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Purchasing intention of new energy vehicle consumers: A discrete choice analysis

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Abstract:

With the intensification of global environmental problems and the development of the automobile industry, new energy vehicles have gradually been praised by many governments in the world. With the promotion of the Chinese government in the upstream and downstream of the new energy vehicle industry, the sales volume of new energy vehicles in the Chinese market increased by 32% in the first half of 2024. Many previous studies were based on analyzing questionnaires from regional censuses, which deviated greatly from the actual purchase. To make up for the lack of this field, this paper constructs a linear regression model, a logit regression model, and a discrete choice model based on the sales data of new energy vehicles in the first half of 2024 and the parameters of nearly 80 popular models in the Chinese market (e.g., endurance, maximum speed, charging time). Research objectives: To explore the willingness of leading consumers to purchase new energy vehicles, to distinguish the popular new energy vehicle models in the Chinese market according to RMB 300,000 and power modes, and to analyze the consumer willingness in different situations in detail. In order to improve the stability of the data, the study merged 80 data points, removed outliers based on the standard squared difference of sales volume, and added brand information and the market share of each car as variables. After these adjustments, regression analysis was conducted again, and it was found that the positive correlation between the existing variables and sales volume reached 81.64%, and the adjusted R-squared value was also within the normal range of 53.8%, indicating that these factors can explain the changes in sales volume of 53.8%.

Keywords: component; formatting; Electric vehicle; Purchase intention;discrete choice model

1. Introduction

Since the invention of the car in the 19th century, engine technologies have continuously evolved, fueled by various energy sources. With the growing scarcity of natural resources, there has been a global shift toward finding cleaner energy alternatives to conventional gasoline[1]. As the 21st century unfolded, governments worldwide began implementing policies to foster the growth of new energy vehicles (NEVs), such as battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs), offering various consumer incentives. In China, the National Development and Reform Commission highlighted the significance of the NEV market for achieving carbon neutrality through the “Development Plan for the Energy-Saving and New Energy Vehicle Industry (2021-2035).” In the first half of 2024, NEV production and sales in China soared to 4.929 million and 4.944 million units, respectively, with year-on-year growth rates of 30.1% and 32%. This surge underscores the increasing prominence of NEVs in the passenger vehicle market, emphasizing the importance of understanding consumer tendencies toward purchasing NEVs[2]. Historically, research, both local and international, has predominantly utilized revealed preference (RP) and stated preference (SP) data combined with questionnaire surveys to examine NEV consumers in specific regions. However, questionnaire surveys are subject to biases[3], and unaccounted variables can significantly impact their reliability. Some studies have also employed data regression analysis to explore comprehensive datasets[4][5].

This paper focuses on the Chinese new energy passenger vehicle market, compiling data on approximately 80 popular NEV models from automaker websites and platforms like ‘Autohome’ and ‘Dongchedi’. Due to limited sample data, oil-electric hybrid vehicles (HEV) and plug-in hybrid electric vehicles (PHEV) are grouped as oil-electric types, while battery-powered vehicles (BEV) are categorized as pure electric types. NEVs are further divided into low-end and high-end categories with a threshold of 300,000 Chinese yuan. Factors such as driving range, charging convenience, acceleration performance, price, speed, exterior design, and interior quality are identified as key influences on consumer choice. To determine consumer inclination toward NEVs and the primary factors influencing their decisions, data regression analysis is conducted on the collected data using R software. Following the preliminary findings on consumer preferences, discrete choice models are applied to minimize biases from basic regression analysis. The study aims to identify the most influential factors on consumers’ willingness to purchase NEVs and to explore the specific purchase intentions of consumers at different price points delineated by the 300,000 Chinese yuan threshold.

2. Literature Review

2.1 Stated Preference Survey(SP)

Since the beginning of the 21st century, there has been an increasing global focus on new energy vehicles. Numerous countries, including France [6], are actively planning to transition from conventional fuel vehicles to electric vehicles in the coming years [7]. In this context, the Chinese government has intensified its efforts to promote the new energy vehicle sector as a means to reduce atmospheric carbon dioxide emissions, capitalizing on the structural advantages of electric vehicles [8].

2.2 Structural Equation Modeling(SEM)

Structural equation modeling is commonly used to explore the relationships between variables through multiple regression analysis. This approach involves collecting reference data for research and subsequently applying structural equation modeling to assess the extent to which various factors influence consumer purchase intentions. For example, conducting a survey of Beijing residents about their intentions to purchase new energy vehicles enables researchers to identify the most significant factors influencing their buying decisions [8].

