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A Study of Electric Vehicle Purchase Intention Based on Latent Class Model

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Abstract

To deeply explore the mechanism of consumers' electric vehicle (EV) purchase behavior and address research gaps related to insufficient consideration of psychological latent variables and neglect of consumer heterogeneity in existing studies, this study constructs a latent class model (LCM) that integrates personal attributes, vehicle attributes, and six psychological latent variables: perceived usefulness, perceived ease of use, perceived risk, environmental awareness, purchase attitude, and purchase intention. Based on 1,044 valid questionnaires collected from Urumqi, latent profile analysis (LPA) is used to classify consumers. The results indicate that EV consumers can be divided into five distinct latent profiles with significant differences in purchase preferences: risk-avoidance type, moderate-low intention wait-and-see type, utility-oriented and low environmental concern type, high utility cognition and low risk proactive type, and all-dimensional high-intention core type. Socioeconomic and vehicle-related factors exert heterogeneous impacts on the psychological variables and purchase decisions of each profile. This study clarifies the intrinsic psychological mechanism of EV purchase behavior, providing a theoretical basis and targeted strategy references for the government and enterprises to promote EV adoption and advance sustainable transportation development.

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1. Introduction

Recently, with the increasingly serious problems of environmental pollution and energy shortage, needs for development and promotion of new energy products are also becoming extremely urgent. Electric vehicles, with the significant features of environmental protection and energy conservation, have become the development direction of the automotive industry in countries around the world. According to statistics from the Ministry of Public Security of the People's Republic of China, in 2023, 7.43 million new energy vehicles were registered, accounting for 30.25% of the total number of newly registered vehicles. Compared with 2022, this figure increased by 2.07 million, showing a growth of 38.76%. By 2024, the total number of new energy vehicles in China had reach 31.4 million, accounting for 8.90% of the total number of vehicles. Among them, the ownership of electric vehicles is 15.52 million, the proportion is 76.04% of the total number of new energy vehicles. It can be seen that with the continuous improvement of Chinese new energy vehicle technology and the intensive promotion of national policies, consumers' acceptance of electric vehicles will also be increasing day by day. However, according to the statistics from MPS, even by June of 2025, electric vehicles still have a low proportion of 7.11% in the total number of vehicles. Therefore, exploring the influencing factors of consumers' choice behavior of electric vehicles and formulating targeted and effective policies for promoting electric vehicles, which are of extremely important practical significance for implementing the country's new energy vehicle development strategy.

2. Literature Review

It is necessary to deeply explore consumers' behavior in choosing electric vehicles to introduce effective policies for promoting electric vehicles. At present, the common method for studying the characteristics of electric vehicle choice behavior is to construct discrete choice models to study the electric vehicle choice behavior of consumers. However, these models still have their shortcomings: First, insufficient consideration is given to variables that are difficult to observe directly, namely latent variables. Zhang et al. used 3 binary logistic models to determine the factors that contribute to consumers' acceptance of electric vehicles, their purchase time and their purchase price, the variables included socioeconomic attributes, consumers' acceptance of electric vehicles, and consumers' awareness of related development measures for electric vehicles[1]. Helveston conducted an investigation into consumers' behavior in choosing electric vehicles based on various vehicle attributes such as model, brand, price, fast-charging capacity, fuel price, and acceleration performance[2]. As the research progressed, some scholars began to explore that certain psychological factors that cannot be directly observed also influence consumers' choice behaviors[3,4]. Schmalfuß et al. and Zhang et al. utilized the theory of planned behavior model (TPB) to introduce non-direct factors of subjective norms in the choice behavior of electric vehicles, and found that subjective norms had a significant impact on the adoption of electric vehicles[5,6]. Song and Adu-Gyamfi respectively explored the influence of perceived usefulness and perceived ease of use on the behavior of choosing electric vehicles[8,9]; Second, the assumption of homogeneity of the model is not in line with reality, a lot of researches assumed that individual consumers are homogeneous entities with the same physiological, psychological states and even the same decision-making rules. However, in reality, significant differences are among individuals in terms of physiology, psychology and decision-making rules, indicating heterogeneity among individuals. Many choice models have also neglected that it exists among individuals[10,11]. With the development of choice models, more researchers treat the assumption of heterogeneity as an important research field[12-16]. Many models can disclose the heterogeneity of the research objects, such as Probit model, mixed logit model[17](ML) and latent class model (LCM) etc. The LCM divides the research samples into a limited number of latent classes, using the differences in parameters among the latent classes to represent the heterogeneity existing in the research samples. Compared with other models, the LCM has unique advantages: it not only can represent the heterogeneity at the group level， and has stronger explanatory power[18], but also does not require assumptions about the distribution of random parameters, thereby improving the computational efficiency of the model[19].

