy (Stadelmann-Steffen and Dermont, 2020), hotel-booking channel selection (Xie et al., 2016), and vehicle choice (Li et al., 2020b). DCM is also commonly used for EV adoption (as mentioned in Section 2.1); therefore, it is appropriate for our investigation.

3. Method

In this section, we focus on how to design the choice experiment, choose the model specification, and collect data using the method flowchart shown in Figure 2.

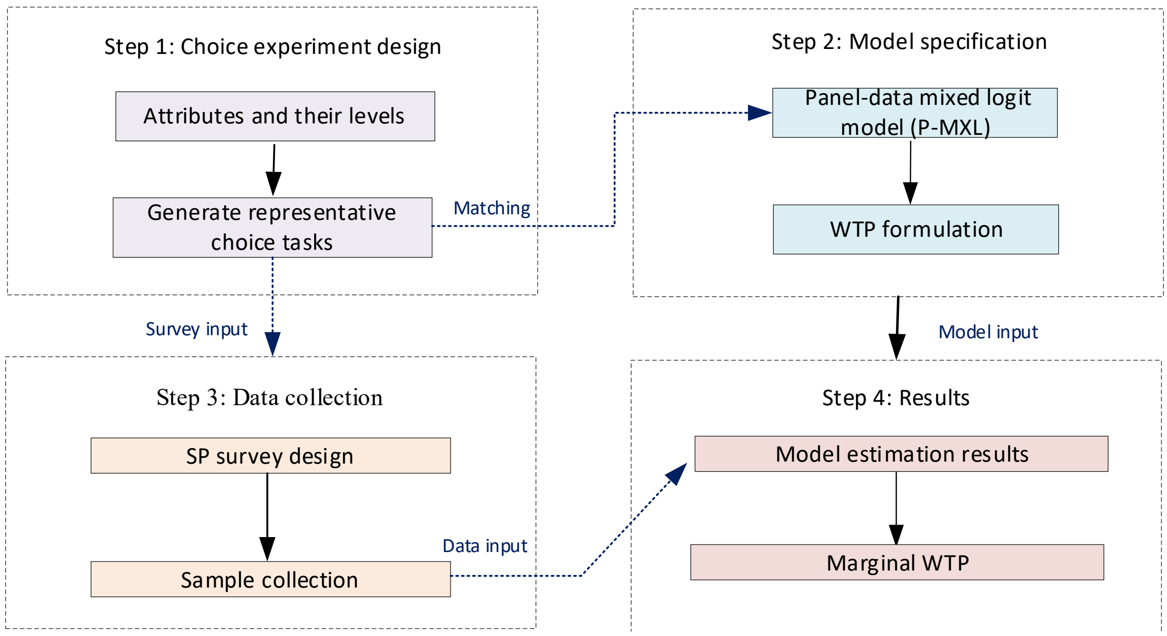

Figure 2. Method flow chart.

3.1 Choice experiment design

A core set of explanatory factors that characterize consumer preferences for EV adoption was determined based on a literature analysis and focus panel discussion (experts in social sciences and policymakers from academia and government). These variables were divided into two categories: product and policy attributes. Table 1 lists these attributes and their levels. Li et al. (2020b), the source of the product characteristics for this analysis, summarized the data relevant to the models represented in the Chinese EV market in 2020. The purchasing prices of EVs are RMB 200,000, RMB 240,000, RMB 280,000, and RMB 320,000. The driving ranges were 400, 500, and 600 km. The charging times were 30, 60, 180, and 360 min. These features are widespread in the Chinese EV markets (Li et al., 2020b).

As for policy attributes, the charging station density (the ratio of charging stations to gas stations) was set to 0.2, 0.4 and 0.6 (Li et al., 2018). Following Li et al. (2021b), the EPR policy states that the primary obligation of EV manufacturers is to recycle discarded batteries. In this case, the obligatory recycling battery value is expected to be 0.2, 0.4, or 0.6. The trade-in policy is an EV battery recycling approach (MIIT, 2018), popular in mobile phones, computers, and other sectors but implemented by only a few EV manufacturers in China. The value of an EV battery trade-in is estimated to be 10%, 20%, and 30% of the cost of a new battery. Following MIIT (2018), the battery decommissioning process can be separated into recycling, echelon utilization, and reclamation. Our study separated the amount of battery traceability into four stages: destination untraceable, traceable to recyclers, traceable to echelon utilization, and traceable to dismantle utilization. Consumer recycling subsidies are another strategy that China pushes producers to implement (MIIT, 2018), with the city of Shenzhen presently utilizing approximately 20 RMB/kWh (CAQN, 2018). As a result, our study considers three subsidy values: 15, 20, and 30 RMB/kWh.

