J. COMBIN. MATH. COMBIN. COMPUT. 127a(2025) 8627--8639

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Consumer Purchasing Behaviour Pattern Recognition with Application of Meta-Analysis and Structural Equation Modelling as a Guide to Marketing Strategies for New Energy Vehicles

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ABSTRACT
With the proposal of sustainable development of energy, countries begin to develop from fuel vehicles to new energy vehicle market. Firstly, we construct a consumer purchase behavior recognition model based on XG Boost algorithm, simulate the gradient enhancement process of purchase behavior recognition, obtain the approximation value based on function calculation to become the learning target of the overflow value, and at the same time, give higher learning weight to the samples with unsatisfactory accuracy in the last round, and after continuous iteration, gradually correct the purchase behavior recognition bias. According to the number of purchase behavior features identified correctly, the number of features that do not have purchase behavior features, and the number of features that are not identified, invalid users are eliminated to improve the accuracy of the algorithm. The Cronbach's alpha coefficients of the four factors are found to be 0.891, 0.895, 0.813, and 0.800, all of which are greater than or equal to 0.800, indicating that the factors are internally consistent. And the relationship values between the factors and purchase intention are 0.439, 0.406, 0.430, 0.387, which are all greater than 0. Therefore, there is a prominent relationship between all four dimensions of consumer purchase behavior factors and consumption impulse, and the identification of purchase behavior patterns has a guiding role in electric energy vehicle marketing strategy.

Keywords: new energy vehicles, XG Boost algorithm, purchase behavior recognition, purchase intention, marketing strategy

1. Introduction

With the development of the overall economy and the promotion of environmental protection and

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Received 05 March 2024; Revised 10 May 2024; Accepted 05 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-477

carbon reduction policies, people's quality of life has not only been improved, at the same time, new energy vehicles have entered thousands of households, which facilitates people's work and study on the basis of reducing carbon emissions [1]. With the rapid development of information technology, people's various behaviors are changing, including training, thinking, lifestyle, etc., which will have a great impact on the new energy vehicle repair industry. However, on the basis of big data, daily marketing will be determined based on consumer buying behavior, which makes the marketing of new energy vehicle market present new characteristics [2]. Consumer purchasing behavior pattern identification is based on the natural behaviors left behind when consumers use the APP, such as clicking, adding to cart, purchasing and other behaviors, guessing preferences from consumer behavior, designing new energy vehicles as well as perfecting the marketing strategy from the consumer's point of view, so as to reduce the loss of consumers [3-4].

In the marketing process of new energy vehicles, which is also known as green marketing, each stage of development of green marketing has its own research emphasis and focus, and therefore its definition has been defined as different concepts. Literature [5] argues that in each specific marketing situation, consumer purchasing behavior is different because of the different focuses of each marketing situation. Consumer buying behavior patterns have also been referred to as sustainable consumption behavior and pro-environmental behavior, among others, in their development. Literature [6], in order to further improve the accuracy of the prediction of the consumer purchase behavior pattern recognition model, proceeded to analyze the transaction data obtained in and mined the potential interest context features based on the historical data in order to achieve the accurate prediction of consumers' future purchase tendency. Literature [7] found that consumers are more inclined to purchase goods that match their interests through in-depth study of transaction data. For example, for those consumers who have already browsed or purchased a large number of products with cartoon patterns, the products with cartoon patterns will be pushed for this group of consumers. Literature [8] points out that analyzing click records can accurately identify consumers' purchasing interests, which is of great value in studying whether consumers will purchase a commodity in the future. If consumers are interested in an item, they tend to purchase it after a long time of browsing. Research in the literature [9] suggests that consumer interest does not depend entirely on the browsing time, but more critically on the number of times a consumer clicks on an item during a particular time period, i.e., click frequency. The higher the frequency of clicking on an item by a consumer means that the consumer is more inclined to buy the item. This is because consumers usually do not decide to buy an item just based on one click, but will make multiple comparisons and make the final decision after repeated comparisons. Literature [10] in its study that, in the decision-making process, consumers will frequently repeat clicking on the recently viewed products, which represent the real needs of consumers over a period of time, and the effective extraction of consumer interest sequences can effectively predict the tendency to buy in the future. Literature [11] brings in big data technology in its researchability, and points out that it is more convenient to obtain the click rate of automobile consumption in the big data environment, and comprehensively analyze the past consumption habits, opportunities, and ways, so as to form a variety of different marketing methods and services, thus realizing precise and effective automobile marketing and promoting the further development of automobile marketing and services. The above research contributes to the effective identification of consumer purchasing behavior patterns in this paper to improve the marketing strategy of the electric energy automobile market.