At first, scholars tended to emphasize the differences between factor analysis and latent structure analysis[20]. After that, researchers developed the LCM continuously on distinguishing the cases where there is prior evidence or theory which leads people to expect there to be latent categories, namely, whether the classes are existed in advance and how many there might be[21-23]. During recent decades, with the continuous improvement of model methodology and the rapid development of electric vehicles, LCM has been utilized to study the heterogeneity of consumers during the decision-making process when choosing to purchase or lease a vehicle, as well as the choice behaviors of different types of consumers[24-25]. However, in the research on the choice behavior of electric vehicles, few studies have considered the psychological latent variables of consumers for modeling, and fewer studies have explored the choice preferences of consumers with different psychological characteristics. Therefore, this study will be based on psychological latent variables, focus on considering the psychological heterogeneity of consumers, construct a latent class model, and explore the preference of consumers for electric vehicle choice behavior

3. Materials and Methods

This study employs a quantitative and descriptive-analytical research design, with attention paid to the heterogeneity of electric vehicle purchasers. Which investigates how personal attributes,

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vehicle attributes and psychological attributes affect purchasers' behaviour. In order to achieve the goal, an analysis tool is deployed, namely, latent class model. The design combines structured survey instruments to capture electric vehicle purchasers' heterogeneity during electric vehicle choice.

3.1. Introduction to Latent Class Model

Latent class model is an effective method for studying heterogeneity. Whose essence lies in the semi-parametric specification within the utility function, which assumes that decision-makers are divided into multiple latent classes. The parameters of the utility function vary among different classes, but are the same within same class. The latent class model can be expressed as:

$$P_n(i|\beta_1,\ldots,\beta_s)=\sum_{s=1}^{S}\pi_{ns}P_n\left(i|\beta_s\right) \tag{1}$$

Where

$$\sum_{s=1}^{S}\pi_{ns}=1 \ and \ 0\leq\pi_s\leq 1$$

In the model, each class has its own parameter vector β_s. The probability that decision-maker n chooses option i is equal to the probability that this decision-maker belongs to category s multiplied by the probability that option i is chosen in category s.

The class membership probability π_{ns} is a function of the explanatory variable Z_n, η_s is the parameter vector of a specific category, and δ_s is the constant term of a specific category:

$$\pi_{ns}=\frac{e^{\delta_s+f(\eta_s,z_n)}}{\sum_{l=1}^{s}e^{\delta_l+f(\eta_l,z_n)}} \tag{2}$$

In the model, choice behaviour is judged based on the utility function:

$$U(i)=V(i)+\varepsilon(i) \tag{3}$$

Where $V(i)$ represents the fixed utility of option i, and $\varepsilon(i)$ represents the random utility, which follows a certain probability distribution. When $U(i)$ is greater than that of any other option, option i is chosen. Therefore, the selection probability $P(i)$ of option i can be expressed as:

$$P(i)=[U(i)>U(j),\quad \forall j\neq i] \tag{4}$$

Substituting equation (4) into equation (3), which yields

$$\begin{aligned} P(i) &= [\varepsilon(j) < V(j) - V(i) + \varepsilon(i), \forall j \neq i] \\ &= \int_{\varepsilon(i)} F[\varepsilon(j) < V(j) - V(i) + \varepsilon(i), \forall j \neq i]\, f_i(x)\, dx \end{aligned} \tag{5}$$

Where $F(x)$ represents the probability distribution function, and $f_i(x)$ is the probability density function of the random variable $x=\varepsilon(i)$. First, assuming that $\varepsilon(i)$ is known, and obtain the probability distribution function value of $\varepsilon(j)$ corresponding to the scheme j. Then, when the probability of $\varepsilon(j)$ changes, multiply it by its probability density and perform integration.

Assuming that $\varepsilon(i)$ in the utility function are mutually independent, and follow the Gumbel distribution, let x be the probability variable representing $\varepsilon(i)$, and θ represent the parameters, the distribution function of the random term can be expressed as follows:

$$F_\varepsilon(x)=\exp\{-\theta\exp(-x)\},(\theta>0,-\infty<x<\infty) \tag{6}$$

Substituting (6) into (5), we can obtain the probability that decision-maker n selects option i:

$$P_n(i) = \frac{e^{V_n(i)}}{\sum_j e^{V_n(j)}} \tag{7}$$

3.2. Questionnaire Investigation

This study adopts the method of field investigation and the location is selected in Urumqi, with a focus on randomly sampling surveys in the major commercial districts with high passenger flow in the city. A total of 1,157 questionnaires are collected. After eliminating 113 incomplete or invalid questionnaires, a total of 1,044 valid questionnaires are obtained, and the effective recovery rate of the questionnaires is 90.23%.

