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Computer Modeling Analysis of Electric Vehicle's Choice Behavior Considering Latent Variables

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Abstract: - At present, there are few researches on the influence of psychological latent variables on the choice behavior of electric vehicles, and lack of consideration of individual heterogeneity. In this study, computer modeling was used to construct not only a traditional discrete choice model that takes into account individual heterogeneity, but also a hybrid choice model,which takes into account psychological latent variables are constructed to explore the mutual effects of observable personal attributes, vehicle attributes and difficult to directly observe psychological latent variables on consumers' choice behavior of electric vehicles. The estimation results of hybrid choice model with psychological latent variables and the traditional discrete choice model without considering psychological latent variables are compared. The result show that perceived usefulness, perceived risk and purchasing attitude have a significant impact on consumers' choice behavior of electric vehicles. Compared with traditional discrete choice model, the hybrid choice model, which takes into account psychological latent variables has significantly higher prediction accuracy and has better interpretation ability and fitting effect. The research results can provide theoretical support for further expanding the electric vehicle market and formulating relevant policieshe usage of the word Power quality in recent times acquired intensified interest due to the complex industrial processes. The usage of intelligent tools to improve power quality is increasing day by day, as assumption of present day power system as a linear model is unsatisfactory. This paper deals with analysis of Differential Evolution (DE), Hybrid Differential Evolution (HDE) and Variable Scaling Hybrid Differential Evolution for harmonic reduction in the source current with optimal tuning of PI controller gain values. Shunt Active power Filter is one of the better solution to suppress the source current harmonics which are induced into power system because of nonlinear loads. Current controller called HBCC is considered for gating operation of switches in Voltage Source Inverter. The Intelligent tuned PQ theory is used for reference current generation. The then obtained compensating currents are injected at point of common coupling for current disturbance mitigation. Simulations of MATLAB/SIMULINK environment of the present work shows the efficacy.

Keywords: Electric Vehicle's Choice Behavior, Psychological Latent Variables, Random Parameters Logit, Hybrid Choice Model

I. INTRODUCTION

Currently, global warming is a serious problem faced by countries worldwide as a result of excessive greenhouse gas emissions and energy shortages [1]. Without timely intervention, greenhouse gas emissions from transportation, currently comprising 14% of the total global emissions, are poised to surge to a staggering 50% by 2030, reducing these emissions is a proven solution. In this context, the development of electric vehicles is increasingly emphasized due to their notable benefits in enhancing energy efficiency and mitigating greenhouse gas emissions. In recent years, the sales of electric vehicles have steadily increased, with electric vehicles accounting for an 18% market share in 2023 [2]. However, some consumers are concerned about issues such as high prices and inconvenient charging related to electric vehicles, leading to lower acceptance, and the current market share of electric vehicles falls significantly short of expectations. Hence, it holds immense practical significance to enhance the market share of electric vehicles by delving into the underlying mechanisms of consumers' choices regarding electric vehicles and proposing constructive policies and recommendations.

In the research model of electric vehicle choice behavior, scholars commonly employ the multinomial logit model and the nested logit model for modeling and analysis. These models are favored for their simplicity, low operational complexity, and ease of comprehension and implementation [3,4]. Nevertheless, these models have inherent limitations, notably their inability to account for individual heterogeneity and varying preferences among individuals, which means the outcomes of studies employing the multinomial logit model and the nested logit model may not fully explain the complexities of real-world [5]. Hence, certain scholars have turned to the random

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coefficient Logit model for their research, discovering that, in comparison to the multinomial Logit model, the random coefficient Logit model can more effectively elucidate the consumer decision-making process [6].

The random coefficient Logit model can be formally seen as an integral form of the multinomial Logit model. In this model, the error term allows for the existence of correlations between options, and it can follow various distributions, such as uniform or normal distributions. As a result, the random coefficient Logit model addresses the problem of Independent of Irrelevant Alternative (IIA effect) observed in the multinomial Logit and nested Logit models. This improvement in model estimation enhances its explanatory capacity, while also better capturing the variations in decision-making mechanisms among different groups of individuals. Nonetheless, the random coefficient Logit model typically treats the individual decision-making process as an unobservable "black box" where inputs include personal attributes and program attributes, and outputs consist of individual choices. The underlying process and mechanisms of decision-making remain unobservable, and psychological factors and other unobservable variables are often considered as random errors during estimation within the random coefficient Logit model and disregarding their influence on the model. Consequently, the random coefficient Logit model falls short in firmly capturing the intrinsic process and psychological aspects of individual behavioral decision-making, making it challenging to delve deeply into these mechanisms.