2.3 Disrete Choice Model(DCM)

Some studies utilize discrete choice models [9] to reanalyze existing regression data, aiming to minimize the bias introduced by varying variables. For instance, the logit model is employed to examine the willingness of Zhengzhou residents to purchase new energy vehicles, while the multinomial logit (MNL) model is applied to conduct linear regression on the aggregate data, ultimately identifying the factors with the greatest impact [10][11].

3. Methodology

3.1 Logit Model

The Logit model is a type of discrete choice model commonly used for empirical analysis. It performs classification using a linear model that maps the input to the interval [0,1] to classify samples. Essentially, logistic regression solves classification problems by estimating the relationship between input features and the probability of an event occurring. In this study, the Logit model was used to analyze the significance of the impact of different

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factors.

3.2 Discrete Choice Model

Since the results based on simple linear regression still have large deviations, we put the data into the Discrete Choice Model (DCM) [12]. In economics, we assume that consumers are rational, so the consumer behind each unit of sales will choose the option that maximizes benefits[13]. That is, choose the vehicle configuration that maximizes benefits. The derivation of the discrete choice model can help this study weaken the interaction between different dependent variables and is also used to replace sales data with market share[14][15].

4. Data

4.1 Data source

Here is the data on the battery life, price, charging speed, maximum speed, appearance score, interior score, space score, acceleration, and quantity sold in half a year of 80 hybrid and pure electric vehicles. These data sources were from different websites, and some grades were evaluated by the website's citations. Therefore, exterior score, interior score, and space score are based on websites.

model	endurance	charge	speed	acceleration	price	exterior	interior	space	citation (30w)	sales	纯电1、油电0
远航Y6	720	0.24	205	5.9	32.98	4.21	3.67	3.87	1	1483	1
Model 3	623	1	261	3.1	33.59	4.5	3.89	4.01	1	70500	1
红旗EH7	760	0.3	190	3.5	30.98	4.5	4.1	4.4	1	1408	1
ZEEKR 001	750	0.25	240	3.5	32.9	4.2	3.99	3.98	1	54568	1
蔚来ES6	500	0.5	200	4.05	33.8	3.99	3.85	4.2	1	31907	1
智界S7	751	0.25	200	3.3	34.29	3.65	4.15	3.56	1	16934	1
小鹏X9	640	0.33	200	5.22	41.98	3.65	3.32	3.99	1	13143	1
宝马ix1	450	0.53	170	5.7	33.99	3.99	4.12	4.34	1	3629	1
奔驰 EQA	619	0.75	160	8.6	32.2	4.2	3.69	4.5	1	1707	1
奥迪Q4 e-tro	605	0.68	160	8.8	33.4	3.75	3.91	3.89	1	7471	1
宝马i5	567	0.53	190	6.7	43.99	4.12	4.19	3.77	1	2193	1
奔驰 EQE SUV	609	0.58	200	5.1	48.68	4.26	3.43	4.02	1	5221	1
奔驰 EQE	717	0.8	180	6.29	53.43	3.52	3.81	4.16	1	2537	1
理想 MEGA	497	0.2	180	5.32	52.98	4.1	3.9	4.24	1	5577	1
宝马i3	592	0.53	180	5.6	41.39	3.52	3.76	3.56	1	28935	1
蔚来 ET5T	680	0.8	200	4	35.6	4.23	3.53	4.38	1	21183	1
蔚来EC6	505	0.5	200	4.4	35.8	4.28	4.1	4.03	1	11701	1
蔚来ES8	465	0.5	200	4.1	51.8	4.31	4.24	3.83	1	4423	1
阿维塔11	730	0.42	200	6.9	33.08	4.62	4.3	3.66	1	5665	1
奔驰EQB	600	0.75	160	6.3	45.28	3.91	3.85	3.12	1	1987	1
蔚来 ET5	710	0.6	200	4	35.6	4.31	4.09	3.83	1	12552	1
小鹏G6	700	0.3	202	4.02	27.69	3.61	3.61	4.33	0	15357	1
丰田bZ3	471	0.45	160	7.13	19.98	3.02	3.53	2.53	0	25092	1
哪吒L	510	0.35	180	7.6	15.29	3.2	4.07	4.02	0	10783	1
唐EV	635	0.5	180	4.4	26.98	4.01	4.03	3.92	0	4893	1
小鹏P7	373	0.48	200	6.39	23.99	4.62	4.01	3.51	0	9110	1
小鹏P5	500	0.5	170	7.5	15.69	3.45	3.59	4.15	0	2687	1
风行雷霆	410	0.5	180	7.9	13.99	3.26	4.02	2.89	0	1399	1
星纪元 ES	720	0.25	100	5.63	26.99	4.08	3.79	4.33	0	2399	1
羿	430	0.5	140	10.2	16.98	3.67	3.13	3.78	0	1064	1
ID.6 X	460	0.67	160	8.74	28.59	4.22	3.81	4.1	0	1252	1
合创Z03	430	0.6	140	7.9	13.48	3.6	3.99	3.71	0	1999	1
艾瑞泽e	405	0.5	130	12	15.8	4.1	3.51	3.19	0	1954	1
飞凡F7	500	0.5	200	6.7	18.99	3.66	3.89	3.86	0	1010	1
海豹	550	0.5	180	7.5	17.98	2.99	4.01	3.51	0	76672	1
元PLUS	430	0.53	160	7.3	12.68	4.19	3.66	3.75	0	118883	1
AION Y	610	0.57	150	8.15	17.56	3.6	3.67	4.7	0	74241	1
海豚	420	0.5	150	10.5	10.68	3.47	3.45	3.78	0	67527	1
小米 SU7	700	0.42	210	5.28	24.59	4.42	3.93	3.37	0	30000	1
阿维塔 12	700	0.33	215	6.62	26.58	4.72	4.14	4	0	12817	1
哪吒 X	501	0.37	150	9.5	12.48	3.97	4.03	4.23	0	1572	1