The questionnaire is divided into three parts. The first part is the scenario selection, the second part is the psychological condition survey, and the third part is the personal socioeconomic attribute survey. In the scenario selection, apart from setting the traditional fuel vehicle as the reference item, this study also sets the hybrid vehicle for comparative analysis. In the study, 3 types of vehicles are provided, including traditional fuel vehicles, pure electric vehicles, and hybrid vehicles. The vehicle attributes include purchase price, energy consumption per 100 kilometers, range, charging/refueling time, and government policies. The psychological condition survey includes 6 latent variables: perceived usefulness, perceived ease of use, perceived risk, environmental awareness, purchase attitude, and purchase intention. These variables are measured using a Likert five-point scale. Personal socioeconomic attributes include gender, age, income level, education, family annual income, occupation, driving years, the number of family vehicles, and vehicle purchase price. The specific variables in the questionnaire are described in Table 1.

Table 1. Variables.

Influence Factors		Variable	Variable specification
Personal attributes	Sex	SEX	0: Male; 1: Female
	Age	AGE	1: 18-25; 2: 26-35; 3: 36-60; 4: over 60
	Education	KNOW	1: High school or below; 2: College; 3: Undergraduate; 4: Master or above
	Annual household income	INC (CNY)	1: Less than 50k; 2: 50k-100k; 3: 100k-200k; 4: 200k-300k; 5: More than 300k
	Occupation	PRO	1: Employee of enterprises; 2: Employee of public institutions; 3: Student; 4: Self-employed; 5: Free agent; 6: Retiree; 7: Other
	Driving experience	DRI	1: No license; 2: Less than 1 year; 3: 1-6 years; 4: More than 6 years
	Number of family vehicles	CAR	1: 0; 2: 1; 3: 2; 4: 3 or more
	Available fund for vehicle purchase	PRI (CNY)	1: 0 2: 50k-100k; 3: 100k-200k; 4: 200k-300k; 5: More than 300k
Vehicle attributes	Purchase price	PRICE	1: 150,000 Yuan; 2: 210,000 Yuan; 3: 225,000 Yuan
	Energy consumption per 100-kilometer,	CONSUM	1: 25 Yuan; 1: 65 Yuan; 2: 100 Yuan
	Cruising range	DIS	1: 200KM; 2: 380KM; 3: 500KM
	Charging time	TIME	1: 10min; 2: 20min; 3: 35min
	Government policy	GUI	0: No policy; 1: Free parking

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Psychological attributes	Perceived usefulness	PU	A five-point Likert scale was adopted, and each attribute was measured by multiple questions.
	Perceived ease of use	PEU	
	Perceived risk	PR	
	Environmental awareness	EA	
	Purchase attitude	ATT	
	Purchase intention	PI	

Descriptive statistical analysis was conducted on the collected valid samples, and the statistical results are shown in Table 2.

Table 2. Survey Sample Statistics.

Attribute	Levels	Proportion
Gender	Male	59.2%
	Female	40.8%
Age	18-25	29.5%
	26-35	36.5%
	36-60	29.7%
	Above 60	4.3%
Education	High school or below	20.9%
	College	26.4%
	Undergraduate	48.1%
	Master or above	4.6%
Annual Household income	Less than 50k	9.7%
	50k-100k	29.3%
	100k-200k	38.7%
	200k-300k	16.4%
	More than 300k	5.9%
Occupation	Employee of enterprises	27.8%
	Employee of public institutions	12.5%
	Student	14.9%
	Self-employed	19.5%
	Free agent	10.6%
	Retiree	3.5%
	Other	11.2%
Driving experience	No license	21.5%
	Less than 1 year	15.6%
	1-6 years	41.2%
	More than 6 years	21.7%
Number of family vehicles	0	17.0%
	1	63.3%
	2	17.2%
	3 or more	2.5%
Available fund for vehicle purchase	0	11.6%
	50k-100k	16.8%
	100k-200k	48.0%
	200k-300k	18.6%
	More than 300k	5.0%

The proportion of males and females in the sample is 59.2% and 40.8% respectively. Since the actual proportion of males purchasing vehicles is higher than that of females, the proportion of males

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is appropriately increased during sampling. The age group of 26-35 years old is the largest, followed by 35-60 years old, accounting for 66.2% in total. These two groups are the main vehicle purchasing population and have strong representative significance. The number of people with an annual household income of over 100,000 accounts for 61%. The number of people with a driving experience of 1-6 years is the largest, accounting for 41.2%. The number of people with one vehicle in the family accounts for 63.3%. The number of people who have purchased a vehicle with a price of 100,000-200,000 is the largest, accounting for 48.0%. Meanwhile, the occupations involved in the survey are relatively comprehensive, and the survey sample has certain representative significance.