With the emergence of new market behaviors, opportunities and challenges, the automobile consumer market has changed dramatically. Based on the development trend of electric vehicles, competitive situation and the importance of marketing strategy in market competition, it is of certain significance to conduct research on topics related to the optimization of marketing strategy for electric vehicles. This paper firstly constructs a consumer purchase behavior recognition model based on XG Boost algorithm, through which we understand the gradient enhancement process of purchase behavior recognition, and give higher learning weights to the samples with unsatisfactory accuracy rate in the purchase behavior recognition model in order to correct the recognition accuracy rate of the purchase behavior recognition model, and gradually correct the purchase behavior recognition deviation. Based on the XG Boost algorithm, the consumer buying behavior perception is divided into four dimensional factors: performance-price-performance ratio, value-price-performance ratio, preference-price-performance ratio, and general environment-price-performance ratio, and the impact of the four factors on the user's consumption impulse perception is analyzed. Subsequently, it is determined that in the future new energy vehicle market, it should be considered from the perspective of consumer purchasing behavior in order to truly cater to the actual needs of automotive marketing, and at the same time to maintain the sustainable development of the enterprise.

2. Consumer purchase behavior recognition model based on XG Boost algorithm

2.1. XG Boost Recognition Model Structure

XG Boost algorithm is an integrated learning method under machine learning model that supports CART trees and linear classifiers as base classifiers and implements additive models based on forward distribution approach [12]. Multiple smaller models are fused together to form a larger model, which is called an integrated model.The GBRT model serial iteration process can be expressed as:

$$\begin{cases} \hat{y}^{(0)} = 0 \\ \hat{y}^{(1)} = vf_1(x;\theta_1) = \hat{y}^{(0)} + vf_1(x;\theta_1) \\ \hat{y}^{(2)} = v\sum_{j=1}^{2} f_j(x;\theta_j) = \hat{y}^{(1)} + vf_2(x;\theta_2) \\ \vdots \\ \hat{y}^{(T)} = v\sum_{j=1}^{T} f_j(x;\theta_j) = \hat{y}^{(T-1)} + vf_T(x;\theta_T) \end{cases} \tag{1}$$

where T is the total number of trees in the integrated model, j is the amount of network intersections between trees and leaves, and v indicates indicators with larger values. When j denotes the exclusion of metrics with larger values, the variable x is used. Based on this, by integrating multiple trees, this spillover value will gradually decrease, while the model effect gradient will increase [13-14].

In the process of gradient enhancement for purchasing behavior recognition based on machine learning, the prediction is assigned to the samples in the training set, and in general the prediction is a constant, the assignment process can be seen as the initialization of the data set samples, and iterative training is required for the model to achieve model accuracy as well as efficiency. Based on the prediction assignment of the samples in the training set to obtain the negative gradient of the loss function in terms of the predicted value, in order to determine the sample error. In order to reduce the value of negative gradient, a decision tree is trained and the negative gradient is fitted by the decision tree to reduce the error value. Assign values to the decision tree weights and bring them into an integrated model made of multiple weak models as a way to re-assign values to the predictions of the model. Iteratively train the trees for multiple decisions and the trained decision trees are combined into the integrated model. The predictions of multiple decision trees are weighted and summed to get the final prediction. In short, the gradient enhancement process of purchasing behavior identification based on machine learning, the most fundamental is to fit the model error through the decision tree, to improve the model's Mirror Lake final concentration and efficiency, based on the analysis of the complex relationship between the data on the basis of the effective identification and prediction of consumer purchasing behavior.