Recognizing these limitations, Ben-Akiva introduced the concept of the hybrid choice model in 2002 [7]. This model integrates unobservable latent variables which means variables that cannot be observed directly, but can be inferred through observable variables with the random coefficient Logit model, creating a hybrid choice model that takes both observable and latent variables into account at its core. By considering the joint impact of these variables on an individual's decision-making, the hybrid choice model offers a deeper comprehension of the underlying psychological factors that shape decision-making processes. This approach enhances the explanatory capacity of research outcomes. In recent research, some scholars have sought to enhance the Logit model by integrating it with the Latent Class Model (LCM) [8,9], while a few researchers have adopted the hybrid choice model to investigate consumers' choices regarding electric vehicles. From a research perspective, most scholars have traditionally examined the influence of consumers' electric vehicle choice behavior based on directly observable personal attributes, such as gender, age, education level, or social influence, as well as vehicle attributes like range, vehicle price, purchase tax, and the environmental friendliness of electric vehicles compared to traditional ones[10]. However, these studies have tended to overlook the impact of underlying psychological factors on consumers' choices of electric vehicles. As research deepens, increasing evidence suggests that these underlying psychological factors often exert a crucial influence on the consumer's decision-making process. Attitudes and emotional perceptions are among the primary perspectives considered in current research [11]. Furthermore, few studies have simultaneously examined the combined impact of both psychological latent variables and observable variables [12]. This omission has hindered in-depth exploration of consumers' decision-making processes when purchasing electric vehicles, leaving room for enhancement in the precision and credibility of research outcomes. From the descriptions provided above, it becomes apparent that the majority of current studies on electric vehicle choices primarily focus on consumers' personal attributes or vehicle characteristics. Moreover, most of these studies rely on multinomial logit models as their research methodology, which tends to overlook individual heterogeneity and variations in preferences. Consequently, the results obtained fail to comprehensively reflect the real complexity of the electric vehicle selection process. In addition to this, although some scholars have now introduced machine learning methods into the field of behavioral choice and concluded that machine learning methods seem to be superior to traditional behavioral choice models in some aspects. But machine learning focuses more on pre-cursing and does not emphasize the interpretability of the results. There are also some scholars who believe that the advantages that machine learning methods have are mainly due to the fact that they ignore heterogeneity that is difficult to observe directly[13]. Choosing an electric vehicle is a multifaceted decision influenced by a multitude of factors, highlighting the necessity for a more holistic approach in understanding this selection process.

Therefore, this study not only establishes a conventional discrete choice model takes into account individual variations but also introduces psychological latent variables into the traditional discrete choice model. It constructs a hybrid choice model that takes into account these psychological latent variables to examines consumers' decisions regarding electric vehicle choices. This model analyzes the combined effects of observable factors like personal attributes, vehicle characteristics, and the less observable psychological latent variables, offering a more comprehensive insight into the inherent psychological processes in consumers' decision-making. The research findings reveal that the hybrid choice model surpasses the traditional discrete choice model in both predictive accuracy and model interpretability.

II. RESEARCH MODEL

A. Discrete Choice Model

Discrete choice models have become widely used in the field of transportation and travel [14]. These models are grounded in the fundamental principle of choice behavior, rooted in the random utility theory. The central assumption of this theory states that individuals consistently opt for the alternative that offers the highest utility among a set of choices.

The multinomial logit (ML) model represents the most fundamental and frequently used form of the discrete choice model. Its probability expression is illustrated in Equation 1, where "n" represents the individual, "i" signifies the ith available choice option, and "J" indicates the total number of alternatives accessible to the individual. Owing to its simplicity and straightforward applicability, scholars have extensively employed the ML model for investigating individual electric vehicle (EV) choice behavior [15,16].

$$P_{in} = e^{V_{in}} \Big/ \sum_{i=1}^{J} e^{V_{in}} \tag{1}$$

Nonetheless, the ML model is constrained by its form as it does not incorporate individual heterogeneity or account for variations in preferences among different individuals. Consequently, it may struggle to provide more plausible explanations for specific scenarios, and the outcomes of research using this model may still deviate somewhat from real-world situations.

To present a more realistic portrayal of the consumer decision-making process involved in purchasing electric vehicles, this study employs the random coefficient Logit model to investigate consumers' choices in electric vehicle selection. The random coefficient Logit model is formally an integral of the multinomial Logit model, and its specific expression is depicted in Equation 2. Within the formula, "n" represents the individual, "i" denotes the alternative, and "β_n" represents the random coefficient. The random coefficient Logit model takes into consideration variations in preferences during individual decision-making processes and acknowledges the heterogeneity among different individuals. The estimation results derived from this model exhibit enhanced explanatory capacity and practical significance.

$$P_{ni} = \int \frac{\exp(\beta_n X_{ni})}{\sum_j \exp(\beta_n X_{ni})} f(\beta_n / \theta) d\beta \tag{2}$$

B. Hybrid Choice Model

Traditional discrete choice models often characterize the individual's behavioral decision-making process as an opaque and unobservable "black box." They tend to regard attitudes and other psychological factors as random errors, which are not adequately integrated into the model. As a consequence, there remains a noticeable disparity between research findings and real-world circumstances.