4. Results

4.1. Analysis of Latent Variable Relationships and Survey Results

In order to clarify the structural relationship between latent variables and manifest variables, this study obtains the loading coefficients between latent variables and manifest variables through measurement equations, and the result is shown in Table 3. From Table.3, loading coefficients are all greater than 0.5, indicating that there is a high degree of causal relationship between latent variables and manifest variables. The consistency and stability of the questionnaire measurement results are tested through Cronbach's α value. When the Cronbach's α value is greater than 0.7, it indicates that the measurement results have a high internal consistency, suggesting that the questionnaire has a high level of reliability. An α value between 0.5 and 0.7 is considered acceptable[26].

The validity of the measurement results is analyzed using composite reliability (CR). A CR value greater than 0.6 indicates that the measurement results of the questionnaire are valid and the questionnaire has high reliability [27]. The results show that the Cronbach's α of each latent variable is greater than 0.6, and the CR values are all greater than 0.7, indicating that the reliability of the questionnaire is high.

Table 3. Test results of loading factors.

Latent variable	Manifest variable	Loading factors	CR	Cronbach's α
PU	PU2	0.706	0.747	0.741
	PU3	0.745		
	PU4	0.649		
PEU	PEU3	0.778	0.731	0.744
	PEU4	0.741		
PR	PR3	0.612	0.684	0.679
	PR5	0.734		
	PR6	0.600		
EA	EA3	0.702	0.689	0.683
	EA4	0.632		
	EA5	0.616		
ATT	ATT1	0.660	0.794	50.804
	ATT2	0.799		
	ATT3	0.770		
PI	PI1	0.812	0.801	0.813
	PI2	0.741		
	PI3	0.732		

4.2. Analysis of Model Results

4.2.1. Analysis of Latent Variable Classification Results

During the modeling process, when the variables in the latent class model are discrete(categorical) manifest variables and discrete latent variables, it is called latent class analysis

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(LCA). When the variables in the latent class model are discrete manifest variables and continuous latent variables, it is called latent trait analysis (LTA) . Besides, when the variables are continuous manifest variables and discrete latent variables, it is called latent profile analysis (LPA). In this study, the manifest variable data collected using the Likert five-point scale can be regarded as continuous variables. Therefore, this study adopts LPA to construct the latent class model. The main test indicators for LPA include Akaike information criterion (AIC), Bayesian information criterion (BIC), adjusted Bayesian information criterion (aBIC), entropy criterion (Entropy), and Lo-Mendell-Rubin test (LMR). Among these indicators, a smaller value indicates a better model fitting effect. When Entropy is greater than or equal to 0.8, it indicates that the classification accuracy exceeds 90%. A significant P-value of LMR(P<0.05) indicates that the fitting effect of the m profiles model is significantly better than that of the m-1 profiles model [23]. The fitting results of each model are shown in Table 4.

Table 4. Classification results of the latent profile model.

Number of Profiles	AIC	BIC	αBIC	Entropy	P-value	Profile Probability(%)
1	45479.9	45648.2	45540.2	—	—	100
2	42646.3	42903.8	42738.6	0.856	0	39.0/61.0
3	41667.7	42014.2	41791.9	0.866	0.001	60.7/21.2/18.1
4	41169.5	41605.1	41325.6	0.864	0.005	8.5/46.6/33.2/11.7
5	40995.5	41520.3	41183.7	0.871	0.032	8.5/31.9/46.1/8.2/5.3
6	40808.7	41422.6	41028.7	0.805	0.684	5.6/20.0/24.6/14.3/10.2 /25.3

As shown in Table 4, when variables are divided into 5 profiles, Entropy has the maximum value. When divided into 6 profiles, the P value of LMR is not significant, indicating that the model with 6 profiles is not superior to that with 5 profiles. Therefore, this study determines 5 profiles as the optimal ones. Figure 1 shows the scores of each profile on different manifest variables when divided into 5 profiles.

