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Analysis of Influencing Factors of Electric Vehicle Purchase Intention based on Product Attributes and Market Environment

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Abstract

In order to achieve green and low-carbon development and energy structure transformation, China promoted the development of electric vehicles (EVs) greatly and implemented a series of policies to stimulate the consumption of the EV market. Existing studies focus on the impact of consumers' perception on purchase intention mostly. Based on product attributes and market environment, this study analyses the sales situation and product characteristics of EVs in China in 2026 through One-Way Analysis of Variance (One-Way ANOVA) and Quantile Regression model (QR model), covering 500 samples. There are significant differences in sales between different brands, and the type of EV and whether there are government incentives do not have a significant impact on purchase intention. The number of charging stations and energy consumption have a significant impact on low sales vehicles and medium sales vehicles separately, and there exists heterogeneity. Battery capacity, vehicle range, charging time, average EV price, market adoption rate, and CO2 reduction have little impact on purchase intention, which shows that the explanatory power of product parameters and market environment declines.

Keywords

product attributes, market environment, electric vehicles, purchase intention

1. Introduction

Developing EVs has become an important strategic direction for China to achieve green and low-carbon development and energy structure transformation. Compared with traditional fuel vehicles, EVs have more advantages, such as less pollution, lower cost, better driving experience, and faster instantaneous acceleration. With the strong promotion of a series of policies such as purchase tax subsidies, China's EV industry has gained more opportunities.

With the expansion of the market and the maturity of technology, factors affecting consumers' purchase intention of EVs have become increasingly complex. Scholars such as Nie et al. use Structural Equation Modeling (SEM) to apply the Theory of Planned Behavior (TPB), and find that perceived value indirectly affects willingness through purchase attributes. Product price not only directly inhibits willingness, but also indirectly affects intention [1]. Scholars such as Sudarsih also used SEM in their research on Indonesia and

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found different conclusions. They find that attitudes and perceived behavior control have no significant direct impact, and environmental concern and perceived value become the main factors [2].

Scholars such as Noor combine the Value-Attitude-Behaviour model and TPB, and find that maintenance costs and infrastructure readiness affect purchase intention directly and indirectly, and price only takes effect indirectly through attitudes [3]. Researchers such as Shah point out that price expectation, endurance concern, and charging infrastructure are still the main obstacles to the purchase intention of EVs, based on America's market data [4]. Zuo, Wang, and Yang establish the Latent Class Model (LCM) and apply Latent Profile Analysis (LPA) to recognize 5 types of consumers, whose perceived usefulness and environmental awareness are the main differences [5]. This provides a basis for refined market segmentation. Mehta, Patel, and Desai integrate machine learning and natural language processing and find that the joint intervention of incentives and infrastructure can greatly increase purchase intention [6]. Simsekoglu and others compare the purchase intention of EVs in Norway and Italy, and find that technical attitudes and emotional attitudes are significant in both markets, but economic attitudes are only significant in Norway [7].

Most of the above researches focus on India, Indonesia, and other countries, and the analysis of the Chinese market is insufficient. And most of them focus on the variables of emotional perception, and pay limited attention to product attributes and market environment. On this basis, this research uses One-Way ANOVA and QR model to explore the impact of factors such as product attributes and market environment on Chinese consumers' purchase intention of EVs, so as to help consumers make more rational decisions.

2. Methods

2.1 Data Source and Description

Data used in this research comes from the Kaggle platform, provided by Muhammad Dastgeer in February 2026 [8]. The dataset includes the EV sales situation and product characteristics information in 10 countries in 2026, covering 5000 valid samples. Each sample represents the annual sales of a specific brand model in a specific national market. The dataset on Kaggle is widely used in academia and has strong reliability, so it is used in this research.

2.2 Index Selection and Description

This research takes the Chinese EV market as the research object, selects Chinese sample data from 5000 samples, and obtains 500 valid samples. This research takes 12 variables. In order to make writing convenient, this research uses S and F_1 - F_{11} to represent these variables in subsequent analysis. Table 1 shows the names, units, symbols, and ranges of these variables. As consumers' emotional state, purchase intention can not be measured directly by the data. So this research considers the sales as the variable measuring consumers' purchase intention. There are 4 EV types, which are truck, bus, car, and SUV. There are 10 EV brands, including Ford, Nissan, Toyota, and so on. As for the variable *Government Incentives*, this research uses 1 for government incentives and 0 for no government incentives.