Hence, this study incorporates psychological latent variables into the conventional discrete choice model and establishes a hybrid choice model that accounts for these psychological latent variables. This approach enables a more comprehensive exploration of consumer’s electric vehicle choice behavior. The Hybrid Choice Model (HCM) was first introduced in 2002, comprising two key components: the traditional discrete choice model and the latent variable model. The fundamental framework of the HCM is illustrated in Figure 1.

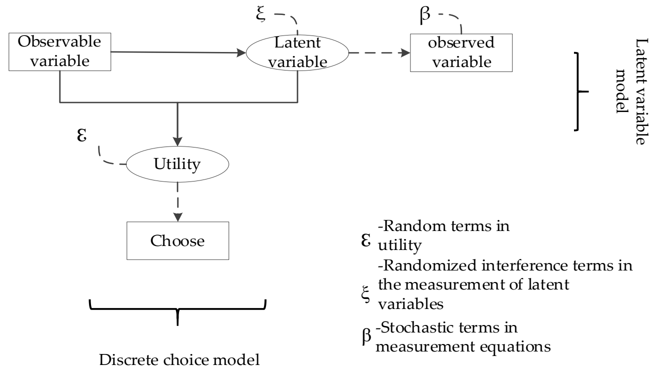

Figure 1: Hybrid Choice Model.

In contrast to traditional discrete choice models, the Hybrid Choice Model (HCM) directly incorporates psychological latent variables into the discrete choice model. This integration accounts for the inherent impact of psychological latent variables on behavioral decisions, which are challenging to observe directly. Research has indicated that introducing psychological latent variables into the model can enhance the model's accuracy to some extent [17].

In the HCM, the utility obtained by an individual choosing the plan "j" is shown in Equation 3.

$$U_j = \alpha_j S + \beta_j Z_j + \gamma_j \eta + \varepsilon_j \tag{3}$$

In this context, "S" represents a vector of personal attributes, encompassing variables that describe an individual's own characteristics, such as gender and age. "Z" denotes a vector of scheme attributes, comprising variables that characterize vehicle attributes like vehicle price and range. "ŋ" signifies the psychological latent variable, which is not directly observable. The term "ε" represents the error term in the model's estimation process.

In this study, we introduce psychological latent variables, which are hard to observe directly, into a random coefficient logit model. We utilize the integrated Hybrid Choice Model (HCM) to perform a comprehensive analysis of consumers' choices regarding electric vehicles. This approach not only considers the inherent impact of these unobservable psychological latent variables on electric vehicle choice behavior but also accounts for the variations among different individuals, thus enhancing the depth and breadth of our analysis.

III. Survey Data Statistics

A. Questionnaire Design and Survey

The questionnaire used in this study comprised three primary sections: scenario design, measurement of latent variables, and questions related to individuals' socio-economic attributes. Among these, scenario design constituted the central focus of the questionnaire. To investigate the influence of scenario attributes, such as vehicle price, 100km energy consumption, and government policies, on consumers' electric vehicle selection behavior, this study considered three alternative types of vehicles: fuel-efficient vehicles, pure electric vehicles, and hybrid vehicles. Using an orthogonal experimental design, a total of 12 scenarios were created. The next portion of the questionnaire involved the measurement of latent variables. Six latent variables were assessed using various observational variables. Each question was measured using a five-point Likert scale, with responses ranging from 1 (indicating "completely disagree") to 5 (indicating "completely agree"). The third section of the questionnaire collected data on the participants' personal socio-economic attributes, including gender, age, and income. This study was carried out in Urumqi, and a total of 1044 valid questionnaires were collected. Since each questionnaire included responses for three scenarios, the overall sample size amounted to 3132 data points.

B. Results of Partial Descriptive Statistical Analysis

The collected valid questionnaires were analyzed with preliminary descriptive statistics, and the specific results are shown in Figure 2.