The structure of the tree is not a single, a gradient-enhanced XG Boost algorithm in the learning algorithm based on the original calculation of the GBRT algorithm, a variety of columns into the GBRT algorithm [15]. the XG Boost model of the can be used as a purchasing behavior identification, in the approximation of the model's negative gradient based on the function of the calculation of the results obtained under the overflow of the learning needs of the overflow value, and for the purchase of the purchase of behavioral identification model of the accuracy of the samples of the less than ideal Higher learning weights are given to refine the purchase behavior recognition model recognition accuracy, which enables successive iterations of multiple models, thus gradually correcting the purchase behavior recognition bias [16-17].

The core task of the gradient boosting tree model is to find each optimal single regression tree and build the decision function j by minimizing the objective computation in step i.e:

$$\begin{aligned}\hat{\theta}_J &= \arg\min_{\theta_j}\left\{\sum_{i=1}^{N} L\left[y_i, \hat{y}_i^{(j-1)} + vf_j(x_i;\theta_j)\right] + \Omega(\theta_j)\right\} \\ &= \arg\min_{\theta_j}\left\{\sum_{i=1}^{N} L\left[\hat{y}_i^{(j-1)} - y_i + vf_j(x_i;\theta_j)\right]^2 + \Omega(\theta_j)\right\}\end{aligned} \tag{2}$$

where N denotes the sample size and θ is based on the square of the function value and the regular term of the j rd tree, whose main formula is:

$$\Omega(\theta_j) = \gamma M_j + \frac{1}{2}\lambda \| w_k \| = \gamma M_j + \frac{1}{2}\lambda \sum_{k=1}^{M_j} (w_k^{(j)})^2 \tag{3}$$

$w_k^{(j)}$ is the leaf fraction of the k rd leaf node of the j nd tree, f_j is the number of leaf nodes of the j tree, γ is the minimum loss of additional leaf node branches, and $\gamma = L2$ denotes the regular term of the leaf fraction of the tree [18].

XG Boost produces better optimal solutions based on function-based computation compared to GBRT, and the regular term on the right side of the computation process penalizes the non-singularity of the tree and reduces the occurrence of overfitting [19]. By introducing function-based computation, the objective function equation (2) results in:

$$\hat{\theta}_J \approx \arg\min_{\theta_j}\left\{\sum_{i=1}^{N} L\left[y_i, \hat{y}_i^{(j-1)} + vg_i^{(j)} f_j(x_i;\theta_j) + \frac{1}{2}v^2 h_i^{(j)} f_j^2(x_i;\theta_j)\right] + \gamma M_j + \frac{1}{2}\lambda \sum_{k=1}^{M_j} (w_k^{(j)})^2\right\} \tag{4}$$

where and are denoted as:

$$g_i^{(j)} = \frac{\partial L(y_i, \hat{y}_i^{(j-1)})}{\partial \hat{y}_i^{(j-1)}} = 2(\hat{y}_i^{(j-1)} - y_i) \tag{5}$$

$$h_i^{(j)} = \frac{\partial^2 L(y_i, \hat{y}_i^{(j-1)})}{(\partial \hat{y}_i^{(j-1)})^2} = 2 \tag{6}$$

Obviously, the greater the number sex of leaves, the longer the penalty period γ, and the larger γ indicates the greater the demand λ for simple structured trees, and the greater the desire for simple structured trees. Since it is a given sample and has been determined in step $j-1$, $j-1$ is an indeterminate constant. After finding each optimal tree, the XG Boost model completes its training and can be used for the final identification of consumer buying behavior patterns [20].

Before customers make purchasing behavior, the intuitive value of electric energy automobile products and services and consumption impulse consumer groups have certain subjective variability, by exploring the different dimensions of value factors in the perception of consumer purchasing behavior, it helps to predict the probability of the occurrence of purchasing behavior as well as to improve the electric energy automobile marketing strategy [21]. From the perspective of enterprises, the cost-effective needs of non-single users are analyzed to position the target group. Enterprises refine the value perception of user items in marketing activities. By optimizing the optimization marketing strategy to enhance the customer's purchase purpose, perfect the user's purchase behavior, highlight the user's trust, and realize the enterprise to create and deliver value [22].

