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*Research Article*

# Accounting for BEV Users' Risk Attitudes and Charging Inertia in En Route Charging Choice Behavior

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This paper innovatively explores BEV (battery electric vehicle) users' risk attitudes and charging inertia, examining their effects on en route charging and charging route choice behavior. An attitudinal survey was conducted to explore the two latent variables of risk attitudes and charging inertia in relation to socioeconomic and travel-related characteristics. ICLV (Integrated choice and latent variable) models are adopted to estimate the latent variables and the charging choice behavior simultaneously. Specifically, uncertainty in energy consumption is first considered in the ICLV model, which is represented by the available range (AR) uncertainty. Multinomial logit (MNL) models directly incorporating socioeconomic attributes are employed as a reference for comparison with ICLV models. Results illustrate that risk attitudes and charging inertia both play significant roles in modeling en route charging choice behavior. Risk-averse users and users having charging inertia value AR uncertainty more. Battery range, charging frequency, and income emerge as the most crucial factors influencing users' intention to charge en route. The results show significant heterogeneity of BEV users in attitudes and charging choice behavior, underscoring the importance of accounting for the heterogeneity in en route charging demand estimation and deployment optimization of public charging stations, particularly for medium-to long-distance trips.

## 1. Introduction

Due to fewer greenhouse gas emissions, less dependence on petroleum, and higher energy efficiency, battery electric vehicles (BEVs) have attracted more and more attention from governments, enterprises, and researchers [1, 2]. Meanwhile, the long charging time and short battery endurance of BEVs also cause range anxiety in travelers and hinder the development of the BEV market [3, 4]. A variety of policies on the construction of charging infrastructure have been proposed and implemented to support the growth of the BEV market. However, the underutilization of public charging stations is still prevalent in China. Take Shanghai as an example, by November 2023, there are 87,100 public chargers, which are not sufficient to support the daily trips of about 1.31 million electric vehicles [5]. Nevertheless, public charging infrastructure faces significant underutilization, with a low utilization rate of 7.5% for DC chargers and 1.6% for AC chargers [6]. Due to limited private parking spaces, private chargers are not available for all BEV users and most of them entirely rely on public chargers. It is expected to have a high utilization rate of public chargers. However, the opposite is found in fact. This highlights a paradox between high charging demand and low utilization rates of chargers. A likely explanation for this phenomenon could be inaccurate estimation of charging demand, and inadequate planning of public charging facilities. It is crucial to analyze BEV users' charging behavior, to facilitate better charging demand estimations and public charging facility deployment.

Many studies have investigated BEV users' charging choice behavior, most of which can be divided into after-trip and en route charging choice behavior [7–10]. After-trip charging behavior investigations assume that BEV users have access to chargers at the destination, such as home, workplaces, entertainment areas, and shopping areas. In these situations, slow chargers are suitable for users as they have a relatively long time to charge. In reality, the state of charge (SOC) of BEV is not always full when starting a trip, as they might not own private chargers at home and not have access to chargers at workplaces. Users sometimes have to recharge during the trip, especially when long-distance travel is involved. Different from after-trip charging, en route charging choices and charging route choices are involved in these situations, in which fast chargers allocated in public charging stations are more suitable to save charging time. There are several research studies on en route charging choice behavior. For instance, Ashkrof et al. [11] found that the classic route attributes (travel time and travel cost), vehicle-related variables (SOC at the origin and destination), and charging characteristics (fast-charging duration and waiting time) can influence the BEV drivers' route choice and charging behavior significantly. Moreover, young female drivers with a higher income and education level are more likely to select routes with fast charging. Sun et al. [12] estimated the charging station choice during a trip and found that the fast-charging station choice behavior is heterogeneous among users. The mixed logit models were used in result estimation and a heterogeneity in choosing fast-charging stations is revealed among users as indicated by the likelihood ratio test.

To our best knowledge, there are few studies exploring BEV users' attitudes and their impacts on en route charging choice behavior. Exploring the attitudinal factors could help further investigate the heterogeneity of users in charging choice behavior [11]. Previous studies have evidenced that incorporating attitudinal variables into choice models could explain the behavior better and lead to better goodness-of-fit [9, 13]. In these studies, the hybrid choice model (HCM) framework is a common method to incorporate the attitudinal factors as latent variables and estimate their influence on choice behaviors [14]. Pan et al. [9] developed a latent class model based on the HCM framework to examine the impacts of risk attitudes on charging choice behavior. Their results showed that the risk-averse class focuses primarily on the available range for the next trip and the risk-seeking class balances the price against their current SOC. Wang et al. [13] proposed latent class models to distinguish two types of BEV users, service concerned class and pragmatic concerned class. The former takes service as the most important indicator, such as SOC, queue, and satisfaction. While the latter is much more realistic, caring about charging fees and parking time. These studies all evidenced that travelers have different characteristics and exhibit heterogeneity when making choices. Their attitudes are closely tied to their sociodemographic characteristics and are important to explain the choice behavior. Therefore, exploring the effects of BEV users' attitudes on en route choice is really needed and meaningful for more precise demand estimations for public charging stations and policymaking to improve users' intention to use public chargers.

This paper specifically investigates the impact of BEV users' risk attitudes and charging inertia on en route charging and charging route decisions, using integrated choice and latent variable (ICLV) models. The main contributions are threefold: (1) BEV users' risk attitudes and charging inertia are investigated and modeled by conducting an attitudinal survey. SEM is employed to quantify the attitude variables in relation to sociodemographic factors; (2) risk attitudes and charging inertia examined as latent variables are incorporated into the en route charging behavior using the ICLV model; and (3) heterogeneity of BEV users in en route charging behavior is explored by investigating sociodemographic and travel-related characteristics. This study fills a research gap by incorporating attitudes into the investigation of en route charging behavior. The results reveal that individual risk attitudes and charging inertia are crucial for understanding and explaining en route charging choice behavior.

The remaining part of this paper is structured as follows. Section 2 provides a review of relevant literature. The experimental design, survey, and data collection process are outlined in Section 3. The modeling methodologies and specifications are detailed in Section 4. The results of model estimations are presented in Section 5, followed by discussions on practical implications in Section 6. The conclusion summarizes the research findings and outlines plans for future research.

## 2. Literature Review

Previous studies have made significant efforts to explore the influencing factors of charging choice behavior. These factors are mainly divided into scenario factors and sociodemographic factors. The scenario factors are constructed according to the alternatives related to travel or vehicle state, such as the battery's state of charge, charging time, and travel distance. Xu et al. [15] suggested that the battery capacity, SOC, and a number of past fast-charging events are the major affecting factors of charging mode and location choice. As for charging time, Acheampong and Cugurullo [16] suggest that fast-charging duration and waiting time in the queue of a fast-charging station can influence the BEV drivers' route choice and charging behavior significantly. Charging cost, duration, and location are also key elements to drivers' charging choices, given assumptions that they are planning a trip for their next working day [7]. The range anxiety also inevitably affects BEV users' charging choices. The research has found drivers are accustomed to choosing closer charging stations to decrease the probability of running out of batteries [17]. In addition, sociodemographic factors, such as age or gender can also significantly affect charging behaviors and capture the preference difference among individuals. Wen et al. [8] developed a latent class logit model to model BEV users' charging choices. The results showed that three major classes of users can be sorted on the basis of socioeconomic characteristics. Recently, studies also considered the heterogeneity of individuals and explored the effects of attitudinal variables on charging behavior, such as risk attitudes. Pan et al. [9] considered risk attitude and the attribute nonattendance in charging choice behavior in terms of whether or not to charge at a destination. The results indicated that EV drivers could be divided into two classes, risk-averse class and risk-seeking class, to explain individuals' different charging preferences. However, there is still a lack of studies considering attitudinal variables in en route charging choice behavior.

Most studies on BEV users' charging choice behavior adopted discrete choice models. The forms of discrete choice models include the binary logit (BL) model, multinomial logit (MNL) model, and nested-logit (NL) model, etc. Jabeen et al. [7] developed a multinomial logit (MNL) model to explore BEV users' charging location preferences. It was found that people preferred to charge EVs at home or at work rather than at a public charging station. Daina et al. [18] presented an ordered probit model to investigate the factors stimulating users' charging demand. Results showed that lower cost, shorter battery range, and daily recharging habits would significantly increase their charging demand. Yang et al. [19] proposed two MNL models and two nested-logit (NL) models to analyze the flexible charging behaviors, which include the charging decision and the route choices corresponding to the charging and no-charging situations, respectively. It was observed that the initial SOC of BEV at origin is the most important factor to consider when making the en route charging decision. The charging station attributes such as charging time and charging station's location greatly affected BEV users' route choice behavior.