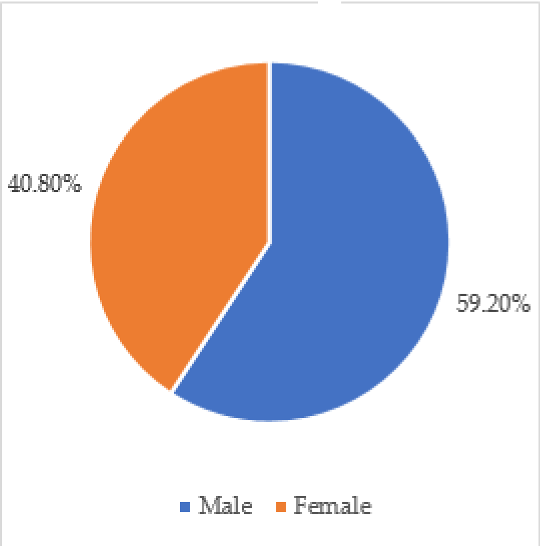

Figure 2 (a) Distribution of Gender

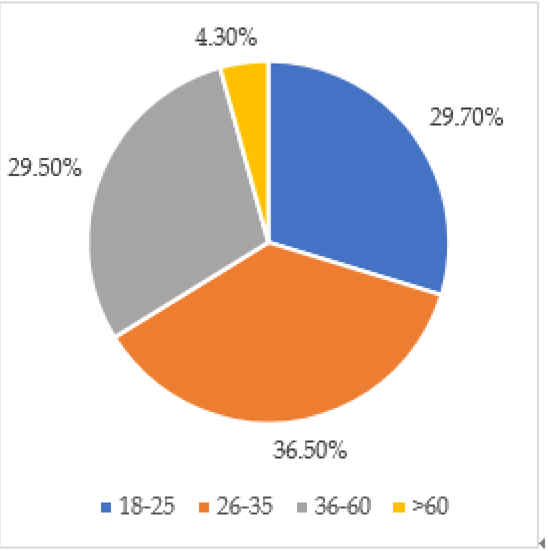

Figure 2 (b) Distribution of Age

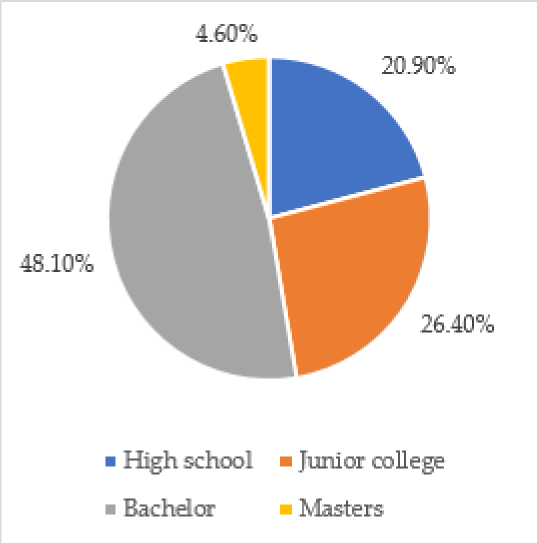

Figure 2 (c) Distribution of Education Level

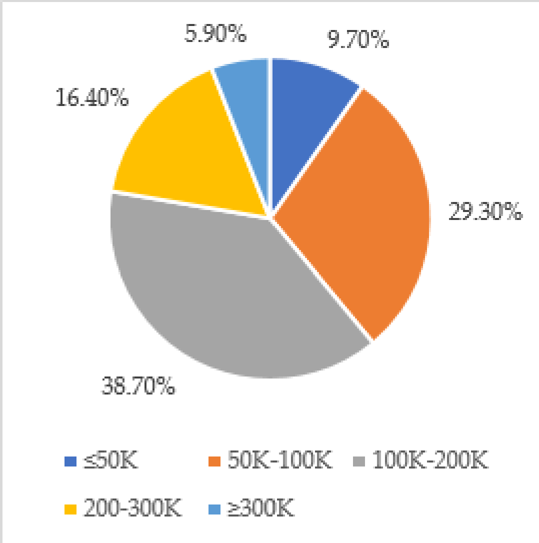

Figure 2 (d) Distribution of Annual Household Income

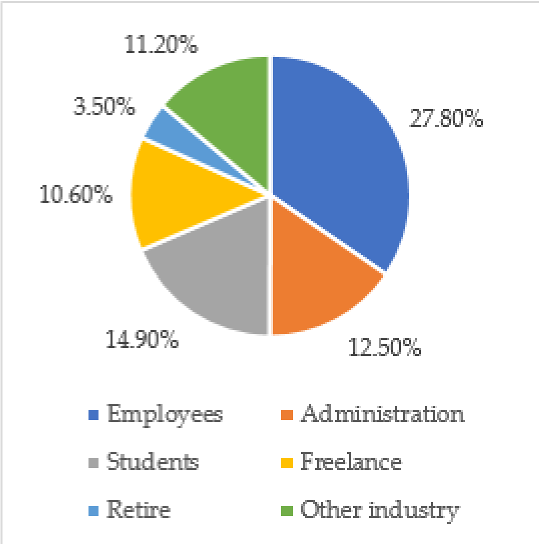

Figure 2 (e) Distribution of Occupation

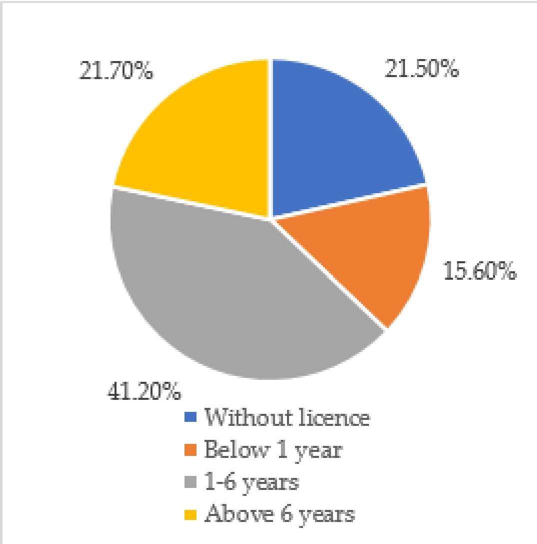

Figure 2 (f) Distribution of Driving Age

Figure 2: Statistical Description

The statistics provided above reveal that males constituted 59.2% of the total sample size, while females accounted for 40.8%. Moreover, as the proportion of males who had actually purchased a car exceeded that of females, the survey sample aligns with the distribution of the overall population. Furthermore, 52.7% of the total respondents possessed a bachelor's degree or above, indicating a generally higher level of education among the surveyed population. Additionally, 62.9% of the respondents had at least one year of driving experience, suggesting that the respondents had a high level of driving experience and knowledge of vehicle performance. Notably, 61% of the respondents reported an annual household income of 100k RMB or more, suggesting that the surveyed individuals had a certain economic foundation and could potentially become buyers of electric vehicles. Furthermore, the survey encompassed a diverse range of occupations. Consequently, the sample obtained from this survey can be considered representative of the broader population.

IV. Analysis of Results Ease of Use

A. Results of Partial Descriptive Statistical Analysis