2.2. Determination of Indicators of Perceived Variables of Consumer Purchasing Behavior

This paper evaluates the intuitive value from the aspects of performance, value, emotion and society of electric energy automobile respectively. Comprehensively considering the different points that electric energy vehicles possess for improvement and refinement, a total of 16 variable index items are obtained, and the variable indexes of consumer purchasing behavior perception are shown in Table 1, including the following:

1) Performance-price ratio contains the actual efficacy characteristics possessed by the product or service, and new energy vehicles belong to consumer durables, and there are certain differences between performance-price ratio and general commodities. The functional value in this paper mainly covers the brand value of electric energy vehicles, the overall service quality of the product, the safety, durability and reliability of the product, and whether or not the product appearance design complies with visual aesthetics and aerodynamics [23]. The core functional value is safety and reliability, which is an important factor that customers are willing to buy, and as an important marketing selling point for companies.

2) Value-price ratio contains the short-term or long-term benefits that consumers get from the cost savings they make when purchasing a product or service. Since new energy vehicles are large, high-priced consumer goods, the selling price of the product will be higher than the average product, consumers tend to be more rational when choosing to buy the product, and will measure the cost-effectiveness of the product in various aspects. Measurement of price value mainly includes the selling price of the product, the value of the product itself and the actual value of whether or not in line with the economy of the car and the cost of maintenance, as a consumable product of the value of the high and low rate of retention.

3) Preference value for money contains the degree of satisfaction of the user's emotional needs in the process of purchasing and using the product, is the project as well as the special effects of the service and can play a role in the customer's emotions. The innovation of new energy vehicles in terms of functionality makes consumers experience the process of generating pleasurable emotions [24]. Factors such as the environmental friendliness, comfort and safety of the product also affect the perceived value of the consumer. Therefore, the emotional value in this paper refers to the emotional state produced by consumers through driving, experiencing and perceiving new energy vehicles, which is reflected in the sense of pleasure, comfort and quiet self-compassionate emotions when using them, etc., and this emotional state largely reflects the consumer's attitude towards new energy vehicles.

4) The cost-effectiveness of the general environment is the purchase of products or services in the social group, which can improve the utility of the consumer's social self-concept. In the modern economy and society, consumers access to products and services is no longer limited to the use value of the product or service itself, but will also consider the added value of the product such as social attributes and cultural attributes [25]. For example, it can reflect the sense of responsibility for environmental protection, as well as as as a way to lead the trend of personalized product consumption and gain the admiration and praise of others. In this paper, the social value is assessed as the social recognition and approval obtained by purchasing new energy vehicles, their own social status and the sense of achievement in social contribution.

Table 1. Indicators of perceived variables of consumer purchasing behavior

Variant	Variable Identification	Variable Definition
Performance-price ratio A	Functional Value A1	New Energy Vehicle Premium Positioning
	Functional Value A2	Better brand service
	Functional Value A3	Technical performance of new energy vehicles is safe
	Functional Value A4	Stylish model with simple interior
Value for Money B	Price value B1	Higher value maintenance of new energy vehicles
	Price value B2	Price acceptable to consumers after subsidy
	Price Value B3	Lower cost of use and maintenance
	Price Value B4	New energy vehicle price and value are in line with each other
Preferred price/performance ratio C	Emotional Value C1	Pleasure of using electric vehicles
	Emotional Value C2	Quietness and comfort brought by electric vehicles
	Emotional Value C3	New Energy Vehicle promotes a sense of inner comfort
	Emotional Value C4	Electric cars increase enjoyment
Value for money in the wider environment D	Social Value D1	Electric cars increase the amount of praise for the user
	Social Value D2	Enhancement of the user's own favorable impression by the new energy vehicle
	Social Value D3	New energy vehicles increase the sense of fulfillment of the user's green contribution
	Social Value D4	New Energy Vehicles enhance users' sense of identity