Besides BL models and MNL models, mixed logit (ML) models and the latent class logit (LCL) models are developed to explore the heterogeneity of BEV users in charging choice behavior. Zoepf et al. [20] estimated a ML model for charging or not at the end of each trip and the results suggested that significant heterogeneity exists among drivers. Sun et al. [21] investigated charging time choices by using a ML model with unobserved heterogeneity. Estimation results showed that the same variables are valued differently in models for commercial and private vehicles. Wang et al. [13] proposed latent class models to further examine the effects of satisfaction of charging facilities and drivers' risk attitudes on charging choice preference. The results revealed the heterogeneity of EV drivers' in charging decision strategies. In addition to the LCL model, studies also proposed ICLV models based on the HCM framework to investigate the heterogeneity. Daina [22] constructed an ICLV model framework for the joint analysis of EV charging and travel behavior. They found that socioeconomic attributes such as age and gender would significantly influence individual attitudes towards BEV range anxiety. Compared with other models, Vij and Walker [23] stated that the ICLV model can identify structural relationships between observable and latent variables, providing more insights into the decision-making process, which would not be possible using the reduced from the choice model. In other fields, Al-Garawi and Kamargianni [24] proposed an ICLV model to explore the factors affecting women's intention to drive, compared with a multinomial logit model. Thorhauge et al. [25] aimed to explicitly account for the impact of inertia on departure time decisions using an ICLV model, with a comparison of the mixed logit model. All their studies showed that the ICLV model has better goodness-of-fit than the traditional logit models.

In conclusion, although some studies have illuminated the heterogeneity in charging choice behavior in light of ML, LCL, or ICLV models, few studies to date have explored the heterogeneity in en route charging and charging route choice behavior, especially the impact of risk attitudes and charging inertia on the en route charging choices. Therefore, this research explores BEV users' en route charging and charging route choice behavior considering two latent variables, risk attitude and charging inertia, which are indirectly related to BEV users' socioeconomic and travel-related characteristics. The ICLV model is applied to estimate the latent variables and their impacts on the charging choice behavior.

## 3. SP Survey and Data Collection

The SP survey is based on our prior research [6] and the same dataset with attitudinal questions is used in this study to especially investigate users' attitudes and their roles in explaining en route charging and charging route choice behavior. The designed questionnaires consist of four parts: current travel-related questions, attitudinal questions, charging choice scenarios, and socioeconomic questions. A web-based survey was conducted to collect the behavioral data from March 2019 to September 2019. We set a prior question "Have you ever driven a BEV?" to select respondents having BEV driving experiences. As the BEV market share is still low, only 2.12% in China, acquiring a large sample set is not easy. In total, we collected 301 valid questionnaires, with 1,804 observations. The methods to screen out invalid questionnaires are given by authors in reference [6].

*3.1. Socioeconomic Questions.* Four sociodemographic factors were used to investigate their effects on en route charging choice behavior, including age, income, education, and gender. These variables were commonly taken as significant factors influencing users' charging choices [8]. Figure 1 shows the summary statistics of respondents' socioeconomic variables. Although we do not have information on the percentage of the population with BEVs, the sample distributions of age adequately follow the same proportions of the population owning motor vehicles in China. According to the statistics data, 70.71% of the drivers are in the age range between 26 and 50, which is very similar to the sample distribution. Although the current ratio of male to female drivers in China is higher than that in the sample distribution, the proportion of female drivers has been increasing recently and BEV also has become popular in the last few years. Therefore, the gender distribution in this study is broadly acceptable. In addition, people with higher education or high income are overrepresented than the average in China, as previous studies reported that most

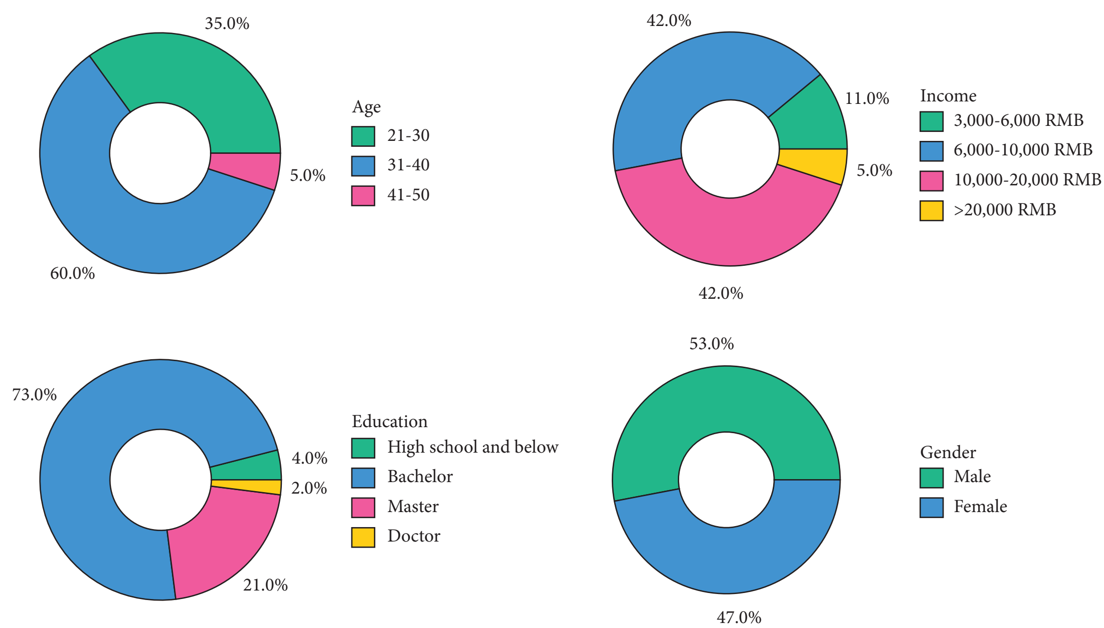


Figure 1: Summary statistics of the socioeconomic variables.

users owning BEVs in general have high incomes and high education levels [26, 27]. In general, sample distributions appear to be representative of the study area so our results may be useful for en route charging behavior analysis in China.

*3.2. Travel-Related Questions.* Travel-related questions, including the battery range, frequent charging locations, daily vehicle kilometres traveled (DVKT), have been asked to collect information on individual BEV characteristics and charging-related characteristics. These characteristics might have impacts on BEV users' charging decisions which will be explored later on. The main characteristics summarized from the survey comprise battery range, driving experience, fixed charging location, travel frequency, and charging frequency (the frequency of using public chargers). The summary statistics of the travel-related characteristics are shown in Figure 2.

Most respondents have a fixed charging location at/near home or workplace. The daily travel distances in most cases are less than 100 km, and the majority of battery ranges are higher than 150 km. It indicates that most BEVs from our sample have battery ranges that are sufficient for daily travel if fully charged when starting the trip.

*3.3. Attitudinal Questions.* A set of attitudinal questions was conducted to capture the latent preference information. The standard Likert scale from 1 to 5, standing for "strongly disagree," "disagree," "neither disagree nor agree," "agree," and "strongly agree," respectively, was adopted to indicate the level of agreement of the respondents on each question [28]. Previous studies on choice behavior typically used two approaches to analyze the impact of attitudinal questions [29]. One involves taking the attitudinal questions directly as explanatory variables. The other utilizes a sequential estimation method based on factor analysis to uncover latent variables and input them into choice models. Moreover, it has been demonstrated that a simultaneously estimated ICLV model tends to exhibit superior goodness-of-fit [23, 30, 31]. This approach allows for the simultaneous estimation of the parameters of the structural equation for latent variable estimation and the parameters of the discrete choice model [32]. In addition, Bierlaire [32] pointed out that the solution of the ICLV would be computationally intensive and time-consuming when including more than one latent variable. Therefore, this paper adopted factor analysis to assist in identifying which questions should be used to uncover latent variables. Section 4 shows a detailed framework of this approach.

First, we conducted an initial questionnaire including 14 questions to explore attitudes about risk and charging inertia, as shown in Table 1. According to previous studies exploring the relation between the number of questionnaires and questionnaire items, the minimum sample is 140 [35, 36]. After collecting 212 presurvey questionnaires, the validity and reliability analysis were applied to the questionnaire data as described in Li et al. [37]. An exploratory factor analysis was used to analyze the validity. The results showed that a total of two common factors were identified, with a Kaiser–Meyer–Olkin (KMO) value of 0.620. The Bartlett's spherical test rejected the original hypothesis, confirming the factorability of the data. In addition, all other criteria were met. The reliability analysis yielded a Cronbach's $\alpha$ value of 0.532, meeting the basic requirement [38]. Figure 3 illustrates the attitudinal questions corresponding to the two latent variables, which were subsequently included in the formal questionnaire.