This study considers six latent variables: perceived usefulness (η_{PU}), perceived ease of use (η_{PEU}), perceived risk (η_{PR}), environmental awareness (η_{EA}), buying attitude (η_{ATT}) and willingness to buy (η_{BI}), and each of the latent variables and their corresponding specific measures are shown in Table 1.

Table 1: Meaning of Latent Variables.

Latent variables	Measurement indicators
η_{PU}	PU1 Electric cars can meet my mobility needs
	PU2 I think electric cars are a better experience than traditional fuel cars
	PU3 Policies such as unlimited electric cars can make it easier for me to get around
η_{PEU}	PEU1 Charging an electric car is easy
	PEU2 It's easy to perform repairs on an electric car
η_{PR}	PR1 Using an electric car doesn't meet my daily travel mileage needs
	PR2 The performance and quality of the electric car did not meet my expectations
	PR3 Using an electric car won't be recognized by my relatives and friends
η_{EA}	EA1 I'm very concerned about the environment and energy issues
	EA2 I think car exhaust is the cause of the haze
	EA3 I use public transportation because it's more environmentally friendly
η_{ATT}	ATT1 I think choosing electric cars are trend
	ATT2 I am interested in buying an electric car
	ATT3 I think we should promote electric cars
η_{BI}	BI1 I would consider buying an electric car in the future
	BI2 I would recommend to my relatives and friends to buy an electric car
	BI3 I am eagerly anticipating the arrival of new electric car brands and models to the market

The AMOS software was used to construct the latent variable model, and after several adjustments to the model structure, the specific latent variable model structure was obtained as shown in Figure 3.

