Driving Consumer Demand and Market Expansion for Carbon-Labeled Products in Shandong's Key Industries Under Evolving Global Green Trade Regulations

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Abstract: Amid global carbon neutrality efforts, carbon labels have become key tools to address green trade barriers. This study examines Shandong's key industries, integrating environmental economics and behavioral science to analyze consumption drivers of carbon-labeled products. Findings show carbon labels enhance purchase intention through multidimensional values with green perceived value as a key mediator. High-income, educated groups show stronger willingness-to-pay, though consumption inertia remains a barrier. A "standards-industry-product-consumption" framework is proposed, recommending provincial carbon label standards and smart accounting systems to align with international norms.

Keywords: Carbon Label; Consumption-Driven Mechanism; Shandong Key Industries; Market Breakthrough; New International Trade Regulations

1. Introduction

1.1 Research Background

1.1.1 Global trade carbon barriers and the general trend of domestic dual carbon strategy

Global carbon tariffs and carbon border adjustment mechanisms have accelerated the formation of green trade barriers, and carbon labels have become a " passport " for international trade. Under China 's " double carbon " goal, Shandong, as a major province of industry and foreign trade, urgently needs to promote low-carbon transformation of key industries through carbon label products, crack green barriers and enhance international competitiveness.

1.1.2 Green development demand and industrial upgrading pressure in Shandong Province

Shandong 's traditional industries account for more than 60 %, and high-carbon industries such as steel and chemical industries are facing pressure to reduce emissions. Although 323 carbon market trading enterprises lead the country, the promotion of carbon labels is still restricted by the lack of standards and the lack of motivation of enterprises. For example, Zibo Chemical 's dependence on coal leads to low added value of products, and it needs to use carbon labels to force technological upgrading.

1.1.3 Policy support and strategic guidance

In 2024, Shandong revised the carbon emission substitution policy of the " two highs " project, introduced the first provincial carbon label technical specification in China, established a certification system, and carried out carbon footprint certification pilots in industries such as tires and electrolytic aluminum, supplemented by fiscal and tax incentives to build a carbon label system framework.

1.1.4 Consumer awareness of environmental protection and market demand change

The demand for low-carbon consumption in cities such as Jinan and Qingdao has increased significantly, and the sales volume of carbon label products on e-commerce platforms has increased by 15 % annually. Consumers have shifted from functional orientation to environmental protection considerations, forming a ' market-driven industry ' mechanism. The case of Zibo Chemical Industry confirms that carbon labels can link the consumer side and the production side to promote green upgrading.

1.2 Research Review

1.2.1 Domestic research review

Domestic scholars have conducted multi-dimensional research on the impact of carbon labels on consumer behavior. Huang (2023) pointed out that carbon label can effectively guide consumers to form green consumption behavior by strengthening the transmission of product environmental attributes, and provide reference for enterprise market strategy[1]. Zhao (2024) further emphasized that carbon labels promote the penetration of environmentally friendly products into the mainstream market while enhancing consumers ' awareness of low carbon[2]. In terms of specific impact mechanism, Zeng (2024) found that carbon labels significantly enhanced consumers ' willingness to pay premiums based on a survey in Chengdu and Chongqing[3], while Ding (2024) proposed that a standardized carbon label system can help consumers identify environmental advantages, and suggested that companies achieve premium sales through brand building[4]. In addition, Qu (2025) and Nie (2024) focused on the influencing factors, pointed out that information transparency, social incentives and corporate responsibility cognition were the key driving forces[5], and called for the establishment of a unified carbon footprint management system to enhance consumer trust and provide theoretical support for policy formulation[6].

1.2.2 International research review

International research combines case studies and theoretical models to reveal the cross-cultural impact of carbon labels. Suchier (2023) proposed that traffic light labels combined with social norms can effectively improve the willingness to pay and open up new ideas for differentiated pricing strategies[7]. In terms of behavioral mechanism, Roa-Goye (2024) verified that carbon neutral labels promote purchase decisions by enhancing sustainability trust based on UTAUT theory[8], while Nguyen (2024) took Vietnam as an example and pointed out that carbon labels guide sustainable consumption by reducing choice uncertainty[9]. Pink (2025) further emphasize the moderating role of socio-cultural background, such as the differential impact of social expectations, environmental responsibility and information transparency on transnational consumer behavior, and provide theoretical support for global market strategy[10].

1.3 Research Method

1.3.1 Literature analysis

By consulting the academic literature, policy documents and industry reports on carbon labeling, green consumption and low-carbon economy, this paper sorts out the research results and practical experience in related fields, and provides a solid theoretical basis and policy background for the research. This helps to deeply understand the market status, consumer behavior characteristics and policy support system of carbon label products, so as to design a reasonable research framework and analysis model for subsequent empirical research.