Table 1

Attributes and their levels.

Attributes	No. of levels	Levels
Purchase price (RMB 10,000)	4	20, 24, 28, 32
Driving range (km)	3	400, 500, 600
Charging time (min)	4	30, 60, 180, 360
Charging station density	3	2:10, 4:10, 6:10
Mandatory recycling battery policy	3	20%, 40%, 60%
Electric vehicle battery trade-in policy	3	10% of new battery price; 20% of new battery price; 30% of new battery price
Electric vehicle battery flow traceability policy	4	Destination untraceable; traceable to recyclers; traceable to echelon utilization; traceable to dismantle utilization
Consumer recycling subsidies for electric vehicle batteries (RMB/kWh)	3	15, 20, 25

Table 1 will generate $4^3 \times 3^5 = 15552$ virtual choice tasks if a full factorial design is adopted (Hidrue and Parsons, 2015). Respondents are presented with 5,184 option sets, even though each set contains three alternative EV profiles. In practice, this is impossible; hence, creating and extracting the most representative choice tasks is recommended (Li et al., 2020b). After 15-20 profiles have been differentiated, the respondent feels exhausted, lowering choice efficiency (Allenby and Rossi, 1999). For that purpose, the researchers employed Sawtooth

Software's random task generating approach (Balanced Overlap) to create 20 efficient questionnaire versions with 100 total choice jobs (5 each version), each including three EV virtual product profiles and one "no-option." To avoid respondent fatigue, one set of 20 questionnaires was chosen randomly and given to respondents, with just five alternatives for each respondent to pick from. The efficacy of the experimental design of this study can be assured, according to the Sawtooth software experimental report, when the research sample size is more than 350. An example task is depicted in Figure 3.

Task 1 of 5

Imagine you are going to purchase a battery electric vehicle. Please evaluate the electric vehicle available to you below and select the option you would most likely purchase. You may also chooose to not purchase either of the electric vehicles.

	Electric vehicle option A	**Electric vehicle option B**	**Electric vehicle option C**
ELECTRIC VEHICLE ATTRIBUTES			
Purchase Price (RMB10,000)	20	28	24
Driving range (km)	600	500	400
Charging time (min)	360	30	30
Charging station density (*relative to gasoline station*)	6:10	4:10	2:10
GOVERNMENT SUPPORTS			
Electric vehicle battery flow traceability	Destination untraceable	Traceable to recyclers	Traceable to echelon utilization
Mandatory recycling battery policy (*Manufacturers according to their production)*	60%	20%	60%
Consumer recycling subsidies for electric vehicle batteries (*RMB/kWh*)	25	15	20
Electric vehicle battery trade-in policy (*Reducing the price of new batteries*)	10% of new battery price	30% of new battery price	20% of new battery price

D

I would *NOT* purchase either of the electric vehicle options

I WOULD CHOOSE: A ○ B ◉ C ○ D ○

Figure 3. Example Task used in the Survey (translated from the Chinese questionnaire).

The study questionnaire also contained a survey of sociodemographic factors in addition to the EV choice experiment. Table 2 lists all the variables in this study and how each variable was coded using a linear, dummy, and label coding. Linear coding was used for continuous variables, dummy coding for categorical variables that were not ordered, and label coding for ordered variables. ASC stands for "alternative specific constant" and is frequently used to examine respondents' heterogeneous preferences (Wang et al., 2017; Huang and Qian, 2018). Finally, an overview of the choice experiment was presented prior to the completion of the questionnaire. It explains the policies around EV batteries and the risks associated with batteries that are not recycled or disposed of appropriately. In addition, a pilot study with 50 participants was conducted to assess the reliability and practicality of the questionnaire. As a result of this method, the questionnaire's content validity can be improved (Qian et al., 2019; Huang et al., 2021a).

Table 2

Variable descriptions and assignment.