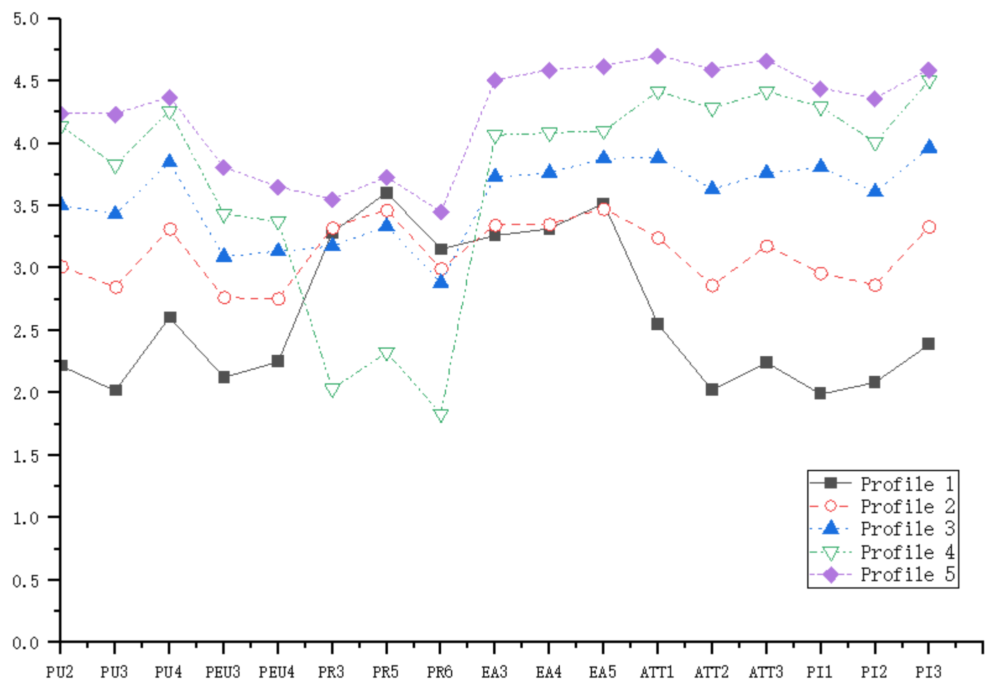

Figure 1. Observed variable scores of five latent classes.

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As shown in Figure 1, the points on the horizontal axis represent the manifest variables, and the vertical axis represents the score of this manifest variable. Based on the data comparison and analysis in Figure 1, it can be observed that individuals in profile 1 have intermediate levels of perceived risk and environmental awareness, but exhibit the lowest scores for perceived usefulness, perceived ease of use, purchase intention, and purchase attitude. We have named this group the 'risk-avoidance type', because they hold high perceived risk and hesitate to purchase due to concerns about practicality and convenience, showing a tendency of risk avoidance

The perceived ease of use, perceived usefulness, perceived risk and environmental awareness of the profile 2 are at medium level among the five profiles, and their purchase intention and purchase attitude are relatively weak. They have no obvious preference or rejection towards electric vehicles and show weak purchase intention, and this group is named after the moderate-low intention wait-and-see type.

As for people of profile 3, except for having a relatively weak environmental awareness, their scores in other latent variables are at an intermediate level, and they account for the largest proportion of the population. We term this group the utility-oriented and low environmental concern type.

People of profile 4 has the poorest perceived risk and the medium level of perceived ease of use, but they have stronger environmental awareness, purchase intention and purchase attitude. Besides, the perceived usefulness of this group is the highest. So this group are named the high utility cognition and low risk proactive type, because they highly recognize the practical value of electric vehicles and have minimal concerns about safety and convenience.

Last, people of profile 5 have the strongest perceived usefulness, purchase intention and purchase attitude, and they also have the strongest environmental awareness, perceived risk and perceived ease of use. They are named as all-dimensional high-intention core type, although their perceived risk is slightly higher, it is completely offset by strong environmental awareness and high recognition of practicality. They have extremely strong purchase intention and are the core potential users for electric vehicle promotion.

Based on the scores of the manifest variables and the loading coefficients, the magnitude of the psychological latent variables of each profile can be further calculated. Through the analysis of variance shown in Table 5, the mean and variance of the psychological latent variables of each profile can be obtained. By further comparing the differences in the psychological latent variables of people of different profiles, it can be seen from the analysis of variance table that the people of profile 1 have a higher perceived risk and lower environmental awareness. The people of profile 5 have the highest perceived ease of use, perceived risk, environmental awareness, purchase attitude and purchase intention. People of profile 4 have the strongest perceived usefulness, which is consistent with the analysis results in Figure 1. This further proves the existence of psychological heterogeneity among the population, and the significance results indicate that there are significant differences among the five groups of people in terms of latent variables such as perceived usefulness, perceived ease of use, perceived risk, environmental awareness, purchase attitude and purchase intention, indicating a good classification result.

Table 5. Table of variance analysis.

Variables	**Psychological types (mean ± variance)**					**Significance**
	Profile 1 n=89	Profile 2 n=333	Profile 3 n=481	Profile 4 n=86	Profile 5 n=55	
Perceived usefulness	2.4±0.7	3.1±0.5	3.6±0.5	4.2±0.7	4.2±0.6	***
Perceived ease of use	2.2±0.7	2.8±0.7	3.1±0.8	3.4±0.8	3.7±0.9	***
Perceived risk	3.4±0.8	3.3±0.6	3.1±0.6	2.1±0.5	3.7±0.5	***

Environmental awareness	3.4±0.8	3.4±0.6	3.8±0.6	4.3±0.6	4.5±0.5	***
Purchase attitude	2.3±0.5	3.2±0.4	3.8±0.3	4.6±0.4	4.6±0.4	***
Purchase intention	2.2±0.5	3.1±0.4	3.8±0.3	4.5±0.4	4.6±0.4	***

*: P<0.1; **: P<0.05; ***: P<0.01, the same significance notation is consistently used in all subsequent tables.