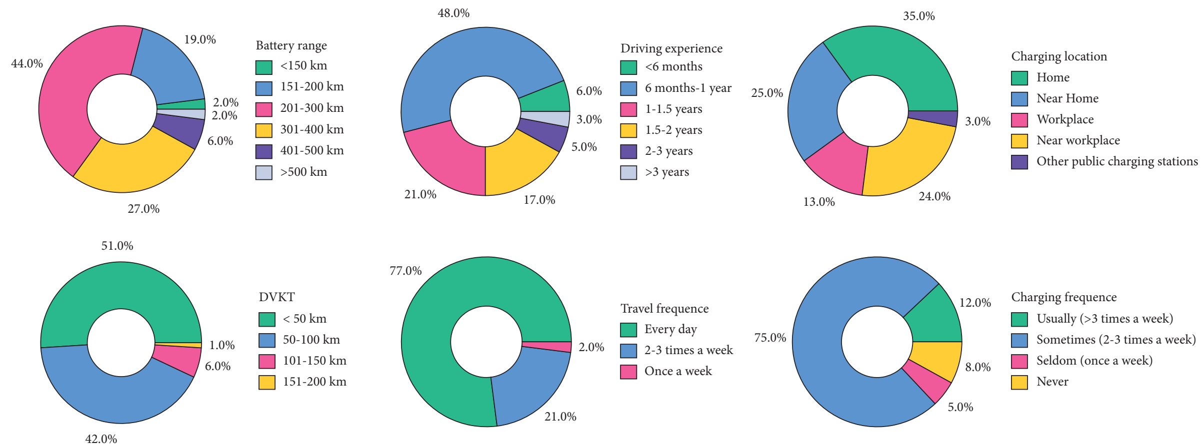


Figure 2: Summary statistics of the travel-related characteristics.

Table 1: List of attitudinal questions in the initial scale.

| Label | Question | Reference |
|---|---|---|
| Risk attitudes-related | I will choose to travel by BEVs only when the remaining battery is more than sufficient for this trip<br>I will not drive a BEV for a long trip when the distance exceeds the total battery range<br>If the remaining battery is lower than expected, I will look for chargers instead of changing travel strategy to save energy<br>If the remaining battery is not enough for the next planned trip, I will charge<br>I don't like to make risky decisions, even though the decision may bring me great benefits | [3, 9, 19, 33] |
| Charging inertia-related | I will charge when the battery drops to a specific level<br>I will charge as soon as I return home<br>I will charge when I approach the charging station that is often used<br>I will charge when I pass by a charging station<br>I will charge when daily trip is over<br>I will charge at a specific time of the day (e.g., midnight)<br>After a specific activity (e.g., working and shopping), I will charge<br>I will compare the electricity price of each station and choose the cheapest one to charge | [18, 25, 34] |

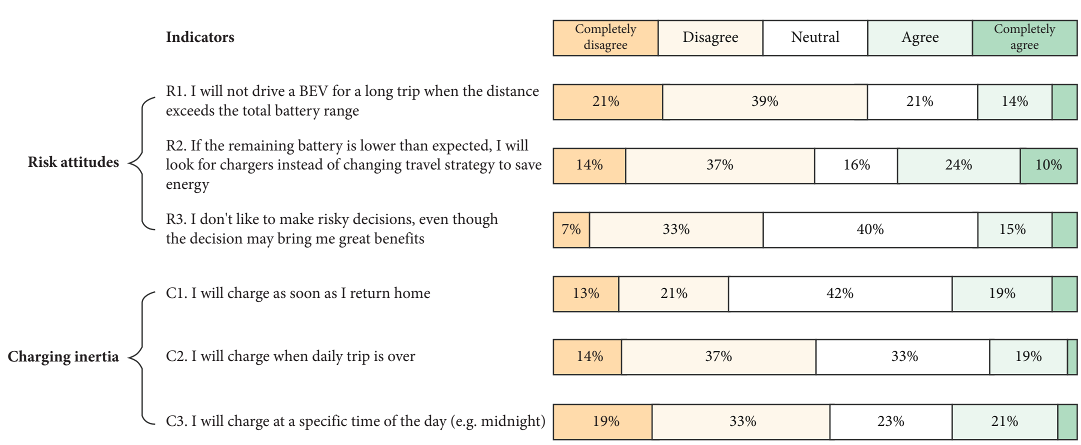


Figure 3: The rating of indicators.

The first latent variable is about risk attitude. Evidence from behavioral and psychological research reveals that risk attitudes play a key role in decision-making [39]. Some studies have illustrated the implications of risk attitudes on travel choices [40, 41]. In these studies, the attitudinal indicators are refined as questions relating to EV driving and charging, which represent risk-seeking and risk-aversion tendencies [9]. In this study, the "risk attitude" is defined as the aversion tendency towards the low remaining battery, i.e., people tend to keep an adequate battery for subsequent trips.

In addition, this paper also explores the effect of inertia on en route charging choice behavior. According to the Oxford Dictionary, habit is defined as "an automatic reaction to a specific situation," while inertia is defined as "a tendency to remain unchanged." Although habit and inertia are sometimes used interchangeably, inertia has a broader definition and encompasses habit [25]. In this paper, charging inertia is defined as a tendency to charge when a certain condition is activated, such as when the trip is over, at a specific time point, and approaching the often-used charging stations.

Both the risk attitudes and charging inertia are considered in explaining the en route charging and charging route choice behavior. Three statements are selected as the indicators for "risk attitudes" and the other three are selected as the indicators for "charging inertia." We originally presented all the statements in Chinese, taking the main rules regarding statement design [42] into consideration. Each statement adopted the form of a traditional 5-point Likert scale [28]. Figure 3 shows the rating of indicators as a diverging stacked bar chart. The bars illustrate the percentages of respondents selecting each level of agreement, for instance, the right bars indicate the percentages of respondents who agree or completely agree with each statement and the left represents disagreed respondents. Likewise, the middle bars show the percentages of respondents holding neutral attitudes. The figure intentionally omits percentages equal to or less than 5%. The responses to the first set of indicators, related to risk attitude, appeared to be more in the disagree group. It can be seen that risk-seeking users take a great portion of the sample and lots of users are not averse to having long-distance trips by BEVs. For the second set of indicators, it is obvious to note that "disagree" and "neutral" dominate the responses, reflecting that a small portion (about 20%) of BEV users in the sample have charging inertia. This is also in line with the previous opinion that there is a higher possibility of charging during travel to complete the entire trip because of forgetting to charge [19].

In general, there are two ways to incorporate the latent variables into choice behavior models, namely, sequential and simultaneous estimations. Sequential estimation means first estimating the latent variables from structural equation modeling (SEM) and then being embedded in the discrete choice modeling [43].

The model framework of simultaneous estimation includes a latent variable model and a discrete choice model. The latent variable model includes a structural equation and a measurement equation [44]. The former uncovers the latent variables and the latter captures the relationship between the latent variables and attitudinal statements. The discrete choice model explores the effects of latent variables and other explanatory variables by constructing utility functions. It is generally recommended to simultaneously estimate the latent variables in the choice behavior and the ICLV model is preferred as the best available technique [24]. Thus, this study adopts the ICLV model to explore the impacts of risk attitude and charging inertia on BEV users' en route charging and charging route choice behavior.

*3.4. Charging Choice Scenarios.* The scenarios for investigating en route charging and charging route choice behavior are designed using an efficient design approach [45, 46]. The same design and the same data as our previous article [6] are used for this study. However, this paper focused on the effects of latent variables, specifically adding latent variable attitudinal questions to further explain users' charging scenario choice behavior. We proposed AR to represent the available range of BEVs [6]. In this study, we introduce AR uncertainty into behavioral modeling, similar to the concept of travel time uncertainty. The energy consumption during a trip is uncertain due to factors such as traffic conditions, weather conditions, road conditions, and driving styles. So, AR at the end of the trip will be uncertain as well. This uncertainty extends to the destination or charging station (CS). For a common travel behavior (e.g., from home to work), there are multiple possible charging situations with different ARs. In this paper, the representation of AR uncertainty refers to Li et al. [6], using an interval with a minimum and maximum value. AR is assumed within a range following a uniform distribution [47] to facilitate the following utility model's estimation. Each scenario involves two charging choices: (1) whether to charge en route considering the initial AR, travel distance, and AR uncertainty at the destination and (2) the choice of charging route, considering the initial AR, travel time, AR uncertainty at the CS, and charging duration. Figure 4 illustrates an example scenario as from our previous article [6]. In each choice scenario, we ensure that the initial AR is always equal to or greater than the travel distance. Charging route choice scenarios are provided to respondents who opt for charging en route in decision 1. Even if a respondent chooses not to charge en route, we inform them that it is assumed that they will charge en route and prompt them to select a charging route.