2.3. *Feature recognition accuracy*

In order to test the effectiveness of the XG Boost algorithm to identify consumer purchasing behavior, the accuracy rate of the identified purchasing behavior characteristics is analyzed, if TP is the actual number of purchasing behavior characteristics identified correctly, FP is the number of not having purchasing behavior characteristics, and FN is the number of purchasing behavior characteristics that are not identified, and the formula for purchasing behavior characteristics identification accuracy rate is:

$$Accuracy = TP / (TP + FP + FN) \tag{7}$$

Among them, when the number of purchase behavior features not identified and the number of not having purchase behavior features are smaller, it proves that the effectiveness of the XG Boost algorithm model for consumer purchase behavior identification is better. It is necessary to rely on iterative training of the model in the process of purchasing behavior characteristics recognition to improve the recognition degree of consumer purchasing behavior characteristics. And eliminate the invalid users who do not have the purchase behavior characteristics to improve the accuracy of the XG Boost algorithm recognition and provide support for the subsequent consumer purchase perception division.

3. Research modeling and assumptions

3.1. *Data collection*

The relevant data in this paper are extracted from a database that covers sales data, network data, after-sales feedback data, and industry report data. The sales data includes data on the models, configurations, and regional sales volume of new energy vehicles. Network data includes data from automotive forums and various media platforms on vehicle models, usage experience, technological innovation, user satisfaction, and user expectations. After-sales feedback data includes data on performance, range, charging, etc. during user use. The industry report data package is consumer trend data analyzed through industry-related reports on consumer behavior of relevant structured new energy vehicles.

3.2. Relationship between research variables

Consumer purchase perception is an important factor influencing the purchase behavior, the high price of electric car sales, users will focus on the cost-effectiveness of the product while determining the purchase [26]. The performance-price-performance ratio, value-price-performance ratio, preference-price-performance ratio, and general environment-price-performance ratio mentioned above all have a positive positive effect on consumer purchasing behavior. The multidimensional aspects of purchase perception are also interrelated, and the four variable dimensions influence each other and are linked to each other, with any of the factors leading to changes in the other factors. In purchase decision making, users will analyze multiple factors together.

3.3. Research Model Design and Assumptions

Combined with the XG Boost algorithm, the consumer purchase perception dimensions of new energy vehicles, the theory of consumer purchase perception and purchase behavior is shown in Figure 1. The specific research hypothesis relationships are as follows:

H1: Performance-price-performance ratio has a significant positive effect on the purchase behavior pattern of electric energy vehicle users.

H2: Value-price ratio has a significant positive influence on the purchase behavior pattern of electric car users.

H3: Preference price-performance ratio has a significant positive effect on the purchasing behavior pattern of electric car users.

H4: There is a significant positive effect of general environment price-performance ratio on the purchasing behavior pattern of electric car users.

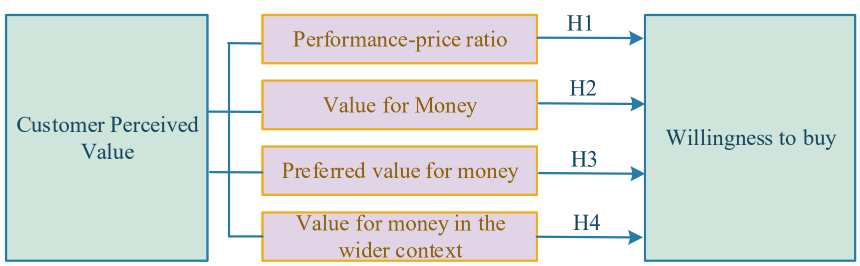

Fig. 1. Theory of Consumer Purchase Perception and Purchase Behavior

4. Marketing strategy results and analysis

4.1. Consumer Purchase Perception Factor Analysis

In order to effectively analyze the factor of consumer purchase perception, here is a decomposition of consumer purchase perception, divided into four factors: function, price, emotion and social value, to observe whether the sample is suitable for factor analysis, Table 2 shows the KMO and Bartlett's test. The KMO value is 0.891, which is greater than the general metric of 0.700, indicating that the correlation between the original variables is strong. Bartlett spherical test Sig. value test results are significant, all indicate that the sample is suitable for factor analysis.