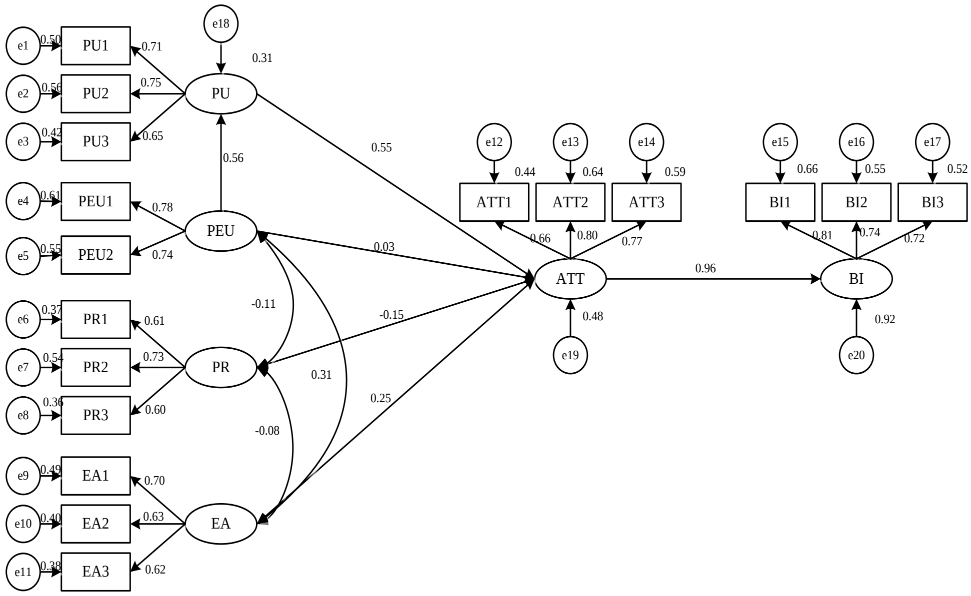

Figure 3: Latent Variable Model.

The primary metrics for evaluating the goodness of fit of the latent variable model encompass the chi-square ratio degrees of freedom (χ^2/df), RMR (Root Mean Square Residual), RMSEA (Root Mean Square Error of Approximation), GFI (Goodness of Fit Index), CFI (Comparative Fit Index), among others. These metrics are typically employed collectively to provide a comprehensive assessment of the model's adequacy. Table 2 displays both the actual and recommended values for each fitting index of the model. It is evident from the table that every fitting index of the model adheres to the recommended values. Consequently, the model can be regarded as well-fitted with a high degree of confidence.

Table 2: Model Fit Indicators.

Fit Indicators	χ^2/df	RMR	RMSEA	GFI	AGFI	CFI	IFI
Actual value	3.97	0.047	0.053	0.95	0.931	0.947	0.947
Suggested value	1-5	<0.05	<0.1	>0.9	>0.9	>0.9	>0.9

B. Analysis of HCM Results

Estimation methods for the Hybrid Choice Model (HCM) encompass both the continuous two-stage estimation method and the simultaneous estimation method. However, due to the greater operational complexity associated with the simultaneous estimation method, it is less commonly employed in practical applications. On the other hand, the continuous two-stage estimation method is more straightforward to implement and has gained recognition among many scholars [18]. Therefore, in this study, we have chosen to utilize the continuous two-stage estimation method to construct the HCM. This method involves calculating the fitness value of each latent variable based on the estimation results from the latent variable model. These fitness values are subsequently introduced as new explanatory variables to be estimated within the traditional discrete choice model. We then compare the HCM, which considers psychological latent variables, with the random coefficients logit model, which does not take such variables into account. After several iterations and model adjustments, this study retains specific variables that exert a significant influence on consumers' electric vehicle choice behavior. Table 3 showcases the comprehensive estimation results.

Table 3: Estimation Result of Model.

<table>
<tr><td colspan="2"></td><td colspan="2">Random coefficients logit without considering latent variables</td><td colspan="2">Hybrid choice models considering latent variables</td></tr>
<tr><td></td><td>choice</td><td>electric vehicle</td><td>hybrid car</td><td>electric vehicle</td><td>hybrid car</td></tr>
<tr><td rowspan="9">MEAN</td><td>Female</td><td>0.895***</td><td>0.652***</td><td>0.357</td><td>0.257*</td></tr>
<tr><td>Age 26-60</td><td>-0.984***</td><td>-0.427**</td><td>-0.785***</td><td>-0.304*</td></tr>
<tr><td>Bachelor and above</td><td>0.460*</td><td>0.128</td><td>0.084</td><td>-0.146</td></tr>
<tr><td>Years as a driver</td><td>-0.296***</td><td>-0.067</td><td>-0.319***</td><td>-0.105**</td></tr>
<tr><td>Annual household income</td><td>0.034</td><td>0.382***</td><td>-0.332</td><td>-0.102</td></tr>
<tr><td>employee</td><td>0.461</td><td>0.396**</td><td>0.329</td><td>0.297*</td></tr>
<tr><td>perceived usefulness</td><td colspan="2">-</td><td>0.527***</td><td>0.289***</td></tr>
<tr><td>Perceived risk</td><td colspan="2">-</td><td>-0.572***</td><td>-0.429***</td></tr>
<tr><td>buying attitude</td><td colspan="2">-</td><td>0.099</td><td>0.163***</td></tr>
<tr><td></td><td>Vehicle prices</td><td colspan="2">-0.013**</td><td colspan="2">-0.013**</td></tr>
<tr><td></td><td>100km energy consumption</td><td colspan="2">-0.119**</td><td colspan="2">-0.042</td></tr>
<tr><td></td><td>dedicated lane</td><td colspan="2">0.429***</td><td colspan="2">0.401***</td></tr>
<tr><td></td><td>Free parking</td><td colspan="2">0.569***</td><td colspan="2">0.565***</td></tr>
<tr><td rowspan="4">SD</td><td>Vehicle prices</td><td colspan="2">0.064***</td><td colspan="2">0.059***</td></tr>
<tr><td>100km energy consumption</td><td colspan="2">0.615***</td><td colspan="2">0.564***</td></tr>
<tr><td>dedicated lane</td><td colspan="2">0.314</td><td colspan="2">0.292</td></tr>
<tr><td>Free parking</td><td colspan="2">-1.170***</td><td colspan="2">-0.971***</td></tr>
<tr><td rowspan="2">Model indicators</td><td>AIC</td><td colspan="2">6072.759</td><td colspan="2">5917.797</td></tr>
<tr><td>BIC</td><td colspan="2">6215.720</td><td colspan="2">6103.646</td></tr>
</table>