model	endurance	charge	speed	acceleration	price	exterior	interior	space	citation (30w)	sales	纯电1、油电0
腾势 D9 DM	1050	0.4	180	9.5	35.98	3.01	3.29	3.17	1	50590	0
坦克 500 Hi4-	790	0.4	180	6.9	33.5	3.99	4.19	3.85	1	20248	0
岚图梦想家 P	1231	0.5	203	5.9	33.99	3.34	3.28	3.21	1	15452	0
蓝山	1285	0.4	190	5.12	30.88	3.29	3.1	3.97	1	13711	0
领克 09 EM-P	1430	0.47	230	4.9	30.78	3.85	3.85	4.01	1	5772	0
传祺 E9 PHEV	1032	0.5	175	8.06	31.98	3.99	3.56	3.75	1	5941	0
理想L8	1135	0.5	200	4.9	46.9	4.2	3.65	4.1	1	37021	0
创维HT-i	1267	0.5	170	7.9	31.68	2.87	3.15	2.86	1	3594	0
坦克700 Hi4-	827	0.4	190	5.67	42.8	4.17	4.21	3.75	1	7673	0
沃尔沃XC60	712	0.7	180	5	52.39	4.28	3.99	3.35	1	2286	0
高山	938	0.43	170	5.7	37.86	4.08	3.82	4.01	1	3937	0
沃尔沃S60	974	0.8	180	4.7	39.99	4.08	3.1	3.34	1	9076	0
仰望 U8	1000	0.3	190	3.85	109.8	3.85	4.2	4.6	1	5500	0
问界 M9	1210	0.5	200	4.49	52.98	4.15	3.99	3.85	1	58823	0
理想L9	1176	0.42	180	5.3	40.98	3.99	4.12	4.32	1	43673	0
极石 01	1115	0.48	190	5.5	34.99	3.42	4.24	4.18	1	1692	0
秦PLUS DM	1245	0.5	185	7.3	10.58	3.23	3.88	4.12	0	152042	0
宋PLUS DM	1415	0.38	180	7.7	14.58	3.45	3.55	3.66	0	119167	0
驱逐舰05	1245	1.1	185	7.3	9.98	2.99	3.75	3.56	0	96650	0
宋 pro DM	1090	1	170	7.9	12.98	3.79	3.55	3.45	0	120721	0
风神L7 PHEV	1400	0.43	170	4.9	12.89	3.99	4.01	3.76	0	3816	0
唐DM	1020	0.33	180	4.3	22.98	4.01	3.76	3.23	0	56544	0
豹5	1200	0.27	180	4.8	27.98	3.99	3.99	3.76	0	18283	0
传祺 E8 PHEV	1200	0.5	170	8.8	20.98	3.11	3.34	2.99	0	13939	0
风云A8	1400	0.32	185	3.4	11.99	3.61	3.32	3.99	0	10713	0
银河L7	1370	0.5	200	6.94	13.97	3.11	3.32	3.41	0	36170	0
银河L6	1370	0.5	235	6.76	11.58	3.41	3.22	3.05	0	29822	0
领克08 EM-P	1200	0.47	190	6.35	19.58	3.11	3.99	3.07	0	35619	0
领克07 EM-P	1400	0.45	190	6.5	16.98	3.21	3.99	3.21	0	8261	0
长安起源A05	1300	0.5	185	6.8	9.39	3.71	3.9	3.55	0	23092	0
风云T9	1400	0.3	180	7.8	12.99	3.21	3.45	3.17	0	6537	0
星途瑶光 C-D	1300	0.33	180	7.9	15.98	3.11	4.1	3.26	0	4099	0
哈弗猛龙	1000	0.47	190	6.46	18.38	2.99	3.1	4.01	0	18783	0
五菱星光PHE	1100	0.5	185	7.59	8.98	2.99	2.5	3.24	0	5962	0
长安启源Q05	1215	0.5	180	7.3	9.69	3.01	3.221	3.21	0	18000	0
零跑 C10	1020	0.5	170	7.95	13.58	4.38	4.04	4.46	0	24106	0
理想 L6	1390	0.33	180	5.4	24.98	4.36	4.37	4.29	0	39210	0
零跑C11	925	0.5	170	7.8	14.88	4.16	3.85	4.21	0	29387	0