Table 2. KMO and Bartlett test

KMO and Bartlett's test		
The Kaiser-Meyer-Olkin test for sampling adequacy		0.891
Bartlett's test of sphericity	Approximate chi-square	4107.064
	df	120

	Sig.	0.000

In order to determine that performance-price-performance, value-price-performance, preference-price-performance, and general environment-price-performance all show consistency in consumer purchase perceptions, the factor analysis of consumer purchase perceptions is shown in Table 3.CR denotes the characteristic root, and CEV% denotes the cumulative explanatory variance.The Cronbach's alpha coefficients are 0.891, 0.895, 0.813, and 0.800, respectively, and the overall Cronbach's alpha coefficient was 0.899, which was greater than 0.800, indicating that the overall scale had good internal consistency. In the process of factor extraction, principal component analysis was mainly used. The factor loadings were obtained by variance-maximizing orthogonal rotation, and the common factors were selected with the principle of factor extraction that the characteristic root was greater than 1. If the factor loadings are less than 0.5, the 16 items are synthesized into 4 common factors. The results show that the rotated factor loadings are all between 0.6 and 0.9, and the four male factors explain 71.228% of the total variance, which exceeds the minimum standard of 60% of the variance contribution rate, indicating that the scale has a good degree of explanation for the consumer purchase perception of new energy vehicles, and it has the ideal structural validity.

Table 3. Consumer Purchase Perception Factor Analysis

Consumer Purchase Perception Program	Factor loading	α	CR	Explanation of % variation	CEV %
New energy vehicle brands are more high-end A1	0.668	0.891	6.504	40.653	40.653
Pre-sales and after-sales services are more complete A2	0.759				
Quality of new energy vehicles is safe and reliableA3	0.854				
Beautiful appearance and stylish interior A4	0.764				
Higher value retention rate of new energy vehicles B1	0.834	0.895	2.095	13.096	53.749
Acceptable purchase price after subsidy B2	0.845				
Lower utilization and maintenance costs B3	0.769				
The price and value of new energy vehicles are in line with each other B4	0.834				
Pleasant feeling brought by new energy vehicles C1	0.833	0.813	1.546	9.662	63.411
New energy vehicles bring a sense of quiet comfort C2	0.835				
New energy vehicles promote a sense of inner comfort C3	0.839				
New energy vehicles increase the sense of enjoyment C4	0.842				
New energy vehicles increase the amount of praise from users D1	0.835	0.8	1.251	7.817	71.228
New energy vehicles enhance the user's own favorable impression D2	0.837				
New energy vehicles enhance users' sense of fulfillment of green contribution D3	0.852				
New energy vehicles enhance users' sense of identity D4	0.866				

4.2. *Validation of the relationship between the value of the four factors and consumer purchasing behavior*

Correlation analysis is used to study the relationship value between the consumption impulse and the performance-price-performance, value-price-performance, preference-price-performance, and general environment-price-performance, and the relationship value expressed by applying the relationship value calculation method. When the relationship value is in the range of [0,1], it means that the relationship value of each factor is positive. When the relationship value is 0, it indicates that the relationship value of each factor does not exist. When the relationship value takes the range of [-1,0], it indicates that the relationship value of each factor is negative. In this paper, the above mentioned factor loading values of diversification are used as the importance index, the mean value of each factor is calculated, and the correlation between each variable is shown in Table 4.