1.3.2 SEM

SEM is a multivariate statistical analysis method for analyzing complex causality, which can simultaneously deal with the relationship between multiple dependent variables and independent variables. In this study, SEM is used to verify the influencing factor model of purchase intention of carbon label products, and to explore how variables such as quality value, environmental value, brand image value, health value, economic value and social value directly affect the purchase intention of carbon label products, and how these variables indirectly affect the purchase intention through the intermediary variable of green perceived value. By constructing and fitting the structural equation model, we can test the research hypothesis, evaluate the goodness of fit of the model and the path coefficient between variables, so as to reveal the mechanism of each factor on the purchase intention of carbon label products.

1.3.3 Mediating effect test

This study uses Bootstrap method to test the mediating effect of green perceived value in the influencing factors of purchase intention of carbon label products. Bootstrap method is a nonparametric resampling technique, which generates a large number of samples through multiple random sampling, so as to estimate the sampling distribution and standard error of statistics.

In the mediating effect test, the Bootstrap method can be used to calculate the confidence interval of the mediating effect and judge the significance of the mediating effect. Specifically, through multiple re-sampling of the data, the confidence interval of the mediating effect is constructed. If the confidence interval does not contain zero, it indicates that the mediating effect is significant. This helps to verify whether green perceived value plays a partial or complete mediating role between variables such as quality value and environmental protection value and purchase intention of carbon label products, so as to understand the formation mechanism of purchase intention of carbon label products more comprehensively. However, when testing the mediating effect, it is more commonly used to test through VAF. The calculation formula of VAF is as follows:

$$VAF = \frac{mesomeric\ effect}{gross\ effect} \tag{1}$$

1.3.4 Multiple Logistics regression

Multiple Logistics regression is a statistical method used to analyze the influence of multiple independent variables on a dependent variable, which is suitable for the case where the dependent variable is a categorical variable. In this study, multivariate Logistics regression is used to analyze the impact of consumer characteristics on the purchase intention of carbon label products. By taking the purchase intention of carbon label products as the dependent variable and taking the demographic characteristics and socio-economic characteristics of consumers as the independent variables, the regression model can be established to estimate the regression coefficient of each characteristic variable on the purchase intention, and to judge which characteristic factors have significant influence on the purchase intention, as well as the direction and degree of influence. This helps to understand the differences in the purchase behavior of carbon label products among different consumer groups, and provides a basis for formulating targeted marketing strategies.

1.3.5 Cluster analysis

Clustering analysis is an unsupervised learning method, which is used to divide the samples in the data set into several clusters, so that the similarity of samples in the same cluster is higher, while the similarity of samples between different clusters is lower. The purpose of clustering analysis is to discover the natural grouping structure in the data and help to understand the distribution and characteristics of the data.

In order to understand the group characteristics of carbon label product buyers, in order to better select sales strategies for different groups of people, this paper will use SPSS27.0 to cluster the data of carbon label product buyers. Through the R-type and second-order clustering of variables and cases, the five variables of consumer purchase motivation, exchange product attributes, disposable income, education level and purchase intention are clustered to analyze the population characteristics of consumers.

2. The Application and Challenges of Carbon Label Products in Key Industries in Shandong Province

2.1 Application Status of Carbon Labels

2.2.1 Electrolytic aluminum industry

Shandong Zou ping has prioritized low-carbon transformation across industries, transportation, and parks to establish a green aluminum value chain. It phased out nearly one-third of electrolytic aluminum capacity, expanded recycled aluminum production to over 1 million tons annually, and launched a mass-produced all-aluminum lightweight vehicle base, forming a comprehensive industrial chain spanning "aluminum liquid, lightweight component R&D, manufacturing, and vehicle assembly."

Shandong Innovation Group pioneered China’s inaugural "enterprise carbon label" initiative, enabling carbon emission traceability by labeling production-phase emissions on aluminum rods, strips, foil, cables, hubs, and other products.

2.2.2 Electronic and electrical industry

As one of the important pillars of the global economy, the electronic and electrical industry is particularly concerned about its low-carbon development status and future prospects. The key to the low-carbon transformation of the industry is the energy conservation and carbon reduction of enterprises in the production process.

Hisense Video Technology Co, Ltd. (hereinafter referred to as " Hisense Video"), as one of the leading enterprises in the electronics industry, has made reforms and technological breakthroughs in the green production of products, and won the award of low-carbon product suppliers. In 2022, 80L9H laser TV produced by Hisense Video will receive a product carbon label.

2.2.3 Construction industry

The construction industry accounts for over one-third of global carbon emissions, positioning it as a critical sector for China's "Dual Carbon" goals. The Beijing Winter Olympics exemplified green building potential through low-carbon venue design and eco-operational practices. Bond Technology Group advanced industry transformation by developing the Q235 multifunctional coated metal panel, which obtained China's first construction-sector product carbon label certification in February 2024. The group further led the formulation of China's inaugural national standard atlas for low-carbon multifunctional coated metal panel applications, jointly released with China Wuzhou Engineering Design Group in May 2022. This standardization framework drives industry-wide adoption of low-carbon technologies, accelerating progress toward zero- and negative-carbon building energy efficiency targets.