Variables	Encoding Type	Variable assignment
Price (RMB 10,000)	Linear	20, 24, 28, 32
Driving range (km)	Linear	400, 500, 600
Charging time (min)	Linear	30, 60, 180, 360
Charging stations (relative to gasoline station)	Linear	20%, 40%, 60%
Mandatory recycling battery policy	Linear	20%, 40%, 60%
Electric vehicle battery trade-in policy (X% of new battery price)	Linear	10%, 20%, 30%
Electric vehicle battery flow traceability policy	Dummy	Destination untraceable = (0,0,0); traceable to recyclers = (1,0,0); traceable to echelon utilization = (0,1,0); traceable to dismantle utilization = (0,0,1)
Consumer recycling subsidies for electric vehicle batteries (RMB/kWh)	Linear	15, 20, 25
ASC	Dummy	Select "Do not select any of them": ASC = 1; No "Do not select any of them" is selected: ASC = 0
Gender	Dummy	Male = 0; Female = 1
Age	Label	[18, 25) = 1; [25, 30) = 2; [30, 40) = 3; [40, 50) = 4; [50, 60) = 5
Income	Label	(0, 100,000] = 1; (100,000, 200,000] = 2; (200,000, 300,000] = 3; (300,000, +∞] = 4
City	Label	Third-tier or below = 1; Second-tier = 2; New first-tier = 3
Education	Label	Junior college or below = 1; Bachelor's degree = 2; Master's degree = 3; Doctor's degree = 4
Household car ownership	Linear	0, 1, 2

3.2 Data collection

After the design of the choice experiment, an SP survey was conducted to facilitate data collection. The SP survey consisted of three parts. In the first part, respondents were asked to understand the basic concepts related to the four used battery recycling policies. They completed a quiz to show that they truly understood these policy tools. In the second section, respondents were asked to read the options and complete different selection tasks to indicate their preference for different vehicles. In the third section, questions related to sociodemographic characteristics were asked. After completing the SP survey design, data were collected for the study.

The study's data come mostly from Chongqing, Chengdu, and Kunming, which are national pilot cities for EV promotion in southwest China, and where respondents are quite familiar with EVs (Huang et al., 2021c; Huang et al., 2021d). The literature examines customer preferences for EVs in Southeast China and first-tier cities, such as Huang and Qian (2018), Li et al. (2020b) and Huang et al. (2021d). The Credamo platform was used for data collection between August 24, 2021, and September 1, 2021, paid usage of the *Credamo* platform[1] for data collecting. The platform, it should be noted, provides precise research services and helps the researcher increase data dependability by removing 30% of the total questionnaires. The following were the precision service rules used in this study: (1) the three target cities of Chongqing, Chengdu, and Kunming were chosen to limit the number of respondents; (2) respondents under the age of 18 or over the age of 60 are not considered possible EV buyers, as China's legal driving age is 18, and EV demand is usually lower for those over 60. Two new questions were added to the sample data processing to filter out invalid data: (1) Do you believe that EVs might be prohibited from the road owing to traffic regulations? (2) Do you have a driver's license or do you intend to purchase a car within the next 3-5 years? Respondents who replied "YES" to the first question but "NO" to the second were deemed unqualified, either because the surveys were not carefully studied before being answered or because the respondents were not potential EV buyers (Wang et al., 2017; Huang et al., 2021c). Finally, with a valid questionnaire rate of 77%, 552 valid data points (717 total sample sizes) were gathered.

3.3 Model specification

Our research used a discrete choice experiment survey. Respondents were asked to select the best product option based on their preferences among several virtual EV profiles, and their WTP was calculated. The customer is portrayed as rational in this process, and he or she strives to maximize his or her utility by evaluating and choosing different product attributes (McFadden, 1986; Train, 2003; Li et al., 2022). The option with the highest utility is chosen in a given choice set (C). As indicated in Eq. (1), the utility of an option (U_{in}) for respondents

[1] https://www.credamo.com/

(n) comprises an observable or systematic component of the explanatory variable ($\beta' X_{in}$) and an unobserved random component or error term (ε_{in}).