Table 1: Variable Description

Variables	Unit	Symbol	Range
EV sales	10^5 units	S	[0.09, 8.99]
Vehicle type	-	F_1	-
EV brand	-	F_2	-
Battery capacity	kwh	F_3	[40, 120]
Vehicle range	km	F_4	[250, 649]
Charging time	hours	F_5	[0.5, 3]
Charging stations	10^4 units	F_6	[0.06, 19.97]
Average EV price	10^4 dollars	F_7	[2.51, 8.50]
Energy consumption	kwh	F_8	[12.1, 24.9]
Government incentives	-	F_9	0 or 1
Market adoption rate	%	F_{10}	[5.5, 64.9]
CO_2 reduction	mt	F_{11}	[5, 300]

2.3 Method Introduction

This research uses One-Way ANOVA and QR model to analyze the data.

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One-Way ANOVA is used to test the influence of a single categorical independent variable on continuous dependent variables. By comparing the mean differences of multiple groups, it judges whether there are significant differences between different groups. By decomposing the total variation into inter-group variation and intra-group variation, this method can quantify the size of inter-group differences relative to random errors, so as to judge the actual impact of classification variables more scientifically. The test statistic is

$$F = \frac{MS_{between}}{MS_{within}} = \frac{SS_{between}/(k-1)}{SS_{within}/(N-k)} \quad (1)$$

Where $MS_{between}$ is the mean square between groups, MS_{within} is the mean square within groups, $SS_{between}$ is the sum of squares between groups, SS_{within} is the sum of squares within groups, k is the number of groups, N is the total sample size. If the F test is significant, it indicates that there is a difference between the mean value of at least one group and other groups, and the specific source of the difference can be further identified through multiple comparisons after the event.

QR model is used to estimate the influence of the independent variable on the dependent variable at different quantiles. This method is insensitive to outliers, and the estimation result is steadier. Simultaneously, it can reveal the heterogeneity of the influence mechanism of dependent variables at different levels and make up for the limitations of mean regression. For the τ quantile, the QR model can be expressed as

$$Q_\tau(y|x) = x'\beta_\tau \quad (2)$$

Where $Q_\tau(y|x)$ is the τ quantile of the dependent variable y when the independent variable x is given, and β_τ is the regression coefficient vector corresponding to the τ quantile.

3. Results and Discussion

3.1 One-Way ANOVA

As categorical variables, this research uses One-Way ANOVA to test F_1, F_2 and F_9, respectively.

The results of the ANOVA of F_1 are shown in Table 2. F = 1.968, p = 0.118 > 0.05, this indicates that there is no significant difference between different groups, and F_1 has little effect on S. Vehicle type has little effect on consumers' purchase intention of EVs.

Table 2: F1 ANOVA Results

Item	Option	n	Mean	S.D.	F	*p* Value
S	Bus	125	4.44	2.53	1.968	0.118
	Car	122	4.87	2.60		
	SUV	118	4.08	2.34		
	Truck	135	4.53	2.65		
	Total	500	4.48	2.54		

** p<0.1 ** p<0.05 *** p<0.01.*

The results of the ANOVA of F_2 are shown in Table 3. F = 2.005, p = 0.037 < 0.05, this indicates that there is a significant difference between different brands.

Table 3: F2 ANOVA Results

Item	Option	n	Mean	S.D.	F	*p* Value
S	BMW	28	4.05	3.04	2.005	0.037**
	BYD	48	4.18	2.40		
	Ford	62	4.91	2.66		
	Hyundai	48	3.41	2.38		
	Kia	47	4.95	2.59		
	Mercedes	53	4.86	2.24		
	Nissan	59	4.52	2.47		
	Tesla	48	4.95	2.62		
	Toyota	50	4.65	2.34		
	Volkswagen	57	4.07	2.61		
	Total	500	4.48	2.54		

** p<0.1 ** p<0.05 *** p<0.01.*

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The results of the ANOVA of F_9 are shown in Table 4. F = 0.020, p = 0.886 > 0.05, this indicates that there is no significant difference between different groups, and F_9 has little effect on S. Government incentives have little effect on consumers' purchase intention of EVs.

Table 4: F9 ANOVA Results

Item	Option	n	Mean	S.D.	F	*p* Value
S	0	251	4.47	2.55	0.020	0.886
	1	249	4.50	2.54		
	Total	500	4.48	2.54		

** p<0.1 ** p<0.05 *** p<0.01.*

3.2 QR Model

Apply QR model to the rest of the variables to study the relationship between these variables and S, and three quantiles of 0.25, 0.50, 0.75 are selected to correspond to low, medium, and high selling vehicles. Results are shown in Table 5.