Fig.1.Data for all model of cars

4.2 Data collection

At first, some data in database are too small or big, they made result uncertain and unsteady.In this scenario, maximum sales was removal and sales under 10000 also removal from database.

These data are used to make regression analyses and discrete selection models to analyze the willingness to buy oil and pure trams. The data is divided into four parts: more than 300,000 pure electricity, less than 300,000 pure electricity, more than 300,000 oil, and less than 300,000 oil and electricity, with 20 vehicles in each part. Take the sales volume as y, use these four parts for regression analysis, and find the relationship and impact of y (sales) with other variables.

5. Result

5.1 . Regression Analysis Results

Pure electric vehicles below 300,000: other variables are positively correlated with sales by 55.14%, and 30.41% of sales can be explained by these variables.

Pure electric vehicles above 300,000: other variables are positively correlated with sales by 73.44%, and 53.93% of sales can be explained by these variables.

Hybrid vehicles below 300,000: other variables are positively correlated with sales by 75.07%, and 56.35% of sales could be explained by these variables.

Hybrid vehicles above 300,000: other variables are positively correlated with sales by 46.72%, and 21.83% of sales could be explained by these variables.

5.2 Data Processing and Optimization

In the initial analysis, the adjusted R-squared was negative, which may be due to the fact that too many independent variables affected the linear regression results.

To improve the analysis, the researchers merged the data of 80 vehicles, calculated the standard squared deviation of sales, and removed the maximum and minimum values that exceeded twice the standard squared deviation.

Existing vehicle brands were added as new variables, and the share of each vehicle in the total market was calculated.

5.3 Results of the Optimized Regression Analysis

81.64% of the existing variables were positively correlated with the model.

The adjusted R-squared value was 53.8%, which was within the normal range, indicating that 53.8% of the dependent variable could be explained.

```
> model<-lm(sales~endurance+charge+speed+acceleration+price+exterior+interior+space+citation,data=Book4)
> summary(model)

Call:
lm(formula = sales ~ endurance + charge + speed + acceleration +
    price + exterior + interior + space + citation, data = Book4)

Residuals:
   Min     1Q Median     3Q    Max
-39577 -21585  -7299  19629  63938

Coefficients: (1 not defined because of singularities)
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  -52798.4   309159.9  -0.171    0.867
endurance       132.2      224.8   0.588    0.568
charge        49046.9   102732.5   0.477    0.642
speed           114.6      486.2   0.236    0.818
acceleration  -3102.1    10032.4  -0.309    0.763
price         -5050.9     2853.9  -1.770    0.104
exterior      15420.8    29817.8   0.517    0.615
interior       2153.8    37504.3   0.057    0.955
space          5539.7    24492.7   0.226    0.825
citation           NA         NA      NA       NA

Residual standard error: 37700 on 11 degrees of freedom
Multiple R-squared:  0.3041,	Adjusted R-squared:  -0.2019
F-statistic: 0.601 on 8 and 11 DF,  p-value: 0.7599
```