In this table, ***indicates significant at 1% level, ** denotes significant at 5% level, * denotes significant at 10% level.

As depicted in Table 3, gender, age, driving experience, occupation, vehicle price, dedicated lanes, and free parking exhibit significant effects on consumer electric vehicle choice behavior in both the random coefficients logit model and the Hybrid Choice Model (HCM). Notably, the estimated parameters for these explanatory variables share the same sign and exhibit consistent trends of influence across both models.

From the estimation results of the random coefficient logit model, it can be seen that females are more inclined to choose new energy models compared to males, which may be due to the fact that females believe that electric vehicles have a better experience than traditional fuel vehicles. Compared to other age groups, 26-35 year olds and 36-60 year olds are less inclined to choose new energy vehicles, probably because 26-35 year olds tend to choose lower-priced fuel vehicles, while 36-60 year olds have already had a long experience in driving fuel vehicles, and are therefore reluctant to buy new energy vehicle. Individuals with a higher level of education are more inclined to select electric vehicles, possibly because highly educated consumers believe that electric vehicles meet their mobility needs. Consumers with higher annual household income are more inclined to choose hybrid vehicles. Consumers with higher driving experience are less inclined to choose new energy vehicles, probably because consumers with higher driving experience think that the performance and quality of electric vehicles do not meet their expectation requirements. Compared with other occupations, corporate employees are more inclined to choose hybrid vehicles. From the coefficients of the program attributes, it can be seen that the higher the purchase price and 100-kilometer energy consumption, the lower the consumers' willingness to buy new energy vehicles, indicating that consumers are not willing to spend too much on the purchase and daily operation costs for the new energy vehicles; and the policy of giving new energy vehicles special lanes and free parking will significantly increase the consumers' willingness to buy new energy vehicles.

From the results of HCM, it is evident that certain psychological latent variables exert a notable influence on consumers' choice behavior when it comes to electric vehicles. Perceived usefulness and purchase attitude have a significant positive effect on consumer choice behavior, indicating that when consumers believe that new energy models can meet their own travel needs, the more inclined they are to choose new energy models. Perceived risk has a substantial adverse impact on consumers' decision-making process, i.e., when consumers perceive that there is a risk that the use of a new energy model will not satisfy their travel needs or fail to meet their expectations, the lower the likelihood of choosing a new energy model. There is a significant positive effect of purchase attitude on hybrid vehicle choice behavior, indicating that when consumers have positive and positive evaluations of hybrid vehicles, the higher the willingness to choose this type of vehicle. As can be seen from the standard deviation of the study results, there is significant variability across the population with respect to vehicle price, 100-kilometer energy consumption, and free parking policies. The standard deviation of vehicle price is the smallest, indicating that individuals' perceptions of vehicle price tend to be consistent and the overall deviation is small; The standard deviation of 100-kilometer energy consumption is the largest, indicating significant deviation in individuals' perceptions; The standard deviation of free parking is moderate, indicating that individuals have more consistent perceptions of free parking and moderate overall bias. The estimation results also indicate that individuals have high demands on the 100-kilometer energy consumption of their vehicles, and that there are significant differences in preferences among different populations.

C. Comparison of Model Results

In this study, we gauge the model's fitting effectiveness using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Smaller values for these metrics indicate a superior model fit [19]. As indicated in Table 3, all the fitting indices for the hybrid choice model, which accounts for psychological latent variables, outperform those for the random coefficient logit model. Consequently, the hybrid choice model exhibits a superior fitting effect. This suggests that considering psychological latent variables can enhance the model's fitting accuracy, and the Hybrid Choice Model (HCM) provides a more accurate estimation compared to the traditional discrete choice model. To further evaluate the predictive capabilities of the models, we utilized the estimation results from both the random coefficients logit model and the HCM to predict choice probabilities. Subsequently, we compared these predictions with the actual survey results, as illustrated in Figure 4. The prediction probabilities from the random coefficients logit model, which does not incorporate latent variables, display discrepancies with the actual choice probabilities, with the maximum deviation approaching 10%. Conversely, the prediction probabilities derived from the HCM, which considers latent variables, closely align with the actual choice probabilities. The prediction accuracy of the HCM significantly surpasses that of the traditional discrete choice model. This highlights that the predictive power of the HCM, accounting for psychological latent variables, is notably superior to that of the traditional discrete choice model.