With a presurvey and actual travel information [6], the attributes with their levels in the experimental design are illustrated in Table 2. Decision 1 includes three attributes: OD distance, initial AR at origin, and AR uncertainty at destination. Decision 2 includes four attributes: detour distance, charging duration, distance from the origin to CS, and AR uncertainty at CS. It should be noted that the detour distance is defined as the additional distance traveled to reach a public CS and is factored into the calculation of travel time. For example, in Figure 4, the OD distance is 30 km and route A entails a 10 km detour distance. Therefore, the entire route would be 40 km (30 km + 10 km). Assuming the average speed is 60 km/h, route A corresponds to a travel time of 40 minutes (assuming average speed to be 60 km/h). Similarly, the entire travel distance and travel time of taking route B are 50 km and 50 min, respectively. There are two main reasons for setting the levels of detour distances which are as follows: (1) ensuring sufficient attribute variation in the SP survey to facilitate significant parameter estimations

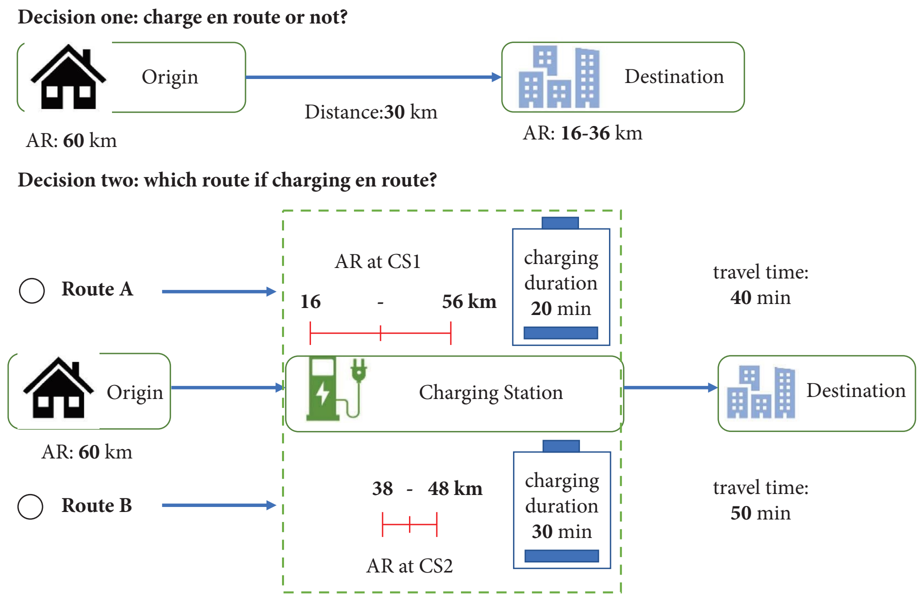


Figure 4: An example of the hypothetical scenarios [6].

Table 2: Attribute levels defined in the experimental design.

| | Attributes | Levels |
|---|---|---|
| Decision one: whether or not to charge en route? | OD distance | 30, 40, 50 km |
| | Initial AR at the origin | 30, 50, 60, 70 km |
| | AR uncertainty (range) at destination | 2, 10, 20, 30, 40 km |
| Decision two: which charging route to choose? | Detour distance | 0, 10, 20 km |
| | Charging duration | 10, 20, 30, 40 min |
| | Distance from the origin to CS in percentile of OD distance | 30%, 50%, 70% |
| | AR uncertainty (range) at CS | 2, 10, 20, 30, 40 km |

and (2) deviation from the original route to the public CS can result in substantial changes in route travel time due to varying traffic conditions. Implicitly, setting larger detour distances acknowledges the longer travel times resulting from charging behavior. Therefore, assigning 10-minute longer travel times corresponding to 10 km detour distances is deemed reasonable.

For generating the scenarios, we used a D-efficient design approach [45] with the help of the professional software, Ngene. It can provide utility-balanced alternatives for each scenario and avoid the dominating alternative situations [48]. A total of 18 choice scenarios were created, and organized into three blocks. Each respondent is required to make choices for only six scenarios.

## 4. Methodology

As aforementioned, various BEV users' socioeconomic and travel-related attributes are involved in en route charging and charging route choice behavior. These attributes not only exert direct effects, but also reflect respondents' psychological attitudes. The ICLV can be adopted to capture this effect in many fields [24, 34]. It offers a method to incorporate latent variables into choice models, thereby enabling a more realistic assessment of individual choice behavior [30]. The model comprises three components: (1) the structural equation model, (2) the measurement equation model, and (3) the discrete choice model. The structural equation studies the construction of latent variables and the measurement equation analyses of its observed indicators. The discrete choice modeling estimates the utilities of each choice, considering the effect of latent variables and other explanatory variables. Different from traditional logit models, the ICLV model explicitly models the effects of latent variables on the choice process. Figure 5 illustrates the integrated framework of the ICLV model.

*4.1. Structural Equation Model.* For an individual $n$, the latent variable structural equation model is given in the following form:

$$Z_n^* = AR_n + \varepsilon_n, \tag{1}$$

where $Z_n^*$ is a $L * 1$ matrix of latent variables, $R_n$ is a $M * 1$ matrix of socioeconomic and travel-related variables, $A$ is a $L * M$ matrix of parameters to be estimated, and $\varepsilon_n$ is a random error term with normal distribution. The structural equation model reflects the relationship between the latent variables and respondents' socioeconomic characteristics.

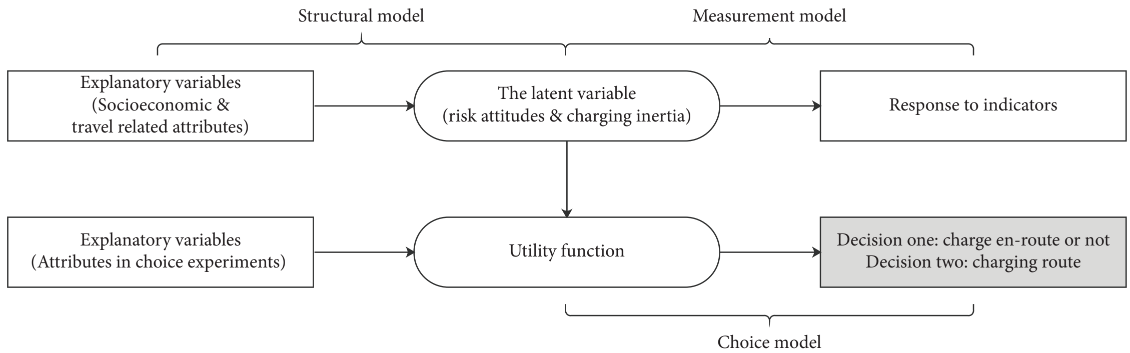


FIGURE 5: The framework of the ICLV model.

*4.2. Measurement Equation Model.* Latent variables are difficult to observe directly, but they can be obtained through measurement indicators. The type of measurement equations depends on the nature of the measurement itself. In our research, the latent variables are mainly attitudinal. Statements are designed and respondents' attitudes are asked with a choice of a Likert scale with five levels. The measurement indicator of the latent variable can be represented as a discrete variable and the measurement equation can be formulated as the ordered probit model as shown in the following equations:

$$I'_{i,n} = \beta_{i,0} + DZ^*_{i,n} + \eta_{i,n}, \eta_{i,n} \sim \left(0, \sigma^{i,n}\right), \tag{2}$$

$$I_{i,n} = \begin{cases} J_{i,1} & \text{if } I'_{i,n} < \tau_{i,1}, \\ J_{i,2} & \text{if } \tau_{i,1} \le I'_{i,n} < \tau_{i,2}, \\ J_{i,3} & \text{if } \tau_{i,2} \le I'_{i,n} < \tau_{i,3}, \\ J_{i,4} & \text{if } \tau_{i,3} \le I'_{i,n} < \tau_{i,4}, \\ J_{i,5} & \text{if } \tau_{i,4} \le I'_{i,n}, \end{cases} \tag{3}$$

where $I'_{i,n}$ is an assumed continuous variable about the attitudinal statement, $\beta_{i,0}$ is an intercept to be estimated, $\eta_{i,n}$ is a random error term following a normal distribution with mean 0 and variance $\sigma^{i,n}$, $D$ is a vector of parameters to be estimated, $I_{i,n}$ is the answer to the attitudinal question $i$ for individual $n$, $J_{i,k}$ is the measurement of attitudinal question $i$, $\tau_{i,k}$ is the assumed threshold, and $k$ is taken from 1 to 5 due to the 5-level Likert scale.

The probability of a given response $J_{i,k}$ for an individual $n$ is

$$\begin{aligned} P_{i,n}\left(I_{i,n} = J_{i,k}\right) &= P\left(\tau_{i,k-1} \le I'_{i,n} \le \tau_{i,k}\right) = F_{\eta_n}\left(\tau_{i,k}\right) - F_{\eta_n}\left(\tau_{i,k-1}\right) \\ &= \Phi\left(\frac{\tau_{i,k} - \beta_{i,0} - DZ^*_{i,n}}{\sigma^{i,n}} - \frac{\tau_{i,k-1} - \beta_{i,0} - DZ^*_{i,n}}{\sigma^{i,n}}\right), \end{aligned} \tag{4}$$

where $\Phi(\bullet)$ is the cumulative distribution function of the standardized normal distribution. The measurement function captures the relationship between the latent variables and the statement indicators.