Fig.2. The regression result of under 30 thousand pure electric vehicle

```
> model<-lm(sales~endurance+charge+speed+acceleration+price+exterior+interior+space+citation,data=Book6)
> summary(model)

Call:
lm(formula = sales ~ endurance + charge + speed + acceleration +
    price + exterior + interior + space + citation, data = Book6)

Residuals:
   Min     1Q Median     3Q    Max
-38743 -20165  -4824   6989 106032

Coefficients: (1 not defined because of singularities)
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  -156701.2   240048.3  -0.653   0.5273
endurance       -123.2      111.0  -1.109   0.2909
charge         29221.9    49610.2   0.589   0.5677
speed           1521.9      737.1   2.065   0.0634 .
acceleration    7289.8     9576.2   0.761   0.4625
price          -1763.2     1362.8  -1.294   0.2222
exterior      -34858.0    52005.0  -0.670   0.5165
interior      -20163.1    35096.9  -0.574   0.5772
space          46928.4    47499.9   0.988   0.3444
citation            NA         NA      NA       NA
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 42250 on 11 degrees of freedom
Multiple R-squared:  0.5393,	Adjusted R-squared:  0.2042
F-statistic: 1.609 on 8 and 11 DF,  p-value: 0.2279
```

Fig.3. The regression result of above 30 thousand pure electric vehicle

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```
> model<-lm(sales~endurance+charge+speed+acceleration+price+exterior+interior+space+citation,data=Book5)
> summary(model)

Call:
lm(formula = sales ~ endurance + charge + speed + acceleration +
    price + exterior + interior + space + citation, data = Book5)

Residuals:
   Min     1Q Median     3Q    Max
-48441 -14357  -2839   8206  62570

Coefficients: (1 not defined because of singularities)
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  -647693.44  314937.56  -2.057   0.0642 .
endurance        -52.37      96.89  -0.541   0.5996
charge         71229.30   56706.27   1.256   0.2351
speed            689.46     756.08   0.912   0.3814
acceleration   19368.67   10009.15   1.935   0.0791 .
price           -345.06    2629.37  -0.131   0.8980
exterior       40700.80   35945.56   1.132   0.2816
interior       26881.14   27544.10   0.976   0.3501
space          67562.01   32144.70   2.102   0.0594 .
citation             NA         NA      NA       NA
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 39660 on 11 degrees of freedom
Multiple R-squared:  0.5635,	Adjusted R-squared:  0.2461
F-statistic: 1.775 on 8 and 11 DF,  p-value: 0.186
```

Fig.4. The regression result of under 30 thousand petrol-electric vehicle

```
> model<-lm(sales~endurance+charge+speed+acceleration+price+exterior+interior+space+citation,data=Book7)
> summary(model)

Call:
lm(formula = sales ~ endurance + charge + speed + acceleration +
    price + exterior + interior + space + citation, data = Book7)

Residuals:
   Min     1Q Median     3Q    Max
-22564 -12093  -1475   6470  34047

Coefficients: (1 not defined because of singularities)
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  -118804.56  156300.38  -0.760    0.463
endurance         65.83      40.32   1.633    0.131
charge        -23369.34   63194.54  -0.370    0.719
speed           -242.12     389.55  -0.622    0.547
acceleration    4767.87    5649.16   0.844    0.417
price            226.13     360.13   0.628    0.543
exterior       25772.59   22058.31   1.168    0.267
interior        3148.09   14539.14   0.217    0.833
space          -7005.88   20907.42  -0.335    0.744
citation             NA         NA      NA       NA