$$U_{in} = \beta' \mathbf{x}_{in} + \varepsilon_{in} \tag{1}$$

Where the observable part is a linear function of the observed attributes ($\mathbf{x}_{in}$), β is the vector of parameters to be estimated for all attributes. Thus, the probability of respondents n selecting an alternative i instead of an alternative j from a certain choice set C can be described in Eq. (2):

$$P_n(i) = Pr(\beta' \mathbf{x}_{in} + \varepsilon_{in} \geq \beta' \mathbf{x}_{jn} + \varepsilon_{jn}, \forall j \in C, i \neq j) = \frac{\exp(\beta' \mathbf{x}_{in})}{\sum_{j \in C} \exp(\beta' \mathbf{x}_{jn})} \tag{2}$$

However, the above is a conventional multinomial logit model (MNL) with the underlying assumption of independence of irrelevant alternatives (IIA); that is, the errors between different alternatives are independent and identically distributed (IID) with a type I extreme value distribution (McFadden, 1986; Cameron and Trivedi, 2005). In our study's choice set, three EV options and one "no-option" alternative are included, which do not meet the IIA assumptions (Li et al., 2020b). To loosen the IIA requirement imposed by McFadden's choice model, the panel-data mixed logit model (P-MXL) was utilized as an extension of MNL to mimic the correlation of choices across alternatives by defining random coefficients for alternative-specific variables. Eq. (3) can be used to rewrite the utility that the respondent n obtains from an option i in the choice scenario t for P-MXL:

$$U_{int} = \beta_i' \mathbf{x}_{int} + \alpha_i' \mathbf{w}_{int} + \delta_n' \mathbf{z}_{int} + \varepsilon_{int} \tag{3}$$

Where β_i are random coefficients that change with the respondents and $\mathbf{x}_{int}$ is a vector of alternative-specific attributes of respondent n selecting an alternative i in the choice scenario t. α_i is the fixed coefficient of $\mathbf{w}_{int}$, a vector of alternative-specific attributes. δ_n is a fixed alternative-specific coefficient of $\mathbf{z}_{int}$, a vector of case-specific attributes. ε_{int} is a random term that follows type-I extreme value distribution. The probability of choosing alternative i ($i \in C$) for respondent n in t ($t \in T$) is represented by Eq. (4):

$$\begin{aligned} P_{int} &= \int P_{int}(\beta) f(\beta|\Omega) d\beta \\ &= \int \frac{\exp(\beta_i' \mathbf{x}_{int} + \alpha' \mathbf{w}_{int} + \delta_n' \mathbf{z}_{int})}{\sum_{j \in C, t \in T} \exp(\beta_j' \mathbf{x}_{jnt} + \alpha' \mathbf{w}_{jnt} + \delta_n' \mathbf{z}_{jnt})} f(\beta|\Omega) d\beta \end{aligned} \tag{4}$$

Note that the density function of β is $f(\beta|\Omega)$, where Ω is a fixed parameter of the distribution.

Because it does not have a closed-form solution, the integral in (4) cannot be solved accurately and must be approximated. In other words, the model parameters can only be estimated using the maximum simulated likelihood, which necessitates sufficiently large randomly selected data to ensure consistency in the estimation (Wang et al., 2017; Li et al., 2020b). To optimizes the simulated log-likelihood estimate, 500 scrambled Halton sequences were used.

As for WTP, when utility is specified as in (3), the partial derivative of utility U_{int} with respect to the k-th attribute $\mathbf{x}_{knt}$ (or $\mathbf{w}_{knt}$) and the cost attribute $\mathbf{x}_{Cnt}$ (or $\mathbf{w}_{Cnt}$) is denoted as $dU_{int} = \beta_k d\mathbf{x}_{knt} + \beta_C d\mathbf{x}_{Cnt}$. Letting this expression equal to 0 and solving for $d\mathbf{x}_{Cnt} / d\mathbf{x}_{knt}$ yields in (5):

$$\frac{d\mathbf{x}_{Cnt}}{d\mathbf{x}_{knt}} = WTP_k = -\frac{\beta_k}{\beta_C} \tag{5}$$

Eq. (5) represents the change in cost incurred to keep the utility constant for a change in $\mathbf{x}_{knt}$, that is, the WTP for $\mathbf{x}_{knt}$.