It can be found that the relationship value between the diversified factors is ⩾ 0 and the correlation is highlighted by a gap, indicating that the variables have a positive relationship value. The performance price-performance ratio, value price-performance ratio, preference price-performance ratio, general environment price-performance ratio and consumption impulse affect each other and the effect is prominent, the relationship value is 0.439, 0.406, 0.430, 0.387, respectively, are above 0. Therefore, the factors of consumer purchasing behavior are all refined out of the factors and the consumption impulse have a prominent relationship, in which the performance price-performance ratio has a prominent role in the effect of performance price-performance ratio. In the process of optimizing the development of marketing strategy, we should fully consider the needs of consumers for new energy vehicle technological innovation and functional comprehensiveness, and constantly add unique new technologies in the car to improve the original function. At the same time to create a more comfortable internal environment, strengthen the sound insulation effect of the car, to promote consumers in the car not only can sit comfortably, but also to keep the car quiet, to improve the degree of user pleasure.

Table 4. Correlation between variables

Variable Factor	Item	Functional value	Price value	Emotional value	Social Value	Purchasing Behavior
Functional value	Correlation coefficient	1	-	-	-	-
	P-value	-	-	-	-	-
Price value	Correlation coefficient	0.300**	1	-	-	-
	P-value	0.000	-	-	-	-
Emotional value	Correlation coefficient	0.351**	0.263**	1	-	-
	P-value	0.000	0.000	-	-	-
Social Value	Correlation coefficient	0.281**	0.261**	0.269**	1	-
	P-value	0.000	0.000	0.000	-	-
Purchasing Behavior	Correlation coefficient	0.439**	0.406**	0.430**	0.387**	1
	P-value	0.000	0.000	0.000	0.000	-

Note: *P < 0.05, **P < 0.01, ** represents significant correlation.

In order to cater to consumer preferences and market demand, the electric vehicle market needs to break away from the original inherent marketing model, the original low-priced output or high-priced high-end output into a cost-effective output, based on consumer purchasing behavior as the basis for the optimization of marketing strategy to promote new energy automobile enterprises to create products to meet the consumer's preferences and market demand, and to promote the optimization of marketing strategy for the embodiment of the effectiveness of the marketing strategy.

4.3. *Hypothesis validation*

The above verified that there is a prominent relationship between the factors of the four dimensions of this paper and consumer purchase behavior, and verified whether the hypotheses of this paper are valid according to the correlation results obtained. Factor extraction is carried out using principal component analysis and maximum variance rotation to obtain the factor rotation matrix, and a total of five factors are completed.A is the functional value, B is the price value, and C, D, and E are the emotional value, social value, and willingness to buy, respectively.T is the total, and Pv stands for the percentage of variance.The structural equation path variance test is shown in Table 5. The variance explained after rotation is 17.914%, 17.914%, 16.303%, 14.481%, 12.393%, respectively, and the cumulative variance contribution rate after rotation is 79.004%, which is greater than the minimum standard of 50%, which indicates that the constructed consumer behavioral pattern recognition is able to explain the information of the user samples of the new energy automobile enterprises well.

Table 5. Path variance test for structural equations

	Initial eigenvalue			Extract the sum of the squares of the loads			Rotating load sum of squares		
	T	Pv	C%	T	Pv	C%	T	Pv	C%
A1	6.932	36.484	36.484	6.932	36.484	36.484	3.404	17.914	17.914
A2	2.580	13.578	50.062	2.580	13.578	50.062	3.404	17.914	35.828
A3	2.352	12.379	62.44	2.352	12.376	62.440	3.097	16.303	52.130
A4	1.867	9.824	72.265	1.867	9.842	72.265	2.751	14.481	66.611
B1	1.280	6.739	79.004	1.280	6.739	79.004	2.355	12.393	79.004
B2	0.489	2.574	81.578	-	-	-	-	-	-
B3	0.462	2.433	84.011	-	-	-	-	-	-
B4	0.415	2.184	86.195	-	-	-	-	-	-
C1	0.383	2.015	88.210	-	-	-	-	-	-
C2	0.326	1.715	89.925	-	-	-	-	-	-
C3	0.302	1.589	91.514	-	-	-	-	-	-
C4	0.245	1.290	92.804	-	-	-	-	-	-
D1	0.232	1.233	94.026	-	-	-	-	-	-
D2	0.215	1.133	95.160	-	-	-	-	-	-
D3	0.208	1.095	96.254	-	-	-	-	-	-
D4	0.201	1.056	97.311	-	-	-	-	-	-
Y1	0.191	1.007	98.318	-	-	-	-	-	-
Y2	0.166	0.873	99.191	-	-	-	-	-	-
Y3	0.154	0.809	99.196	-	-	-	-	-	-