Residual standard error: 21210 on 11 degrees of freedom
Multiple R-squared:  0.2183,	Adjusted R-squared:  -0.3501
F-statistic: 0.3841 on 8 and 11 DF,  p-value: 0.9076
```

Fig.5. The regression result of above 30 thousand petrol-electric vehicle

At present, through all data, the adjusted R square is negative because there are too many independent variables, which affects the result of linear regression. We found that the data measured in the four tables were not very stable, so we combined the 80 data calculated the standard square difference of sales, and then removed the maximum and minimum data of twice the standard square difference. Then several variables were added to the table, which are the brands of existing vehicles. The share of each car in the total market is also calculated. After that, I did a regression analysis again. The obtained data found that 81.64% of these existing variables can be used to be positively related to the model, and the adjusted R square is also in the normal range of 53.8%. It shows that 53.8% can be explained by these factors.

model	endurance	charge	speed	acceleration	price	exterior	interior	space	sales	Dp	De	D3特斯拉	D4理想	D5蔚来	D6小鹏	D7红旗	D8阿维塔	D9比亚迪	D10长安	D11问界	D12领克	D13奔驰	D14哪吒	D15ZEEKR	D16远航	D17五菱	D18宝马	D19沃尔沃	D20坦克	D21零跑
腾势 D9 DM	1050	0.4	180	9.5	35.98	3.01	3.29	3.17	50590	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
坦克 500 Hi4	790	0.4	180	6.9	33.5	3.99	4.19	3.85	20248	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
岚图梦想家 P	1231	0.5	203	5.9	33.99	3.34	3.28	3.21	15452	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
蓝山	1285	0.4	190	5.12	30.88	3.29	3.1	3.97	13711	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
领克 09 EM-I	1430	0.47	230	4.9	30.78	3.85	3.85	4.01	5772	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
传祺 E9 PHEV	1032	0.5	175	8.06	31.98	3.99	3.56	3.75	5941	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
理想L8	####	0.5	200	4.9	46.9	4.2	3.65	4.1	37021	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
创维HT-i	####	0.5	170	7.9	31.68	2.87	3.15	2.86	3594	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
坦克700 Hi4-	827	0.4	190	5.67	42.8	4.17	4.21	3.75	7673	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
沃尔沃XC60	712	0.7	180	5	52.39	4.28	3.99	3.35	2286	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
高山	938	0.43	170	5.7	37.86	4.08	3.82	4.01	3937	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
沃尔沃S60	974	0.8	180	4.7	39.99	4.08	3.1	3.34	9076	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
仰望 U8	1000	0.3	190	3.85	109.8	3.85	4.2	4.6	5500	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
问界 M9	1210	0.5	200	4.49	52.98	4.15	3.99	3.85	58823	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
理想L9	1176	0.42	180	5.3	40.98	3.99	4.12	4.32	43673	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
极石 01	1115	0.48	190	5.5	34.99	3.42	4.24	4.18	1692	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
秦PLUS DM	1245	0.5	185	7.3	10.58	3.23	3.88	4.12	152042	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
宋PLUS DM	1415	0.38	180	7.7	14.58	3.45	3.55	3.66	119167	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
驱逐舰05	1245	1.1	185	7.3	9.98	2.99	3.75	3.56	96650	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
宋 pro DM	1090	1	170	7.9	12.98	3.79	3.55	3.45	120721	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
风神L7 PHEV	1400	0.43	170	4.9	12.89	3.99	4.01	3.76	3816	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
唐DM	1020	0.33	180	4.3	22.98	4.01	3.76	3.23	56544	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
豹5	1200	0.27	180	4.8	27.98	3.99	3.99	3.76	18283	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
传祺 E8 PHEV	1200	0.5	170	8.8	20.98	3.11	3.34	2.99	#####	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
风云A8	1400	0.32	185	3.4	11.99	3.61	3.32	3.99	#####	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
银河L7	1370	0.5	200	6.94	13.97	3.11	3.32	3.41	#####	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
银河L6	1370	0.5	235	6.76	11.58	3.41	3.22	3.05	#####	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
领克08 EM-P	1200	0.47	190	6.35	19.58	3.11	3.99	3.07	35619	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
领克07 EM-P	1400	0.45	190	6.5	16.98	3.21	3.99	3.21	8261	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
长安起源A05	1300	0.5	185	6.8	9.39	3.71	3.9	3.55	#####	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
风云T9	1400	0.3	180	7.8	12.99	3.21	3.45	3.17	6537	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
星途瑶光 C-D	1300	0.33	180	7.9	15.98	3.11	4.1	3.26	####	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
哈弗猛龙	1000	0.47	190	6.46	18.38	2.99	3.1	4.01	18783	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
五菱星光PHE	1100	0.5	185	7.59	8.98	2.99	2.5	3.24	5962	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
长安启源Q05	1215	0.5	180	7.3	9.69	3.01	3.221	3.21	18000	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
零跑 C10	1020	0.5	170	7.95	13.58	4.38	4.04	4.46	24106	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
理想 L6	1390	0.33	180	5.4	24.98	4.36	4.37	4.29	39210	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
零跑C11	925	0.5	170	7.8	14.88	4.16	3.85	4.21	29387	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

D22丰田	D23腾势	D24豹	D25奥迪	D26传祺	D27仰望	D28高山	D29蓝山	D30风行	D31AION	D32极石	D33哈弗	D34小米	D35星途	D36岚图	D37创维	D38雷诺江铃	D39广汽	D40上汽	D41大众	D42奇瑞	D43油车份额	D44
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.04376366	-0.8212363
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01751584	-0.8474842
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0.01336699	-0.851633
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01186091	-0.8531391
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00499316	-0.8600068
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00513935	-0.8598606
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.03202559	-0.8329744
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0.00310904	-0.861891
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00663765	-0.8583624
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00197754	-0.8630225
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00340576	-0.8615942
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00785133	-0.8571487
0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00475786	-0.8602421
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.05088574	-0.8141143
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.03778	-0.82722
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0.00146369	-0.8635363
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.13152627	-0.7334737
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.10308725	-0.7619128
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.08360857	-0.7813914
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.10443156	-0.7605684
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00330109	-0.8616989
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.04891426	-0.8160857
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01581599	-0.849184
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01205815	-0.8529419
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00926745	-0.8557326
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.03128941	-0.8337106
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.02579798	-0.839202
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.03081276	-0.8341872
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00714631	-0.8578537
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01997609	-0.8450239
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00565493	-0.8593451
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0.0035459	-0.8614541
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0.01624852	-0.8487515
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00515752	-0.8598425
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01557118	-0.8494288
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.02085327	-0.8441467
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.03391921	-0.8310808
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.02542168	-0.8395783

Fig.6. Data for all model cars with share in the market