*4.3. Choice Model.* The utility function of the choice model can be formulated as follows:

$$U_n = BX_n + CZ^*_n + \delta_n, \tag{5}$$

where $U_n$ represents the total utility of each choice, $X_n$ are the explanatory variables, $Z^*_n$ are the latent variables, $\delta_n$ is the random error term, and both $B$ and $C$ are parameters to be estimated.

In decision one, in one of the ICLV models, the probability of individual $n$ choosing not to charge en route can be formulated as

$$P_n^{\text{notcharge}} = \frac{e^{U_n^{\text{notcharge}}}}{\left(e^{U_n^{\text{notcharge}}} + e^{U_n^{\text{charge}}}\right)}, \tag{6}$$

where $U_n^{\text{notcharge}}$ is the utility of not charging en route, for individual $n$, as formulated in equation (5). $U_n^{\text{charge}}$ is the utility of charging en route, which is set to zero as a reference as given in detail in Section 5.2 with equations (8)–(10).

In decision two, the probability of individual $n$ choosing route $i$ is

$$P_n^{\text{route}i} = \frac{e^{U_n^{\text{route}i}}}{\left(e^{U_n^{\text{route}i}} + e^{U_n^{\text{route}j}}\right)}, \tag{7}$$

where $U_n^{\text{route}i}$ and $U_n^{\text{route}j}$ are the utilities of individual $n$ choosing route $i$ or $j$ for en route charging, involving the explanatory variables and the latent variables.

In recent years, the advantages of the ICLV model are increasingly acknowledged [49]. Vij and Walker [23] undertook a systematic comparison between the ICLV model and a reduced form choice model. They found that the ICLV model under certain conditions lead to an improvement than the reduced form choice model. In addition, they synthesized a general process of evaluation and defined criteria to assess the application of an ICLV framework. In this study, we will follow the criteria. In addition, a multinomial logit (MNL) model without latent attitudes is developed as a benchmark for comparison, aiming to evidence the benefits of ICLV models.

## 5. Model Estimation Results

*5.1. Structural and Measurement Model Estimations.* With the use of Biogeme, the relationship between the latent variables and explanatory variables can be derived. The upper part of Table 3 presents the results of the structural models of the two latent variables, and the lower part presents the estimation results of the measurement models. Figure 6 illustrates the relationship between the significant explanatory variables and the latent variables, as well as the relationship between the latent variables and the measurement indicators.

The parameters of structural equations correspond to the parameter matrix $A$ in (1) and the parameters of measurement equations correspond to the parameters $\beta_{i,0}$ and $D$ in (2). The first latent variable risk attitude seems to be strongly related to age, battery range, charging frequency, education, and income. It is observed that respondents older than 30 years exhibit a risk-averse attitude compared to younger people. This result is in line with other findings, which found that attitudes towards risk can be affected by age. For example, Tsirimpa et al. [50] found that travelers aged 35–55 are less prone to risk than younger travelers when they investigated the effect of the travelers' risk aversion on travel pattern-switching behavior. Our results also show that users with lower incomes and lower education levels show a greater risk-seeking attitude than higher-income and higher-educated users. This observation aligns with the existing research, which suggests that the risk-averse attitude normally increases with income and generally well-educated people earn more [51]. It is also noticed that users with large battery range vehicles are risk-seeking as they think they have sufficient energy and are less worried about the shortage of batteries.

The second latent variable charging inertia is substantially related to age, battery range, charging frequency, driving experience, DVKT, and education. It is found that age, battery range, and education level all exhibit a negative effect on charging inertia. Users with a young age, lower battery range, and lower education level are more prone to having charging inertia. Charging frequency, driving experience, and DVKT are found to have a positive effect on charging inertia, illustrating that BEV users with higher charging frequency, more driving experience of BEVs, and longer average DVKT would have a stronger charging inertia. The findings are in line with the results from other research, showing that the elderly dislike charging while rich-experienced drivers prefer to charge [13].

As for the measurement model, it links the latent variables to the attitudinal statements. It should be noted here that existing literature has suggested that not all the parameters in the measurement model can be estimated [52]. Therefore, the unit of the latent variable needs to be set initially. In this study, the coefficients of the risk attitudes statement R1 and the charging inertia C1 are set as a reference by normalizing the intercept to 0 and the factor loading to 1. As shown in Table 3, except the intercepts of R2 and R3, all other coefficients are significant at a 1% significance level and exhibit the expected signs. The factor loadings of all the statements for both latent variables are positive, indicating that risk-aversion users and users having charging inertia are more likely to agree with the statements.

*5.2. Discrete Choice Models.* For the en route charging choices, we developed three models. The utility of charging en route is set to zero to be used as a reference. The utility of not charging en route is defined as a function of alternative attributes with parameters to estimate. First, a MNL model (M1), including the choice scenario variables and socioeconomic and travel-related variables, was estimated as a benchmark. Second, an ICLV model (M2) incorporating the latent variables is examined. Socioeconomic and travel-related variables are incorporated in the MNL choice model, while the ICLV choice model does not include these variables directly as they have already been included in the latent variables indirectly. To examine whether risk attitude and charging inertia have impacts on the valuation of AR uncertainty, an ICLV model with interactions (M3) between the two latent variables and AR uncertainty is examined as well. The models have been developed and estimated using Python Biogeme [32]. Table 4 presents the results of the MNL and the ICLV model estimations.

Table 3: Structural and measurement equation results.

| Structural equation | Value | $T$-test |
|---|---|---|
| *Latent variable 1: risk attitudes* | | |
| Constant | 0.769*** | 5.5 |
| Age (more than 30 years old = 1, otherwise = 0) | 0.117* | 1.65 |
| Battery range (more than 300 km = 1, otherwise = 0) | −0.128* | −1.74 |
| Charging frequency (often charge or above = 1, otherwise = 0) | 1.09*** | 10.2 |
| Driving experience (more than 18 months = 1, otherwise = 0) | 0.0646 | 0.924 |
| Driving frequency (everyday = 1, otherwise = 0) | −0.000869 | −0.0109 |
| DVKT (more than 50 km = 1, otherwise = 0) | 0.0438 | 0.653 |
| Education (master or above = 1, otherwise = 0) | 0.165** | 2.01 |
| Gender (female = 1, otherwise = 0) | 0.0184 | 0.271 |
| Income (more than 10,000 RMB, otherwise = 0) | 0.41*** | 3.79 |
| *Latent variable 2: charging inertia* | | |
| Constant | 0.304*** | 3.48 |
| Age (more than 30 years old = 1, otherwise = 0) | −0.178*** | −3.93 |
| Battery range (more than 300 km = 1, otherwise = 0) | −0.365*** | −7.53 |
| Charging frequency (usually charge = 1, otherwise = 0) | 0.394*** | 4.97 |
| Driving experience (more than 18 months = 1, otherwise = 0) | 0.108** | 2.52 |
| Driving frequency (everyday = 1, otherwise = 0) | −0.00529 | −0.108 |
| DVKT (more than 50 km = 1, otherwise = 0) | 0.109*** | 2.6 |
| Education (master or above = 1, otherwise = 0) | −0.178*** | −3.47 |
| Gender (female = 1, otherwise = 0) | 0.0203 | 0.489 |
| Income (more than 10,000 RMB, otherwise = 0) | −0.109 | −1.63 |
| **Measurement equation** | **Intercept ($\beta_{i,0}$)** | **Factor loading ($D$)** |
| *Latent variable 1: risk attitudes* | | |
| (R1) I will not drive an EV for a long trip when the distance exceeds the total battery range | 0 (fixed) | 1 (fixed) |
| (R2) If the remaining battery is lower than expected, I will look for chargers instead of changing travel strategy to save energy | −0.00862 (−0.151) | 0.352*** (6.41) |
| (R3) I don't like to make risky decisions, even though the decision may bring greater benefits | 0.0869* (1.77) | 0.452*** (7.96) |
| *Latent variable 2: charging inertia* | | |
| (C1) I will charge as soon as I return home | 0 (fixed) | 1 (fixed) |
| (C2) I will charge when I approach a commonly used charging station | −0.411*** (−11.7) | 0.61*** (14) |
| (C3) I will charge when daily trip is over | −0.177*** (−3.25) | 1.64*** (14.1) |

***Significance at 1% level; **significance at 5% level; *significance at 10% level. The intercept and factor loading of R1 and C1 are preset in advance. Risk attitudes (+), risk averse; risk attitudes (−), risk seeking.