4. Results

4.1 Sample description

Table 3 shows the sociodemographic characteristics of the 552 respondents, revealing that males accounted for 52.9 percent of the total, a somewhat larger number than females. The young and middle-aged demographic, which should be the major force in acquiring EVs, accounted for 63.04 percent of the respondents, 25-40 years old. Furthermore, 80.65% were from new first- or second-tier cities, with 71.56% earning a higher education. In terms of their family's yearly income, 44.93% earned between RMB 100,000 and RMB 200,000, whereas 21.74% earned between RMB 200,000 and RMB 300,000. Because this is a precise poll, 66.49% of the respondents' households possess a car, with 15.76% owning two. Furthermore, to provide a more realistic picture of respondents' opinions, we examined consumers' judgments of EVs' environmental friendliness, i.e., "*to what degree do you believe electric vehicles can considerably help the environment?*". According to the survey, 75% of people believed that EVs would assist the environment, while 25% were skeptical.

Table 3

Descriptive statistics of respondent characteristics.

Variables	Definition	Answer	Percentage (%)
Gender	Gender of the respondent	Male	52.90
		Female	47.10
Age	Age of the respondent	[18, 25)	11.59
		[25, 30)	39.13
		[30, 40)	23.91
		[40, 50)	19.20
		[50, 60)	6.16
Income	Annual family income of the respondent	⩽10,000	21.37
		(100,000, 200,000]	44.93
		(200,000, 300,000]	21.74
		>300,000	11.96
City	City level of the respondent	New first-tier	47.10
		Second-tier	23.55
		Third-tier or below	29.35
Household car ownership	Household car ownership of the respondent	0	17.75
		1	66.49
		2	15.76
Education	Educational background of the respondent	Junior college or below	28.44
		Bachelor's degree	43.84
		Master's degree	22.64
		Doctor's degree	5.07
Environmental friendliness of electric vehicles	To what degree do you believe electric vehicles can considerably help the environment	Disapprove	6.70
		Undecided	18.30
		approve	48.91
		Strongly approve	26.09

4.2 Model estimation

The P-MXL approach is used in this section to study customer preferences for EVs by adding influencing elements one by one. The projected results of P-MXL with the error component specifications are listed in Table 4. First, all the coefficients of vehicle attributes are highly significant at the 1% significance level, including purchase price, charging time, driving range, and charging station density, as shown in column (1) of Table 4. The first two attributes (price and charging time) have a negative impact on customer utility, whereas the others have a positive impact. This indicates that the greater the price and the longer the charging time, the less likely buyers will purchase an EV. The higher the number of charging stations and the larger the driving range, the more likely buyers will purchase EV.

Second, all the coefficients of policy attributes are highly significant at the 1% significance level, including Policy_MRB, Policy_BTI, Policy_BFT, and Policy_CRS, as shown in columns (2) – (5) of Table 4. Policy_MRB has a larger estimated coefficient than Policy_BFT, suggesting that consumers prefer production-oriented recycling policies for used batteries to consumption-oriented policies. Specifically, "Policy_MRB" is used as an explanatory variable in column (2) of Table 4 to examine how the mandated recycling of end-of-life batteries (EPR) influences consumer adoption of EVs. The estimated results demonstrate that this policy is significant for consumer utility at the 1% confidence level. This indicates that consumers are worried about end-of-life battery concerns and are more likely to purchase EVs from responsible producers. "Policy BTI" is used in column (3) to determine whether customers are concerned about the trade-in policy for old batteries. If the end-of-life battery can be redeemed to reduce the price of a new battery by 10%, then “Policy_BTI” is 1 and it can increase to 3, meaning that the redemption reduces the price of a new battery by 30%. The estimated results indicate that "Policy_BTI" is significantly positive for consumer utility. The larger the manufacturer's trade-in offer, the more willing consumers are to buy EV products. In column (4), “Policy_BFT” is added to measure whether consumers are concerned about the traceability of the flow of end-of-life EV batteries. According to Table 2, the flow is not traceable as a reference group, and the results show that increasing the traceability of used batteries significantly affects the consumer adoption of EVs. In column (5), “Policy_CRS” is used to evaluate whether subsidies for battery recycling practices help stimulate consumers' willingness to buy EVs. The subsidy amount was divided into 15, 20, and 25 RMB/kWh. The estimated results show that "Policy_CRS" has a significantly positive relationship with consumer utility. The more subsidies there are for end-of-life battery recycling, the more likely consumers will buy EVs.