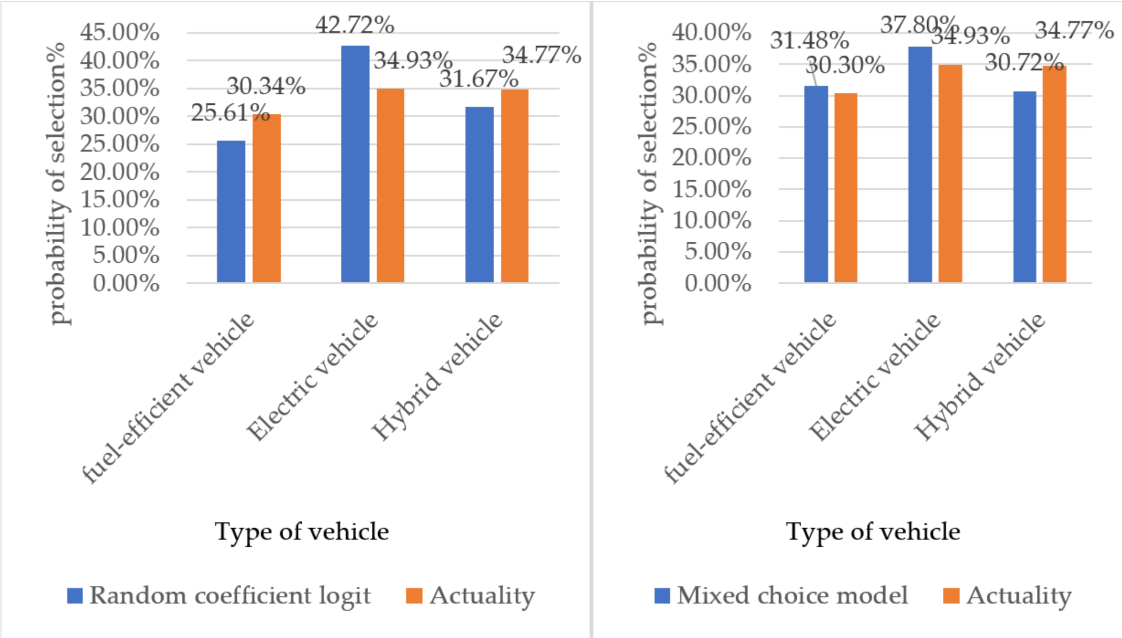

Figure 4: Comparison of Two Types of Prediction Model.

V. Conclusion and Outlook

In response to the lack of exploration of psychological latent variables in the current research on consumers' electric vehicle choice behavior, and the fact that most of the models in the research use multinomial logit models that ignore individual heterogeneity and lack the exploration of preference differences between different populations, this study conducts an in-depth research on consumers' electric vehicle choice behavior by using the HCM that takes into account psychological latent variables, which not only takes into account heterogeneity between consumers but also takes into account the psychological latent variables that affect consumers' electric vehicle choice behavior, and the results have a stronger explanatory capacity than the traditional discrete choice model; In terms of prediction accuracy, the HCM has higher predictive power than the random coefficients logit model and the prediction results are closer to the actual situation. Specifically, the following conclusions were drawn from this study:

1)Gender, age, education, driving age, annual household income, and occupation among socioeconomic attributes, as well as price, energy consumption, and government policies among vehicle attributes, all have a significant impact on consumers' EV choice behavior, and there are significant differences in preference for vehicle price, 100-km energy consumption, and free parking among individuals, reflecting heterogeneity among different individuals.

2)Consumers' intrinsic perceived usefulness, perceived risk, and purchase attitude significantly impacts consumers' choice behavior when it comes to electric vehicles, in which perceived usefulness and purchase attitude have a significant positive effect on consumers' electric vehicle choice behavior, while perceived risk has a significant negative effect on electric vehicle choice behavior.

3)Compared with the traditional discrete choice model, the hybrid choice model considering psychological latent variables has a better fit, is more consistent with the real situation, and has a stronger predictive ability, which can better reflect the real situation of individuals in the decision-making process of electric vehicle behavior.

In addition, given the advantages of machine learning in prediction, it is possible to improve the interpretability of behavioral choice predictions and expand research methods by improving algorithms in a way that incorporates heterogeneity that is not directly observable into machine learning.

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