$$M1\begin{cases} U(\text{charge}) = 0, \\ U(\text{not charge}) = \text{cons} + \beta_{\text{in}}D_{\text{in}} + \beta_{\text{avg}}D_{\text{avg}} + \beta_{\text{un}}D_{\text{un}} + \varepsilon, \end{cases} \tag{8}$$

$$M2\begin{cases} U(\text{charge}) = 0, \\ U(\text{not charge}) = \text{cons} + \beta_{\text{in}}D_{\text{in}} + \beta_{\text{avg}}D_{\text{avg}} + \beta_{\text{un}}D_{\text{un}} + \beta_{\text{risk}}D_{\text{risk}} + \beta_{\text{inertia}}D_{\text{inertia}} + \varepsilon, \end{cases} \tag{9}$$

$$M3\begin{cases} U(\text{charge}) = 0, \\ U(\text{not charge}) = \text{cons} + \beta_{\text{in}}D_{\text{in}} + \beta_{\text{avg}}D_{\text{avg}} \\ + \left(\beta_{\text{un}} + \beta_{\text{risk-un}}D_{\text{risk}} + \beta_{\text{inertia-un}}D_{\text{inertia}}\right)D_{\text{un}} + \varepsilon, \end{cases} \tag{10}$$

where $\varepsilon$ is the error term, cons represents alternative specific constants in each model, $D_{\text{in}}$ represents the initial AR at the departure point, $D_{\text{avg}}$ and $D_{\text{un}}$ denote the average AR and uncertainty in AR at the destination, $D_{\text{risk}}$ is the latent variable of risk attitudes, $D_{\text{inertia}}$ is the latent variable of charging inertia, and $\beta_{\text{in}}$, $\beta_{\text{avg}}$, $\beta_{\text{un}}$, $\beta_{\text{risk}}$, and $\beta_{\text{inertia}}$ are the parameters to be estimated for $D_{\text{in}}$, $D_{\text{avg}}$, $D_{\text{un}}$, $D_{\text{risk}}$, and $D_{\text{inertia}}$, respectively.

Overall, all the estimated parameters have the expected signs. In general, the average AR at the destination and the initial AR exhibit a positive effect, while the uncertainty in AR at the destination has a negative effect. It indicates that a higher initial AR and an average AR at the destination correspond to a greater likelihood of choosing not to charge en route. Conversely, a higher uncertainty in AR at the destination is associated with a higher probability of

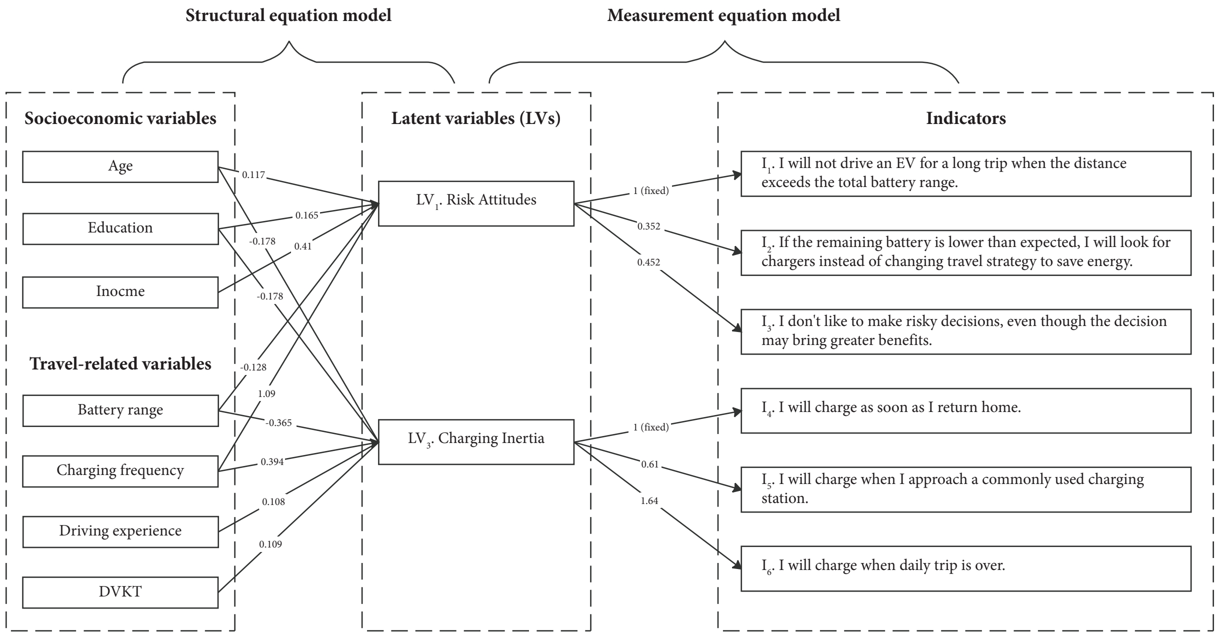


Figure 6: Structural and measurement equation results.

Table 4: Estimated results for the en route charging choice model (decision 1).

| Variables | ICLV (M2) | | ICLV with interactions (M3) | | MNL (M1) | |
|---|---|---|---|---|---|---|
| | Coefficient | $t$-test | Coefficient | $t$-test | Coefficient | $t$-test |
| *Choice model* | | | | | | |
| ASC, not charge | $-3.41^{***}$ | −8.88 | $-3.29^{***}$ | −8.62 | $-2.83^{***}$ | −6.36 |
| Average AR at destination (in kilometres) | $0.217^{***}$ | 18.9 | $0.22^{***}$ | 18.8 | $0.219^{***}$ | 19.1 |
| Initial AR at origin (in kilometres) | $0.0169^{**}$ | 2.34 | $0.0187^{**}$ | 2.55 | $0.0169^{**}$ | 2.35 |
| AR uncertainty at destination (in kilometres) | $-0.0484^{***}$ | −7.78 | $-0.0673^{***}$ | −8.25 | $-0.0487^{***}$ | −7.83 |
| Risk attitudes | $-0.286^{***}$ | −2.95 | | | | |
| Charging inertia | $-0.168^{*}$ | −1.8 | | | | |
| Risk attitudes $*$ uncertainty in AR | | | $-0.0218^{***}$ | −3.64 | | |
| Charging inertia $*$ uncertainty in AR | | | $-0.0129^{**}$ | −2.4 | | |
| Age (more than 30 years old = 1, otherwise = 0) | | | | | — | — |
| Battery range (more than 300 km = 1, otherwise = 0) | | | | | — | — |
| Charging frequency (usually charge = 1, otherwise = 0) | | | | | $-0.936^{***}$ | −4.53 |
| Driving experience (more than 18 months = 1, otherwise = 0) | | | | | — | — |
| Driving frequency (everyday = 1, otherwise = 0) | | | | | — | — |
| DVKT (more than 50 km = 1, otherwise = 0) | | | | | — | — |
| Education (master or above = 1, otherwise = 0) | | | | | — | — |
| Gender (female = 1, otherwise = 0) | | | | | — | — |
| Income (more than 10,000 RMB, otherwise = 0) | | | | | — | — |
| *Model fitness* | | | | | | |
| #Parameters | 42 | | 42 | | 14 | |
| Final log-likelihood | −590.8914 | | −580.7882 | | −751.0192 | |
| Adjusted rho-square | 0.419 | | 0.419 | | 0.389 | |
| No. of observations | 1808 | | 1808 | | 1808 | |

$^{***}$Significance at 1% level; $^{**}$significance at 5% level; $^{*}$significance at 10% level. DVKT, daily vehicle kilometres traveled; —, the corresponding variable is not significant.

charging en route. This may be attributed to the fact that a higher initial AR and an average AR at the destination would alleviate users' range anxiety, thereby reducing the likelihood of en route charging.

As for the latent variables, it is observed that both latent variables significantly affect the en route charging choices. Risk attitude has a negative effect on not charging en route, which is logical that risk-averse users are more likely to charge en route to reduce the risk of running out of battery. Based on the SEM estimation results as discussed in Section 5.1, the elderly, the users with a higher income, a higher education level, and a lower battery range are more risk averse and are more prone to charging en route. Likewise, charging inertia also has a negative influence on not charging en route, which is also logical since users who have a charging inertia are more inclined to choose to charge en route. Again, based on the SEM estimation results, users with a lower battery range and more driving experience have stronger charging inertia and are more prone to charging en route. With charging inertia, it is noticed that younger users and users with a lower education level have a stronger charging inertia and are more prone to charge en route. Although the effects of age and education level on the intention to charge en route are offset to a certain degree, their overall effects could be obtained by analyzing their marginal effects as discussed in Section 6. The significance of the latent variables evidences heterogeneity in attitudes which directly influences users' en route charging choices. The heterogeneity is closely related to variables such as age, education, driving experience, and battery ranges, and should not be neglected when forecasting BEV charging demand.