```
> model<-lm(D44~endurance+charge+speed+acceleration+price+exterior+interior+space+sales+Dp+De+D3特斯拉+D4
理想+D5蔚来+D6小鹏+D7红旗+D8阿维塔+D9比亚迪+D10长安+D11问界+D12领克+D13奔驰+D14哪吒+D15ZEEKR+D16远航+D17五菱+D18宝
马+D19沃尔沃+D20坦克+D21零跑+D22丰田+D23腾势+D24豹+D25奥迪+D26传祺+D27仰望+D28高山+D29蓝山+D30风行+D31AION+D32极石
+D33哈弗+D34小米+D35星途+D36岚图+D37创维+D38雷诺江铃+D39广汽+D40上汽+D41大众+D42奇瑞+D43份额,data=Model3)
> summary(model)

Call:
lm(formula = D44 ~ endurance + charge + speed + acceleration +
    price + exterior + interior + space + sales + Dp + De + D3特斯拉 +
    D4理想 + D5蔚来 + D6小鹏 + D7红旗 + D8阿维塔 +
    D9比亚迪 + D10长安 + D11问界 + D12领克 + D13奔驰 +
    D14哪吒 + D15ZEEKR + D16远航 + D17五菱 + D18宝马 +
    D19沃尔沃 + D20坦克 + D21零跑 + D22丰田 + D23腾势 +
    D24豹 + D25奥迪 + D26传祺 + D27仰望 + D28高山 +
    D29蓝山 + D30风行 + D31AION + D32极石 + D33哈弗 +
    D34小米 + D35星途 + D36岚图 + D37创维 + D38雷诺江铃 +
    D39广汽 + D40上汽 + D41大众 + D42奇瑞 + D43份额,
    data = Model3)

Residuals:
       Min         1Q     Median         3Q        Max
-1.207e-16 -2.361e-17  0.000e+00  1.985e-17  1.745e-16