In this paper, AMOS software is used to test the fit indicators of the research data, and Table 6 shows the fit indicators of structural equation modeling, and the fit values, if they are all within the standard requirements, indicate that it is feasible to use structural equation modeling to verify the relevant hypothetical problems.

Table 6. Fit metrics for structural equation modeling

Goodness-of-fit metrics	Recommended Value	Fitted value
Cardinal degrees of freedom ratio (CMIN/df)	<3.0	1.208
Goodness-of-fit index (GFI)	>0.9	0.967
Adjusted Goodness of Fit Index (AGFI)	>0.9	0.955
Root Mean Square of Approximation Error (RMSEA)	<0.1	0.02
Normative Fit Index (NFI)	>0.9	0.976
Value Added Fit Index (IFI)	>0.9	0.996
Comparative Fit Index (CFI)	>0.9	0.996

The standardized loadings, AVE values and CR values of each factor are shown in Table 7, the AVE values of the sample data are all greater than 0.5, implying that the intrinsic quality of the preset model is ideal, and the CR values are all greater than 0.7, indicating that the data are internally consistent and have a high degree of aggregation validity. The path coefficients of functional value, price value, emotional value, and social value on purchase intention are all greater than 0 and show high significance $p=0.000<0.001$, thus indicating that functional value, price value, emotional value, and social value all have a significant positive relationship on purchase intention. In the marketing strategy, innovative technology, powerful functions, comfortable and quiet environment, reasonable price, and honor and respect as the main promotional points, to fully cater to the needs of consumers, in order to promote the effectiveness of the marketing strategy, and improve the marketing volume.

Table 7. Standardized loadings, AVE values and CR values for each factor

Variant	Variable identification	Standard load factor	AVE	CR
Functional Value A	A1	0.756	0.561	0.836
	A2	0.721		
	A3	0.747		
	A4	0.771		
Price Value B	B1	0.788	0.685	0.897
	B2	0.766		
	B3	0.878		
	B4	0.873		
Emotional Value C	C1	0.885	0.795	0.939
	C2	0.872		
	C3	0.916		
	C4	0.894		
Social Value D	D1	0.917	0.790	0.938
	D2	0.887		
	D3	0.883		
	D4	0.867		
Willingness to buy Y	Y1	0.886	0.743	0.896
	Y2	0.826		
	Y3	0.872		

5. Conclusion

This paper analyzes the relationship between consumers' perception of purchasing behavior and marketing on the basis of optimizing and perfecting marketing strategies to enhance customers' purchasing motivation and promote customers' purchasing behavior. And the consumer buying behavior perception is divided into four dimensions: performance-price-performance ratio, value-price-performance ratio, preference-price-performance ratio, and general environment-price-performance ratio. The validation found that the rotated factor loadings were all between 0.6 and 0.9, and the four male factors explained 71.228% of the total variance, which exceeded the minimum standard of 60% of the variance contribution rate, and had a better degree of explanation for the consumer purchase perceptions of new energy vehicles with ideal structural validity. The correlation coefficient values of the factors on purchase intention are 0.439, 0.406, 0.430, 0.387 which are all greater than 0. There is a strong positive correlation between the four factors and purchase intention, and the cumulative variance contribution rate after rotation is 79.004%, which is more than the standard requirement of 50%, and the hypotheses H1-H4 are all valid. The research in this paper proves that there is a prominent relationship between consumer purchasing behavior pattern recognition and users' consumption impulse of electric energy vehicles, and through consumer purchasing behavior pattern recognition, the value recognition of electric energy vehicle products is strengthened, while the marketing strategy of electric energy vehicle enterprises is improved.

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