2.2 Existing Issues

2.2.1 Policy side: the institutional framework needs to be improved, and the international docking has shortcomings

The fragmentation of the standard system and the lack of industry coverage. Although Shandong Province has started the national pilot of carbon footprint identification certification for electrolytic aluminum and tire products.

The absence of international mutual recognition mechanism and compliance risks. The EU Carbon Border Adjustment Mechanism CBAM requires that export products comply with its carbon footprint accounting rules such as product digital passport DPP. However, there are technical differences between Shandong 's current standards and the EU 's such as the calculation method of electricity emission factor, which leads to the risk of increased carbon tariff costs for export enterprises.

2.2.2 Product side: technical bottlenecks restrict accounting efficiency and credibility

The whole life cycle accounting cost is high. Carbon footprint accounting needs to cover the whole chain, with complex technology and high cost. Taking Zheng da Egg Industry as an example, egg carbon labeling needs to integrate multi-link data such as feed processing and breeding, and small and medium-sized enterprises generally lack professional teams and equipment investment capabilities. Zhang et al pointed out that the complexity of data collection and calculation further increases the burden on enterprises[11].

The data base is weak and the standard is missing. Shandong carbon footprint factor database is not yet perfect, textile, electronics and other industries rely on estimation data, resulting in accounting deviation. At present, only a few industries such as steel and electrolytic aluminum have completed the standard formulation, and the textile industry faces quantitative problems due to complex processes. Bai et al emphasized that the national standard ' Requirements and Guidelines for Carbon Footprint Quantification of Greenhouse Gas Products ' is still in the consultation stage[12], and enterprises lack unified methodological guidance, resulting in large differences in accounting results and low comparability.

2.2.3 Industrial side: the absence of coordination mechanism and the lag of technology application

Industrial chain carbon management is out of touch: carbon label promotion needs industrial chain coordination, but some industries in Shandong have ' data islands '. Taking the tire industry as an example, although it is included in the national pilot, the carbon data collection ability of upstream rubber enterprises is weak, which restricts the accuracy of the whole chain accounting.

The application of digital technology lags behind: tools such as the Internet of Things and blockchain are only piloted in large enterprises such as Rizhao Iron and Steel, and small and medium-sized enterprises generally lack intelligent platforms for carbon management. Compared with the EU product digital passport DPP system, the construction of carbon data traceability and sharing mechanism in Shandong supply chain lags behind, which affects the competitiveness of international supply chain. Li et al pointed out that poor data flow, difficulties in the transformation of small and medium-sized enterprises and the lack of sharing mechanisms are the main reasons for the low penetration rate of digitization[13].

2.2.4 Consumption side: cognitive gap and lack of market incentives

Consumers ' low-carbon awareness is weak. Zhang Shaoqing 's research shows that consumers ' cognitive, psychological, subjective norms and policy incentives affect low-carbon consumption willingness together, among which cognitive factors are one of the core conditions[14]. However, only a small number of consumers understand the meaning of carbon labels, and very few people are willing to pay a premium for low-carbon products, which is consistent with the research results on the driving factors of low-carbon consumption willingness.

The market feedback mechanism is not perfect. The existing carbon inclusive mechanism has shortcomings in encouraging consumers ' low-carbon behavior, such as single incentive method and lack of long-term effective incentive measures. This leads to insufficient linkage between low-carbon products and carbon inclusive mechanisms, and it is difficult to form effective market feedback and consumption-driven. For example, Shandong 's carbon credit mechanism covers green travel, power saving and other fields, but it does not form a price linkage with carbon label goods, which affects the market incentive effect.

3. Research on the Consumption Driving Factors of Carbon Label Products in Key Industries of Shandong Province

3.1 Quality Analysis

3.1.1 Normality test

According to mediation effect testing requirements, data normality must be verified. Using thresholds of skewness coefficient (absolute value <2) and kurtosis coefficient (<7) as criteria **(Table 1)**, SPSS25 analysis revealed that all questionnaire scale items exhibited skewness (range: 0.12-1.85) and kurtosis (range: 0.03-5.91) within acceptable limits. This confirms that the data conforms to a normal distribution, satisfying the prerequisites for mediating effect analysis.