If the latent variables are not considered, the en route charging choice will be simply determined by the observable attributes including initial AR, average AR, and AR uncertainty at the destination, leading to biased outcomes. Capturing users' psychological attributes such as risk attitude and charging inertia in this study helps better explain BEV users' en route charging choice behavior.

Furthermore, it can be seen from Table 4 that with MNL estimation, only charging frequency is significant and has a negative impact on not charging en route, while with ICLV models age, income, education level, battery range, driving experience, and charging frequency are all significant. It can be evidenced that the ICLV model outperforms the MNL model, especially in uncovering the heterogeneity affected by socioeconomic and BEV-related attributes.

For ICLV with interactions, it can be seen that the cross-term between risk attitude and AR uncertainty is significantly negative at a 95% confidence level, implying that risk-averse users value AR uncertainty more. With the SEM results, we can further infer that people with older age, higher education levels, higher income, frequent public charging, and lower battery range value AR uncertainty more as they are more risk averse. In addition, the interaction between charging inertia and AR uncertainty is also negative, which means that users having a stronger charging inertia value AR uncertainty more. Users having stronger charging inertia dislike uncertainty in available ranges and are more prone to charging when there is a charging opportunity to guarantee sufficient AR. Two ICLV models exhibit higher adjusted rho-square values than the MNL model, indicating improved model fitness with the inclusion of latent variables.

After making the en route charging choices, a BEV user was asked to decide which charging route to take. We developed three models to investigate the charging route choice behavior: (1) a MNL model (M4) directly including scenario factors such as charging duration and travel time; (2) a nested-logit model (M5) with the upper level of en route charging choices and lower level of charging route choices; and (3) an ICLV model (M6) including the interactions among the latent variables and AR uncertainty. Considering that the route alternatives are unlabeled, adding socioeconomic variables such as age, income, education level, and latent variables directly into the utility function will make no sense, only if interactions are considered with these variables. Therefore, we simply consider a MNL model without socioeconomic variables and an ICLV model considering the interaction terms. Table 5 illustrates the estimation results of the three models.

$$M4\begin{cases} U(\text{route } i) = \beta_{\text{avg}} D_{\text{avg}_i} + \beta_{\text{un}} D_{\text{un}_i} + \beta_{\text{cd}} T_{\text{cd}_i} + \beta_{\text{tt}} \text{TT}_i + \varepsilon_i, \\ U(\text{route } j) = \beta_{\text{avg}} D_{\text{avg}_j} + \beta_{\text{un}} D_{\text{un}_j} + \beta_{\text{cd}} T_{\text{cd}_j} + \beta_{\text{tt}} \text{TT}_j + \varepsilon_j, \end{cases} \tag{11}$$

$$M5\begin{cases} U(\text{not charge}) = \text{cons} + \beta_{\text{in}} \text{D}_{\text{in}} + \beta_{\text{avg}} \text{D}_{\text{avg}} + \beta_{\text{un}} \text{D}_{\text{un}} + \varepsilon, \\ U(\text{route } i|\text{charge}) = \beta_{\text{avg}} D_{\text{avg}_i} + \beta_{\text{un}} D_{\text{un}_i} + \beta_{\text{cd}} T_{\text{cd}_i} + \beta_{\text{tt}} TT_i + \varepsilon_i, \\ U(\text{route } | \text{ charge}) = \beta_{\text{avg}} D_{\text{avg}_j} + \beta_{\text{un}} D_{\text{un}_j} + \beta_{\text{cd}} T_{\text{cd}_j} + \beta_{\text{tt}} TT_j + \varepsilon_j, \end{cases} \tag{12}$$

$$M6\begin{cases} U(\text{not charge}) = \text{cons} + \beta_{\text{in}} D_{\text{in}} + \beta_{\text{avg}} D_{\text{avg}} + \beta_{\text{un}} D_{\text{un}} + \varepsilon, \\ U(\text{route } i|\text{charge}) = \beta_{\text{avg}} D_{\text{avg}_i} + \beta_{\text{cd}} T_{\text{cd}_i} + \beta_{\text{tt}} \text{TT}_i \\ + (\beta_{\text{un}} + \beta_{\text{risk-un}} D_{\text{risk}} + \beta_{\text{inertia-un}} D_{\text{inertia}}) D_{\text{un}_i} + \varepsilon_i, \\ U(\text{route } j|\text{charge}) = \beta_{\text{avg}} D_{\text{avg}_j} + \beta_{\text{cd}} T_{\text{cd}_j} + \beta_{\text{tt}} \text{TT}_j \\ + (\beta_{\text{un}} + \beta_{\text{risk-un}} D_{\text{risk}} + \beta_{\text{inertia-un}} D_{\text{inertia}}) \text{D}_{\text{un}_j} + \varepsilon_j, \end{cases} \tag{13}$$

where $\varepsilon_j$ denotes the error term for charging route $j$. $D_{\text{un}_j}, D_{\text{avg}_j}, T_{\text{cd}_j}$, and $\text{TT}_j$ represent AR uncertainty at CS, average AR at CS, charging duration, and travel time, respectively, for charging route $j$. $\beta_{\text{avg}}$, $\beta_{\text{un}}$, $\beta_{\text{cd}}$, $\beta_{\text{tt}}$, $\beta_{\text{risk}}$, and $\beta_{\text{inertia}}$ are the parameters to be estimated for $D_{\text{avg}}$, $D_{\text{un}}$, $T_{\text{cd}}$, TT, $D_{\text{risk}}$, and $D_{\text{inertia}}$, respectively.

Table 5: Estimated results for the charging route choice model (decision 2).

| Parameters | ICLV with interactions (M6) | | NL (M5) | | MNL (M4) | |
|---|---|---|---|---|---|---|
| | Estimate | $t$-test | Estimate | $t$-test | Estimate | $t$-test |
| Average AR at CS (in kilometres) | 0.0304*** | 3.33 | 0.00195 | 0.443 | 0.0296*** | 3.26 |
| Charging duration (in minutes) | −0.0398*** | −5.49 | −0.0021 | −0.436 | −0.0396*** | −5.48 |
| Travel time (in minutes) | −0.0734*** | −11.5 | −0.00513 | −0.435 | −0.0729*** | −11.4 |
| AR uncertainty at CS (in kilometres) | −0.0127*** | −2.92 | −0.000625 | −0.447 | −0.00683** | −2.13 |
| Risk attitudes ∗ AR uncertainty at CS | −0.0064* | −1.91 | | | | |
| Charging inertia ∗ AR uncertainty at CS | −0.0035 | −0.98 | | | | |
| *Model fitness* | | | | | | |
| #Parameters | 42 | | 9 | | 4 | |
| Final log-likelihood | −1142.725 | | −1375.113 | | −1151.049 | |
| Adjusted rho-square | 0.396 | | 0.302 | | 0.0773 | |
| No. of observations | 1808 | | 1808 | | 1808 | |

***Significance at 1% level; **significance at 5% level; *significance at 10% level.

On the whole, all the estimated coefficients show the expected signs and most of them appear statistically significant at a 5% level except for the NL model, as seen in Table 5. About the model fitness, it is noticed that the ICLV model and the NL model have a higher adjusted rho-square than the MNL model. However, since all the variables in the NL model are insignificant, we can infer that a nest effect does not exist and the charging route choice behavior could be modeled directly by using the MNL model. The ICLV model outperforms all other models in explaining route choice behavior. The results of both the ICLV and MNL models show that the average AR at CS, uncertainty in AR at CS, charging duration, and route travel time are all decisive attributes influencing charging route choices. Users prefer higher average AR and lower uncertainty, as they are afraid of not being able to reach the charging station with sufficient power. Charging duration and travel time all have negative effects as users dislike long travel time and charging duration. Regarding the latent variable, the interaction between risk attitude and AR uncertainty is statistically significant, while the charging inertia interaction term is insignificant. The negative interaction term coefficient for risk attitude and AR uncertainty implies that risk-averse users value AR uncertainty more and prefer the route with a charging station where AR uncertainty is lower. Based on the SEM results, users with a higher income, a higher education level, a lower battery range, and the elderly value AR uncertainty more and are more prone to choosing the route with a charging station at which AR uncertainty is lower. In terms of the insignificance of charging inertia, it is reasonable that both routes have charging opportunities and charging inertia does not play a role in the charging route choices.

## 6. Further Analyses and Discussions

From Tables 4 and 5, we can find the associations between these latent variables and various sociodemographic and travel-related factors. Moreover, certain variables such as age and income influence both latent variables. Therefore, exploring the overall effects of each variable on the likelihood of choosing en route charging became of interest. Inspired by previous research [53], Figure 7 selects the variables that have at least a 90% significance level in the model. Then the average marginal effect of each variable is calculated to illustrate their overall effects on the probability (percentage change) of choosing en route charging. These marginal effects were calculated based on the ICLV model (M3) as it has a better goodness-of-fit in modeling en route charging. We referred to Anderson and Newell [54] and Aguirregabiria and Carro [55] to get the calculation functions of the average marginal effect, and the calculations were conducted using Biogeme [32].