4.2.2. Influencing Factors for the Classification of Electric Vehicle Purchasers

Taking the profile 1 as a benchmark, this study explores the influencing factors of purchasers profile classification. The results are shown in Table 6.

Table 6. Influencing factors for the classification.

Influencing factor	Coefficient	Standard error	Influencing factor	Coefficient	Standard error
INTERCEPT2	1.029*	0.738	INTERCEPT4	-2.128**	1.085
GENDER2	0.585**	0.296	GENDER4	1.105***	0.358
AGE2	-0.184	0.192	AGE4	-0.003	0.246
KNOWLEDG2	0.376**	0.163	KNOWLEDG4	0.392*	0.213
INCOME2	0.103	0.157	INCOME4	-0.07	0.199
PRO12	0.768*	0.431	PRO14	-0.188**	0.082
PRO22	-0.249	0.479	PRO24	1.97***	0.726
PRO32	0.238	0.406	PRO34	1.239	0.768
PRO42	0.511	0.615	PRO44	0.991	0.74
PRO52	0.322	0.471	PRO54	2.124***	0.875
PRO62	-0.172	0.679	PRO64	1.201	0.797
DRIVE2	0.07	0.15	DRIVE4	-0.11	0.191
NUMBER2	-0.545**	0.222	NUMBER4	-0.723**	0.289
PRICE2	0.028	0.165	PRICE4	0.477***	0.203
INTERCEPT3	1.689**	0.711	INTERCEPT5	-0.996*	1.074
GENDER3	0.736***	0.287	GENDER5	1.122***	0.398
AGE3	-0.223	0.186	AGE5	-0.28	0.281
KNOWLEDGE3	0.327**	0.157	KNOWLEDG5	0.002	0.233
INCOME3	0.104	0.152	INCOME5	0.28	0.219
PRO13	0.623	0.415	PRO15	0.342	0.648
PRO23	-0.093	0.452	PRO25	0.294	0.681
PRO33	-0.011	0.389	PRO35	-0.262	0.649
PRO43	0.406	0.595	PRO45	1.061	0.824
PRO53	-0.154	0.459	PRO55	0.586	0.671
PRO63	-0.101	0.629	PRO65	0.48	0.966
DRIVE3	0.023	0.144	DRIVE5	0.255	0.215
NUMBER3	-0.385*	0.213	NUMBER5	-0.331	0.316
PRICE3	-0.048	0.16	PRICE5	-0.116	0.226

According to Table 6, compared to the purchasers of profile 1, purchasers of profile 2 are mainly male. As for profile 3, there are more males and have a higher level of education but fewer family vehicles. The purchasers of profile 4 are mainly male and have a higher level of education, they own fewer vehicles compared to profile 1, but the purchase price of their vehicles is higher. Compared to other professions, there are more public institution employees and self-employed individuals among people of profile 4, while there are fewer employees from enterprise units. Compared to the purchasers of profile 1, purchasers of profile 5 are mainly male.

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4.3. Analysis of Influencing Factors of Purchasers' Choice Behaviour

This part analyses the effects of each influencing factor on the perceived usefulness(PU), perceived ease of use(PEU), perceived risk(PR), environmental awareness(EA) and purchase intention(PI) of five profiles.

4.3.1. Comparative Analysis of Influencing Factors of Purchase Intention

From Table 7, it indicates that gender and occupation have less influence on the purchase intention of five profiles of purchasers. Age and driving experience only have significant influence on the PI of profile 1. Education background has significant effect on the PI of profile 1 and profile 5. As for annual household income and the number of family vehicles, they influence the PI of profile 2 and profile 3 significantly. And vehicle purchasing price only influences the PI of profile 4.

Table 7. Influencing factors of purchase intention.

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
GENDER	-0.419	-0.171	0.031	-0.300	0.898
AGE	0.268	-0.077	0.045	0.238	-1.115***
KNOWLEDGE	0.771***	0.016	-0.06	0.156	-1.306***
INCOME	-0.297	-0.299**	-0.236**	-0.322	-0.257
PROFESSION	0.125	-0.031	0.054	0.036	-0.139
DRIVE	0.117	0.145	0.06	0.111	1.053***
NUMBER	0.256	0.366*	-0.256*	0.098	-0.457
PRICE	0.329	-0.051	0.124	0.414*	0.533

4.3.2. Comparative Analysis of the Influencing Factors of Purchase Attitude

As can be seen from Table 8, neither the annual household income nor the driving experience has a significant influence on the purchase attitude of the five profiles. Occupation, the number of family vehicles, and the vehicle purchase price only have a significant influence on the PA of profile 1; education has a significant influence on the PA of profile 2, but not on the other profiles; gender only has a significant influence on the PA of the profile 3; and only age has a significant influence on the PA of profile 4.