Third, in terms of customer perception and heterogeneity, most coefficients of the demographic factors are significant at the 1% significance level, except for income. This implies that environmental conservation remains a strong intrinsic motivator for EV adoption, with typical youth groups in higher-tier cities favoring EVs. As defined in Section 3.1, ASC is often used in MXLs to analyze consumer heterogeneity preferences (Wang et al., 2017; Huang and Qian, 2018). Our study also uses ASC of “No-option” to analyze individual heterogeneous preferences. As for individual characteristics, estimated results show only “Income ⋆ ASC” is not significant. Specifically, “Gender ⋆ ASC” is positively significant at the 10% significance level, implying that men are more likely to buy EVs. “Age ⋆ ASC” is positively significant at a 5% significant level. This implies that younger people are more likely to buy EVs, while older people tend to stay put or maintain the status quo. “Education * ASC” is positively significant at a 5% level, indicating that the highly educated group prefers to maintain the status quo. “City * ASC” is negatively significant at a 1% significant level, meaning consumers living in high-level cities are more willing to buy EVs, such as the new first-tier city, and consumers in lower-level city classes are more willing to maintain the status quo. Finally, “Household car ownership * ASC’ is negatively significant at the 5% significance level. This means that consumers who already own family vehicles are more likely to purchase EVs.

Table 4
Product and policy attribute preferences of consumers.

Variables	(1)	(2)	(3)	(4)	(5)
Vehicle attributes					
Purchase price	-.037***	-.037***	-.036***	-.034***	-.035***
	(.006)	(.006)	(.006)	(.006)	(.006)
Charging time	-.002***	-.002***	-.002***	-.002***	-.002***
	(0)	(0)	(0)	(0)	(0)
Driving range	.002***	.002***	.002***	.002***	.002***
	(0)	(0)	(0)	(0)	(0)
Charging station density	.46***	.448***	.457***	.594***	.595***
	(.128)	(.13)	(.13)	(.131)	(.132)
Policy attributes					
Policy_MRB		.562***	.552***	.546***	.561***
		(.161)	(.161)	(.165)	(.166)
Policy_BTI			.059*	.075**	.079**
			(.031)	(.032)	(.032)
Policy_BFT (ref. Destination untraceable)					
Traceable to recyclers				.545***	.548***
				(.085)	(.085)
Traceable to echelon utilization				.691***	.698***
				(.081)	(.081)
Traceable to dismantle utilization				.825***	.837***
				(.082)	(.082)
Policy_CRS					.017***
					(.006)
Demographic Factors Interacted with ASC					
Gender * ASC	.551*	.584*	.571*	.558*	.571*
	(.306)	(.322)	(.316)	(.309)	(.315)
Age * ASC	.379**	.395**	.387**	.38**	.386**
	(.159)	(.166)	(.163)	(.16)	(.163)
Income * ASC	.054	.064	.061	.048	.05
	(.196)	(.205)	(.201)	(.195)	(.198)
Education * ASC	.516**	.535**	.524**	.514**	.52**
	(.22)	(.231)	(.226)	(.22)	(.224)
City * ASC	-.858***	-.895***	-.879***	-.858***	-.869***
	(.249)	(.26)	(.256)	(.251)	(.255)

Household car ownership * ASC	-.649**	-.686**	-.67**	-.64**	-.651**
	(.287)	(.301)	(.295)	(.286)	(.292)
Log simulated likelihood	-2343.451	-2337.245	-2335.444	-2272.149	-2268.295

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

4.3 Willingness to pay

Table 5 shows the marginal WTP for the vehicle and policy attributes based on the computed coefficients in Table 4. These values were calculated as the ratio of the change in the utility value of the corresponding attributes to the purchase price. First, we find that consumers have a greater WTP for policy attributes and a lower WTP for vehicle attributes, as shown in Table 5. Specifically, consumers have the greatest WTP for the policy (traceable to dismantle utilization) of all attributes, willing to pay RMB 239,142.86 than destination traceable. Second, consumers appreciate producer-oriented incentives more than consumer-oriented incentives, such as “Policy_MRB” and “Policy_BFT” with additional WTP of RMB 160,285.71 and RMB 239,142.86, respectively. Third, consumers place a larger WTP on charging station density than on vehicle attributes. According to Table 5, in terms of charging station density, consumers are prepared to pay an additional RMB 170,000 for a 20% increase in charging stations while only willing to pay RMB 571.43 for the next level of improvement in charging time and driving range.