Table 5: QR model Results

	Quantile 0.25	Quantile 0.50	Quantile 0.75
Constant	4.731***(3.546)	6.646***(4.156)	6.516***(4.854)
F_3	-0.004(-0.670)	-0.013(-1.646)	-0.007(-1.056)
F_4	-0.001(-0.825)	-0.000(-0.124)	-0.000(-0.275)
F_5	0.103(0.467)	0.062(0.241)	-0.253(-1.172)
F_6	-0.060**(-1.980)	0.011(0.324)	0.022(0.776)
F_7	0.023(0.265)	0.098(0.943)	0.092(1.021)
F_8	-0.052(-1.188)	-0.100**(-2.078)	0.039(0.963)
F_{10}	-0.002(-0.183)	0.001(0.101)	-0.003(-0.275)
F_{11}	-0.001(-0.773)	0.000(0.064)	-0.002(-1.064)
n	500	500	500
R-squared	0.011	0.014	0.015

** p<0.1 ** p<0.05 *** p<0.01, t value in parentheses.*

The results show that F_6 and F_8 are significantly negative at a specific quantile, and others fail to pass the significance test at any quantile.

In detail, F_6 is significantly negative at the 0.25 quantile. For low-selling vehicles, F_6 is negatively correlated with S. This might be related to the potential risk of charging infrastructure. In the research of fire incidents in South Korea, Kim and other researchers find that potential risk will decrease consumers' purchase intention [9]. F_8 is significantly negative at the 0.50 quantile. For medium-selling vehicles, F_8 is negatively correlated with S. This phenomenon is in line with the law of the market. The increase in price leads to a reduction in purchase intention.

Product parameter factors such as F_3, F_4, F_5, and F_{11} have no significant differences on S, which shows that with the continuous iteration of products, product parameters are no longer the main obstacles affecting purchase intention. Market environment variables such as F_7 and F_{10} have no significant difference on S, which indicates that consumers are not that sensitive to the price, and EVs have a certain degree of popularity in the Chinese market. Simultaneously, consumers do not perceive the specific CO_2 reduction directly, which leads to little effect of F_{11} on purchase intention.

3.3 Discussion

R-squared values of the QR model are only 0.011-0.015, which indicates the low model fit. The relationship between EV sales and other variables might be nonlinear. However, as a linear conditional quantile model, QR model is difficult to effectively reflect such complex relationships. As a result, R-squared values are low. Nonlinear methods such as XGBoost and random forest can be used in subsequent research, and the R-squared value may be improved.

F_6 and F_8 are only significantly negative at partial quantiles, indicating that the effects of the number of charging stations and energy consumption exhibit heterogeneity. Wolbertus and other researchers find that

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there are cross effects between charging infrastructure-related policies, and some of them affect purchase intention negatively [10]. This showcases that there may exist some other related variables affecting purchase intention. Future research can introduce data concerning charging behaviors, such as charging station efficiency, to further analyse their influence mechanism. As for the heterogeneity of energy consumption, it may be that consumers of medium-sized vehicles are the most sensitive to the cost brought by energy consumption. Subsequent research can verify this explanation by segmenting types of consumers.

4. Conclusion

Based on 500 sales data in the Chinese EV market in 2026, this research uses One-Way ANOVA and QR model to analyze the effects of 11 factors on EV sales to explore their effects on Chinese consumers' purchase intention of EVs. This research draws the following conclusions.

The results of One-Way ANOVA show that there are significant differences in sales between different brands. This indicates that brands become the key factor affecting Chinese consumers' purchase intention of EVs. Vehicle types and government incentives do not have a significant difference.

Results of QR model show that battery capacity, vehicle range, charging time, average EV price, market adoption rate, and CO_2 reduction do not pass the significance test at any quantile. This reveals that the influence of product parameters and market environment on purchase intention is weak.

QR model cannot effectively reflect the relationship between nonlinear variables, which may lead to the low R-squared values. The number of charging stations and energy consumption are significantly negative only at the partial quantile. The possible reasons for this heterogeneity are the influences from other related variables, and different types of consumers pay attention to different product attributes. Subsequent research can choose other nonlinear methods, introduce data concerning charging behaviors, and segment consumer type to explain the influence mechanism of EV purchase intention more comprehensively.

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Conflicts of Interest

The authors declare no conflict of interest.

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