According to the results in Figure 7, it is observed that battery range, charging frequency, and income are the main influencing factors. The increase in BEV battery range will reduce users' intention to charge en route by 2.35%, from which it can be inferred that it will become less and less necessary for private BEVs to charge en route in urban travels with the promotion of high-range BEVs. Moreover, having a higher income increases the probability of the intention to charge en route by 2.75%, as they are more risk averse. Charging en route could reduce the likelihood of battery depletion. Regarding the charging frequency, users who often charge in public chargers have a higher probability of the intention to charge en route by 8.53%. This also verifies that having charging inertia can contribute to the utilization rate of public chargers in the country. As for other variables such as education, DVKT, and driving experience, the probabilities of en route charging changes are less than 1%. While this percentage may appear modest, it is still a substantial increase given the large population in Shanghai. The marginal effects of age seem to be very low, it can be explained by that age has opposite effects on the two latent variables and the en route charging intention and overall its effects are offset. Although as aforementioned, education level also has opposite effects on the two latent variables and the en route charging intention, its overall effect on the en route charging intention is positive and nonneglectable.

In terms of the goodness of ICLV models, it should be noted that an ICLV model does not necessarily lead to a significant improvement in the goodness-of-fit [23, 24]. The result of en route charging modeling in this study also verifies this point, as it is seen that the ICLV model only has

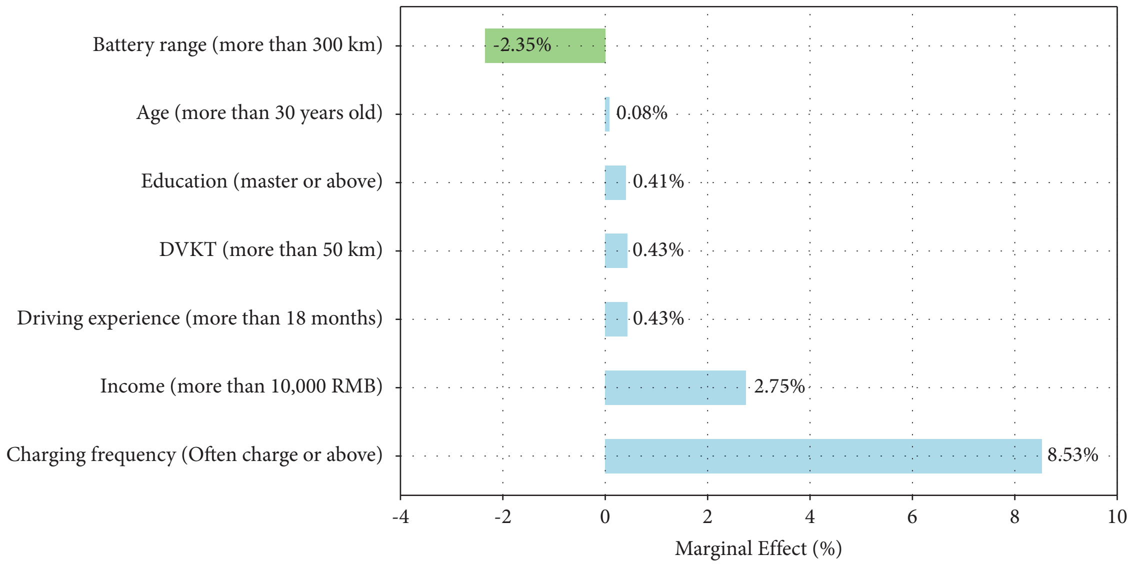


Figure 7: Marginal effects of variables on the probability of intention to charge en route.

a trivial improvement in the adjusted rho-square compared to the MNL model. We should refer to the proposed criteria to evaluate the ICLV model [23]. One criterion involves assessing whether the ICLV model could provide deeper insights into the decision-making process by breaking down the influence of explanatory variables into various parts, thereby aiding policymaking. This is what we have found in this study that the ICLV models could explain the charging choice behavior better and explore the heterogeneity in a more comprehensive manner. Identifying the constituent effects of the socioeconomic and travel-related attributes through the latent variables can provide valuable insights to policymakers.

Some policy insights from the ICLV analyses are discussed herein. First, BEV users' risk attitudes and charging inertia, strongly related to socioeconomic and travel-related variables, are of crucial importance to be considered in the charging demand estimations for public charging stations. It implies that the heterogeneity caused by age, income, education level, battery range, and driving experience cannot be ignored when estimating the charging demand. Precise charging demand estimation is fundamental for better planning of public charging stations. Second, fast chargers should be installed at public CS to reduce the charging duration and advertisements and campaigns could be launched to encourage users to charge en route and use public chargers. If users have more frequent charging activities at public chargers, they might get used to charging en route and will have a stronger charging inertia, which has a strong positive influence on charging en route and will contribute to increasing the utilization of public CS. Third, with the structural equation results, it also becomes clearer that advertisements and campaigns could target special segments of the population. For instance, the campaigns could target at the risk-seeking users, i.e., those who are young, poorly educated, and poor in China. Finally, emergency chargers especially on the main roads with heavy traffic in urban areas should be allocated. As congestion often occurs on these roads, the energy consumption of BEVs fluctuates greatly leading to higher uncertainty in the AR. Emergency chargers would help release the range anxiety.

It should be mentioned that for daily inner-city trips and with the increasing vehicle battery range, in most time the battery is sufficient and en route charging is not really necessary. Public CSs in urban areas should be deployed especially considering the charging demand of BEV taxi drivers and buses with long daily travel distances. This study is particularly important for estimating en route charging demand for medium to long-distance trips, and therefore important for public CSs deployment along highways.

## 7. Conclusions

This study in particular explores users' risk attitudes and charging inertia and their impacts on en route charging and charging route choice behavior. We developed ICLV models to examine the two latent variables in relation to socioeconomic and travel-related characteristics. The MNL models incorporating socioeconomic and travel-related attributes were also estimated as a benchmark model. The main findings and conclusions are summarized as follows:

(a) In addition to observable variables such as AR-related attributes and travel time, risk attitude and charging inertia are crucial and significant factors influencing BEV users' en route charging choice behavior.

(b) A risk-averse attitude and charging inertia both have a positive effect on users' intention to charge en route.

(c) Users with old age, short battery range, high charging frequency, higher education level, and high income tend to exhibit a more risk-averse attitude.

(d) Users with young age, short battery range, high charging frequency, more driving experience, lower education level, and long DVKT are more inclined to have charging inertia.

(e) Users having a risk-averse attitude value AR uncertainty more in both en route charging and charging route choices.
(f) Users having charging inertia value AR uncertainty more when making en route charging choices.
(g) Risk-averse attitude has a negative effect on choosing the route with higher AR uncertainty, and charging inertia does not play a role in choosing the charging route.
(h) Age and education level exhibit opposite effects on en route charging choices. Older users and users with higher education levels are more risk-averse and more prone to charge en route. While younger users and users with lower education levels have stronger charging inertia and are more prone to charge en route. An overall effect can be derived from the marginal effect analyses.
(i) Battery range, charging frequency, and income are the most crucial factors influencing users' intention to charge en route.
(j) Capturing users' psychological attributes such as risk attitude and charging inertia in this study helps explain BEV users' en route charging choice behavior better.
(k) The ICLV model outperforms other logit models in exploring the heterogeneity affected by socioeconomic and BEV-related attributes and provides deeper insights into the heterogeneity of BEV users.

From all the findings, it is evident that there is a significant heterogeneity in BEV users' en route charging choice behavior. The heterogeneity, influenced directly or indirectly by the socioeconomic attributes and travel-related attributes, is of crucial importance and should be considered in improving public CS utilization rates. The utility function proposed in this paper can be used for traffic assignment with a mixture of BEVs and fuel vehicles, to estimate the route flows and charging flows at public CS. Furthermore, considering the heterogeneity across BEV users, advertisements and campaigns could be launched to encourage users to charge en route and use public chargers. Special segments of the population could be targeted, for instance young, poorly educated, and poor users in China.

In future work, varied charging cost rates and their impacts on the en route charging and charging route choice behavior could be investigated as an extension to facilitate the optimization of charging pricing strategy at public CS.

## Data Availability

The data used to support this study are available from the corresponding author upon request. The data are not publicly available due to privacy.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Authors' Contributions

Zhicheng Jin and Hao Li contributed equally to this work. Zhicheng Jin and Hao Li conceptualized this study and proposed the methodology. Zhicheng Jin was responsible for the software and prepared the original draft. Hao Li validated the study. Chen Di and Yu Lu curated the data. Huizhao Tu reviewed and supervised the study. All authors have read and agreed to the published version of the manuscript.

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