Table 5

Marginal WTP for changes in vehicle and policy attributes.

Attribute	WTP (RMB)
Charging time	571.43
Charging station density	170000.00
Driving range	571.43
Policy_MRB	160285.71
Policy_BTI	22571.43
Policy_BFT (ref. Destination untraceable)	
Traceable to recyclers	156571.43
Traceable to echelon utilization	199428.57
Traceable to dismantle utilization	239142.86
Policy_CRS	4857.14

5. Discussion

5.1 Theoretical contributions

Our work adds to the current body of knowledge in two ways: the first is related to the effect of battery recycling policies in encouraging EV adoption, and the second is related to the use of discrete choice models to investigate the EV battery policy effect.

First, it contributes to the literature by exploring the influence of battery recycling-related policies on EV adoption, which emphasizes EV battery recycling policies. As mentioned in the literature review, previous studies have placed more emphasis on the impact of EV-related policies, such as subsidies (Wang et al., 2018; Xiao et al., 2020), taxes (Liu et al., 2017), license plate lottery (Zhuge et al., 2020), free vehicle licensing (Qian et al., 2019), carbon trading (Li et al., 2020b) and related policy mix (Li et al., 2020c), and ignored the impact of end-of-life battery-related policies on EV adoption. Moreover, existing studies fail to examine the impact of non-financial policies on EV adoption, particularly battery recycling, from a full life-cycle perspective, as these policies can minimize vehicle aftermarket costs and environmental impacts. To the best of our knowledge, this study is the first to use discrete choice experiments to examine consumer preferences for these regulations and how they affect the uptake of EVs from a full life-cycle perspective. Our study indicates that all EV battery recycling policies significantly impact EV adoption. We quantify the impact of the four policies on EV adoption, as shown in Table 5. Results indicate that consumers seem to be more willing to pay for "Policy_MRB," "Policy_BTI," and "Policy_BFT" and less willing to pay for the remaining two consumer-side incentives (*see* Table 5). This may be due to the current lack of recycling mechanisms and systems for EV batteries in China (Tang et al., 2019; Li et al., 2021b). As a result, our findings add to the existing literature and provide a better understanding of the factors influencing EV adoption.

The second implication is the application of discrete choice models to study EVs using the battery policy effect. Previous research has focused on the influence of battery recycling policies on EV manufacturing decisions and the use of game theory models (Gu et al., 2017; Tang et al., 2019; Ding et al., 2020). These studies also regard the battery recycling policy as a recycling subsidy, which is rather monolithic and general. In contrast, our study refines recycling subsidy policies and focuses on the influence of these policies on consumer behavior. The results reveal that "Policy_MRB" and "Policy_BFT" have more market power, which opens up a new situation for studying EV producers' operational decisions.

5.2 Managerial implications

Governments and producer policymakers will benefit from the findings of this study. First, consumers place a larger WTP on charging station density than that for other vehicle attributes.

This finding is consistent with the existing research and suggests that convenience factors have become more important for consumer adoption (Globisch et al., 2019; Hardman, 2019; Huang et al., 2022). In this study, this may be because participants of the survey were mostly automobile owners who had a better grasp of EVs and placed greater emphasis on convenience, particularly in light of China's multiple non-fiscal policy requirements, such as limitless traffic, unlimited numbers, and access to bus lanes (Wang et al., 2018; Huang et al., 2021c). Insufficient charging infrastructure has been a key impediment to EV adoption, with a charging facility to EVs ratio of 1:3.5 in China in 2019 (Huang et al., 2021c; Huang et al., 2022). Consequently, the government's responsibility to increase the market supply of charging stations remains critical.