Coefficients: (6 not defined because of singularities)
               Estimate Std. Error    t value Pr(>|t|)
(Intercept)  -8.650e-01  6.488e-16 -1.333e+15  < 2e-16 ***
endurance     5.410e-19  2.033e-19  2.661e+00  0.01647 *
charge       -3.393e-16  2.892e-16 -1.173e+00  0.25679
speed        -3.001e-19  1.208e-18 -2.480e-01  0.80679
acceleration  2.378e-17  2.265e-17  1.050e+00  0.30844
price        -4.947e-18  4.486e-18 -1.103e+00  0.28546
exterior      4.766e-17  6.763e-17  7.050e-01  0.49047
interior      1.532e-16  7.536e-17  2.033e+00  0.05802 .
space         2.380e-17  6.697e-17  3.550e-01  0.72671
sales         1.314e-06  1.948e-21  6.746e+14  < 2e-16 ***
Dp            2.836e-17  8.028e-17  3.530e-01  0.72822
De            3.025e-16  1.564e-16  1.934e+00  0.06989 .
D3特斯拉             NA         NA         NA       NA
D4理想        2.962e-16  1.304e-16  2.271e+00  0.03640 *
D5蔚来        1.881e-16  1.257e-16  1.496e+00  0.15300
D6小鹏        1.594e-16  9.680e-17  1.647e+00  0.11789
D7红旗        4.173e-17  1.208e-16  3.450e-01  0.73409
D8阿维塔     -7.023e-17  1.201e-16 -5.850e-01  0.56644
D9比亚迪      9.966e-17  1.442e-16  6.910e-01  0.49890
D10长安       2.565e-17  8.403e-17  3.050e-01  0.76389
D11问界              NA         NA         NA       NA
D12领克       4.339e-18  8.423e-17  5.200e-02  0.95952
D13奔驰       2.878e-16  1.380e-16  2.086e+00  0.05234 .
D14哪吒       4.419e-17  1.207e-16  3.660e-01  0.71876
D15ZEEKR             NA         NA         NA       NA
D16远航      -7.921e-19  1.268e-16 -6.000e-03  0.99509
D17五菱       3.688e-16  1.475e-16  2.500e+00  0.02295 *
D18宝马       1.679e-16  1.184e-16  1.417e+00  0.17442
D19沃尔沃     5.636e-16  1.767e-16  3.190e+00  0.00536 **
D20坦克       2.557e-16  1.499e-16  1.706e+00  0.10626
D21零跑       2.265e-17  1.308e-16  1.730e-01  0.86455
D22丰田       1.624e-16  1.309e-16  1.240e+00  0.23166
D23腾势              NA         NA         NA       NA
D24豹        -1.797e-16  1.958e-16 -9.180e-01  0.37152
D25奥迪       1.598e-16  1.593e-16  1.003e+00  0.32993
D26传祺       1.988e-16  1.208e-16  1.646e+00  0.11822
D27仰望       3.916e-16  3.645e-16  1.074e+00  0.29764
D28高山       2.973e-16  1.540e-16  1.930e+00  0.07041 .
D29蓝山       1.394e-16  1.260e-16  1.107e+00  0.28387
D30风行       2.268e-16  1.420e-16  1.598e+00  0.12856
D31AION              NA         NA         NA       NA
D32极石       1.647e-16  1.611e-16  1.022e+00  0.32106
D33哈弗       3.515e-16  1.452e-16  2.420e+00  0.02698 *
D34小米      -4.968e-17  1.349e-16 -3.680e-01  0.71726
D35星途       4.848e-19  1.126e-16  4.000e-03  0.99662
D36岚图       2.703e-16  1.223e-16  2.210e+00  0.04114 *
D37创维       2.217e-16  1.538e-16  1.441e+00  0.16769
D38雷诺江铃   2.508e-16  1.458e-16  1.721e+00  0.10347
D39广汽       1.553e-16  1.412e-16  1.100e+00  0.28663
D40上汽       1.624e-16  1.479e-16  1.098e+00  0.28754
D41大众       1.910e-16  1.660e-16  1.151e+00  0.26571
D42奇瑞       4.213e-17  1.270e-16  3.320e-01  0.74414
D43份额              NA         NA         NA       NA
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.005e-17 on 17 degrees of freedom
  (6 observations deleted due to missingness)
Multiple R-squared:      1,     Adjusted R-squared:      1
F-statistic: 3.435e+28 on 46 and 17 DF,  p-value: < 2.2e-16
```

Fig.7. The regression result of the discrete choice model

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6. Conclusion

This study explored the factors that affect the sales of different types of electric and hybrid vehicles through detailed data analysis. In order to improve the accuracy of the analysis, the researchers optimized and adjusted the data several times.

Research has found that within the price range of less than 300000 yuan, the positive correlation rate between other indicators and sales of pure electric vehicles is 55.14%, while the positive correlation rate of gasoline-electric hybrid vehicles reaches 75.07%. For pure electric vehicles worth over 300000 yuan, the positive correlation rate of pure electric vehicles increases to 73.44%, but the positive correlation rate of gasoline and electric hybrid vehicles decreases to 46.72%. After data optimization and merging data points and outliers, the positive correlation between existing indicators and sales volume increased to 81.64%, and the adjusted R^2 increased to 53.8%, indicating that these structures can well explain the evolution of sales volume.

Due to the limited sample data and the uncertainty of consumer choice, the results of this article are still biased.

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