Table 8. Analysis of the influencing factors of purchase attitude.

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
GENDER	-0.451	-0.259	-0.381**	-0.033	-0.890
AGE	-0.434	0.142	-0.014	0.485*	-0.297
KNOWLEDGE	-0.17	0.299**	-0.009	0.398	-0.413
INCOME	-0.007	-0.198	-0.031	-0.093	0.525
PROFESSION	-0.185*	0.035	0.002	-0.065	-0.105
DRIVE	0.188	-0.022	-0.016	-0.002	0.303
NUMBER	-0.900**	0.163	-0.120	-0.348	-0.655
PRICE	0.623**	-0.089	0.070	0.086	0.221

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

4.3.3. Comparative Analysis of the Influencing Factors of Perceived Risk

Table 9 indicates that driving experience has little significant influence on the perceived risk of five profiles. Gender and occupation only influence the PR of profile 2 significantly. Gender and the number of family vehicles influence the PR of profile 3. As for profile 4, their PR is influenced greatly by gender and the vehicle purchase price. The PR of profile 5 is only influenced by the annual household income.

Table 9. Analysis of PR influencing factors.

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
GENDER	1.017**	-0.098	-0.652***	0.996**	-0.772
AGE	-0.407	0.534***	0.142	0.038	-0.470
KNOWLEDGE	-0.55**	-0.022	-0.063	-0.460	-0.607
INCOME	0.483**	-0.160	0.144	-0.157	0.587*
PROFESSION	0.090	0.085*	-0.022	-0.197	-0.053
DRIVE	0.047	0.151	-0.058	0.156	-0.200
NUMBER	0.079	-0.009	0.317**	-0.031	0.367
PRICE	-0.021	0.092	-0.104	0.529**	-0.288

4.3.4. Comparative Analysis of the Influencing Factors of Environmental Awareness

It can be seen from Table 10 that gender, occupation, driving experience and the number of family vehicles do not influence the environmental awareness of profile 5 significantly. The annual household income only influences that of profile 4. Vehicle purchase price has a significant influence on the EA of profile 3. The EA of profile 2, profile 3 and profile 5 is influenced by age greatly.

Table 10. Analysis of EA influencing factors.

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
GENDER	0.529	0.020	0.175	0.565	0.260
AGE	0.091	0.314**	0.290***	0.271	0.632*
KNOWLEDGE	0.050	0.057	0.048	-0.039	0.723
INCOME	-0.371	-0.178	-0.091	-0.494*	-0.285
PROFESSION	0.143	0.010	-0.020	0.092	0.042
DRIVE	-0.125	-0.061	-0.078	0.320	-0.289
NUMBER	0.219	0.241	0.038	0.018	-0.092
PRICE	0.058	0.004	0.180*	-0.173	-0.061

4.3.5. Comparative Analysis of the Influencing Factors of Perceived Usefulness

From Table 11, age, education background, annual household income and vehicle purchase price don't have a significant influence on the perceived usefulness of five profiles. Gender and driving experience only influence the PU of profile 2. The number of family vehicles only has a significant influence on the PU of profile 3.

Table 11. Analysis of PU influencing factors.

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
GENDER	-0.043	0.369*	0.170	-0.048	-0.043
AGE	0.438	0.003	0.177	0.367	0.438
KNOWLEDGE	0.126	-0.097	-0.139	0.191	0.126
INCOME	-0.250	-0.086	0.055	-0.305	-0.250
PROFESSION	-0.029	0.043	-0.042	-0.014	-0.029
DRIVE	0.074	-0.225*	-0.092	0.001	0.074
NUMBER	0.354	-0.135	-0.349**	0.449	0.354
PRICE	-0.564	0.203	-0.045	0.170	-0.564

4.3.6. Comparative Analysis of the Influencing Factors of Perceived Ease of Use

From Table 12, it indicates that age education background, occupation and vehicle purchase price have no significant influence on the perceived ease of use of all profiles. Age and driving experience only influence the PE of profile 2. For profile 3, the purchasers are only influenced greatly by the number of family vehicles.

Table 12. Analysis of PEU influencing factors

	Profile 1	**Profile 2**	**Profile 3**	**Profile 4**	**Profile 5**
GENDER	-0.043	0.369*	0.170	-0.048	-0.043
AGE	0.438	0.003	0.177	0.367	0.438
KNOWLEDGE	0.126	-0.097	-0.139	0.191	0.126
INCOME	-0.250	-0.086	0.055	-0.305	-0.250
PROFESSION	-0.029	0.043	-0.042	-0.014	-0.029
DRIVE	0.074	-0.225*	-0.092	0.001	0.074
NUMBER	0.354	-0.135	-0.349**	0.449	0.354
PRICE	-0.564	0.203	-0.045	0.170	-0.564

5. Discussion

In the previous chapters, this study constructs a latent class model to fit the survey data and demonstrates the heterogeneity of purchasers in different profiles through LPA method. For purchasers of different profiles, this study recommends adopting differentiated sales strategies to enhance the purchase intention.