Second, consumers have the greatest WTP for the policy (“Policy_MRB” and “Policy_BFT”) among the policy attributes. This means that EV battery policies play an important role in EV adoption, with customers preferring producer-oriented policies to consumer-oriented incentives. This is a fascinating finding, and one possible explanation is the insecurity caused by an imperfect recycling system for EV batteries. There is currently no complete EV waste battery recycling system in China, and relevant vehicle enterprises lack an incentive to recycle waste batteries (Ding et al., 2020; Li et al., 2020d). Consumers seem to be concerned that in the absence of a complete battery recycling system. Their adoption of EVs will cause more harm to society and the environment; thus, consumers also expect manufacturers to take the initiative to take responsibility for recycling used batteries, especially by establishing relevant recycling mechanisms, including disposal and tracking. This finding supports the idea that manufacturers should establish a recycling system that allows customers to send back their spent EV batteries for reuse, recycling, or disposal (Li et al., 2021b). In addition, this finding also supports the use of the EPR policy in the field of EVs, and this policy was proposed by the New Energy Automobile Industry Development Plan (2021-2035)" (GOSCC, 2020). As a result, vehicle companies should actively participate in developing battery recycling systems to stimulate potential consumer demand for EVs. In contrast, government incentives need to prioritize incentives for car companies to establish recycling systems, followed by incentives for consumers to send back used batteries.

6. Conclusion and policy implications

Large-scale EV battery retirement poses a risk to society and the environment, and the lack of a recycling system for used batteries may deter consumers from purchasing EVs. Previous research has examined consumer policy preferences and their influence on EV adoption. However, none have investigated the impact of policies linked to battery recycling on customer preferences and EV adoption. To close this gap, we utilized a discrete choice model to assess 552 real consumer choice data items from Southwest China acquired via an online survey. Our study seeks to determine whether policies on used batteries might affect consumer adoption of EVs given the current lack of or deficiencies in the battery recycling system used. Which recycling policies should consumers take seriously, and how much of a quantitative effect do they have on EV adoption? This study addresses the knowledge gaps mentioned above.

Our study puts forward several findings and implications. First, 75% of the respondents felt that electric vehicles enhanced the environment and were eager to embrace them. However, the lack of strong recycling policies may hinder their adoption of electric vehicles. Specifically, the four battery recycling policies significantly impact electric vehicle adoption. This means that consumer environmental awareness is becoming a significant psychological barrier to EV adoption. Therefore, from a consumer perspective, it is crucial for EV adoption to focus on waste battery recycling and adhere to the extended producer responsibility system for waste batteries. Second, consumers appreciate producer-oriented incentives more than consumer-oriented incentives to a lesser extent. This means that establishing an EV waste battery recycling system should adhere to the strategy of producer responsibility as the main focus, supplemented by the consumer. Therefore, producers should actively assume responsibility for EV waste battery recycling and establish a waste battery recycling system. Government policy design should prioritize supporting the establishment of the recycling system, followed by encouraging consumer participation. Third, consumers place a larger WTP on charging station density than vehicle attributes. The shortage of charging service facilities has gone beyond the technical shortcomings of the vehicles themselves. It is more important to vigorously improve the level of service of supporting facilities to encourage EV adoption. Therefore, the government and enterprises should shift their focus to the investment and layout of charging facilities, such as developing new business models and setting reasonable tariffs, to solve the problem of difficult charging. Finally, in terms of customer perception and heterogeneity, environmental conservation remains a strong intrinsic motivator for EV adoption, with typical youth groups in higher-tier cities favoring EVs adoption. Consequently, while developing appropriate initiatives, the government and enterprises should pay more attention to this group's demands and proposals.

Compared to previous studies, our study is novel in the following regard. First, we developed a novel discrete choice model that accounts for the influence of battery recycling policies on EV uptake. To the best of our knowledge, this study is the first to propose a choice model that considers the impact of battery recycling policies. Second, we refine the battery recycling policies and quantify the impact on EV adoption. Our research shows that consumers prefer production-oriented policies to consumer-oriented ones. The research has not yet proposed this finding, and it provides a theoretical foundation for production-side battery recycling policies such as extended producer responsibility.

Finally, despite the significant advances proposed here, this study has a few limitations. First, this analysis only considers four sample policies from the existing EV recycling policies; there may be more relevant but unconsidered regulations. Future studies should examine the policy framework in greater detail and develop more persuasive measures to encourage the use of EVs and their recycling systems. Second, while this study reveals consumer preferences for EV recycling policies, the underlying influencing mechanisms remain unknown. Under market constraints, future studies should reveal how these policies affect firms' operational decisions, such as production and pricing. Third, this study only analyzes the impact of battery recycling policies on EV adoption, and a potentially new circular causality seems to be forming; that is, whether firms recycle batteries depends on consumer adoption of EVs and whether consumers adopt EVs depends on whether used batteries can be recycled effectively. Future research could reveal the impact of this kinetic relationship through simulation analysis.

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