The core characteristics of profile 1 are high perceived risk, weak perceived usefulness and ease of use, strong concerns about the practicality and safety of vehicles, and their purchase attitude and perceived risk are significantly influenced by factors such as education background, annual household income, occupation, and vehicle purchase price. In response to their risk-averse nature, sales strategies should focus on alleviating the risk perception of the group and emphasizing the safety and practical aspects of electric vehicles.

Profile 2 represents a group with moderate-low purchase intention, characterized by average levels of psychological variables, no clear preferences or aversions, and weak purchase intention. Age, education background, gender, and driving experience significantly influence their environmental awareness and perceived usefulness. This group is classified as a convertible wait-and-see group. For this group, sales strategies should focus on awakening their needs, developing experiential scenarios, and offering purchasing discount.

The purchasers of profile 3 values utility and has weak environmental concerns, making up the highest proportion (46.1%). Their core characteristics include prioritizing vehicle practicality and having low environmental awareness. The number of family vehicles and the vehicle purchase price significantly influence their perceived usefulness and ease of use. This group is considered the core group for scale conversion, and sales strategies should emphasize the practical attributes and cost advantages of electric vehicles.

The characteristics of purchasers belong to profile 4 are the highest perceived usefulness, low perceived risk, and strong environmental awareness. The vehicle purchase price and gender significantly influence their purchase intention. This group is considered an easily convertible proactive group, and it is crucial to meet their quality and personalized needs.

Purchasers of profile 5 are the core potential user of electric vehicles, characterized by the strongest purchase intention and attitude, high environmental awareness, significant influence of age and education background on purchase intention, low sensitivity to price, and a need to focus on ensuring the purchase experience of this group of purchasers and continuously enhancing their brand recognition.

Future research can explore other psychological factors that may influence the purchase intention of electric vehicles based on this model, and supplement and integrate the existing model.

6. Conclusions

This study analyzes the purchasers' heterogeneity during electric vehicle choice based on latent class model, and effectively improved the prediction accuracy of the model. Based on the latent profile analysis, purchasers can be classified into 5 latent profiles, and each exhibiting a distinct characteristic of choice behavior. For instance, the first profile of purchasers have higher perceived risk and environmental awareness, the fifth profile of purchasers have the highest perceived ease of use, perceived risk, environmental awareness, purchase attitude and purchase intention, while the perceived usefulness of the forth profile of purchasers is the strongest. The research results reveals the intrinsic formation mechanism and psychological process in purchasers' decisions for electric vehicles, and reflects the influence of different socioeconomic attributes of each profile of purchasers on various psychological latent variables. The following conclusions are drawn:

(1) Age and driving experience have a significant influence only on the purchase intention of the fifth profile of purchasers, and education background has a significant influence on the purchase intention of both profile 1 and profile 5; annual household income and the number of family vehicles have a significant influence on profile 2 and profile 3; vehicle purchase price has a significant influence only on the purchase intention of profile 4.

(2) Occupation, number of family vehicles and vehicle purchase price only influence the purchase attitude of people belonging to profile 1; education background has significant influence on the purchase attitude of profile 2; gender only influences the purchase attitude of profile 3.

(3) Gender, education background and annual household income influence the perceived risk of the first profile of purchasers significantly; age and occupation only have a significant influence on the PR of profile 2; as for the purchasers of profile 3, age and the number of family vehicles have a significant influence on their PR; the PR of the profile 4 is influenced by gender and vehicle purchase price; annual household income only influences the PR of profile 5.

(4) Annual household income only influences the environmental awareness of the forth profile of purchasers significantly; vehicle purchase price has a significant influence on the EA of profile 3; the EA of profile 2, 3 and 5 is significantly influenced by age.

(5) Gender and age influence the perceived usefulness and perceived ease of use of the profile 2 significantly; the number of family vehicles has a significant influence on the perceived usefulness and perceived ease of use of profile 3.

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Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric vehicle
LCM	Latent class model
TPB	Theory of planned behavior model
ML	Mixed logit
PU	Perceived usefulness

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PEU	Perceived ease of use
PR	Perceived risk
EA	Environmental awareness
ATT	Purchase attitude
PI	Purchase intention
CR	Composite reliability
LTA	Latent trait analysis
LPA	Latent profile analysis
AIC	Akaike information criterion
BIC	Bayesian information criterion
aBIC	adjusted Bayesian information criterion
LMR	Lo-Mendell-Rubin test

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