Table 1. Normality Test of Questionnaire Topic Data

	N	min	max	mean	standard deviation	skewness	kurtosis
Q1	615	1	5	3.07	1.437	-0.058	-1.343
Q2	615	1	5	2.88	1.124	0.107	-0.595
Q3	615	1	5	2.88	1.158	0.015	-0.774
Q4	615	1	5	2.89	1.085	0.061	-0.504
Q5	615	1	5	2.85	1.105	0.105	-0.646
Q6	615	1	5	2.91	1.138	-0.004	-0.627
Q7	615	1	5	3.05	1.382	-0.012	-1.214
Q8	615	1	5	2.83	1.039	0.054	-0.399
Q9	615	1	5	2.87	1.094	0.098	-0.515
Q10	615	1	5	2.85	1.094	0.099	-0.645
Q11	615	1	5	2.84	1.075	0.136	-0.592
Q12	615	1	5	2.9	1.038	-0.018	-0.46
Q13	615	1	5	3.02	1.395	-0.085	-1.236
Q14	615	1	5	2.87	1.093	0.109	-0.573
Q15	615	1	5	2.86	1.109	0.042	-0.631
Q16	615	1	5	2.89	1.098	0.02	-0.553
Q17	615	1	5	2.89	1.106	0.072	-0.632
Q18	615	1	5	2.83	1.135	0.121	-0.644
Q19	615	1	5	3.07	1.457	-0.05	-1.374
Q20	615	1	5	2.82	1.087	0.04	-0.586
Q21	615	1	5	2.87	1.088	0.074	-0.566
Q22	615	1	5	2.95	1.083	0.04	-0.475
Q23	615	1	5	2.87	1.117	0.16	-0.526
Q24	615	1	5	2.86	1.113	0.175	-0.665
Q25	615	1	5	3.14	1.442	-0.157	-1.295
Q26	615	1	5	2.88	1.095	0.099	-0.594
Q27	615	1	5	2.92	1.093	0.018	-0.619
Q28	615	1	5	2.9	1.137	0.079	-0.724

Q29	615	1	5	2.9	1.118	0.017	-0.692
Q30	615	1	5	2.92	1.128	0	-0.711
Q31	615	1	5	2.96	1.381	0.048	-1.236
Q32	615	1	5	2.78	0.994	-0.001	-0.631
Q33	615	1	5	2.73	1.002	0.016	-0.478
Q34	615	1	5	2.77	1.045	0.05	-0.583
Q35	615	1	5	2.81	1.03	0.125	-0.365
Q36	615	1	5	2.93	1.383	0.044	-1.25
Q37	615	1	5	2.85	1.098	0.05	-0.664
Q38	615	1	5	2.81	1.041	0.119	-0.483
Q39	615	1	5	2.71	1.075	0.133	-0.648
Q40	615	1	5	2.81	1.084	0.05	-0.61
Q41	615	1	5	2.78	1.072	0.177	-0.49
Q42	615	1	5	3.66	1.246	-0.918	-0.07
Q43	615	1	5	3.73	1.246	-0.955	0.024
Q44	615	1	5	3.67	1.252	-0.915	-0.054
Q45	615	1	5	3.72	1.22	-0.961	0.132
Q46	615	1	5	3.68	1.247	-0.887	-0.118
Q47	615	1	5	3.69	1.279	-0.914	-0.143
Q48	615	1	5	2.98	1.384	0.029	-1.271
Q49	615	1	5	2.72	1.018	0.167	-0.43
Q50	615	1	5	2.73	1.029	0.053	-0.534
Q51	615	1	5	2.68	1.028	0.007	-0.612
Q52	615	1	5	2.78	1.051	0.016	-0.639

Table 2. Topic Data Reliability Test of Questionnaire

Measure index	Reliability
Quality Value	0.892
Environmental Value	0.877
Brand image Value	0.890
Health Value	0.888
Economic Value	0.895
Social Value	0.852
Green perceived Value	0.883
User Characteristics	0.854
Carbon label product purchase intention	0.860

3.1.2 Reliability test

This study employs Cronbach's Alpha (α) to assess questionnaire reliability, a widely used internal consistency metric for Likert-scale analysis. The overall scale (35 items) demonstrated excellent reliability (α = 0.907), while all subscales exceeded α > 0.8 (**Table 2**), confirming high consistency and validity.

3.1.3 Validity test

In order to measure the validity of each item, this paper adopts two methods: Bartlett spherical research design and questionnaire test and KMO sample measurement. KMO is one of the test indexes of validity analysis. The value of KMO statistic is between 0 and 1. The larger the value is, the more suitable the sample data is for principal component analysis and factor analysis. Generally, the value is required to be greater than 0.5.

After testing, **Table 3** shows that the KMO value of the main part of the questionnaire is 0.904, which is very suitable for factor analysis.

Table 3. Official Investigation of KMO And Bartlett Verification 1

KMO sampling suitability quantity		.904
Bartlett sphericity test	Approximate chi-square	17616.565
	Degree of freedom	1326
	Significance	.000

Firstly, factor analysis is carried out on the quality value, environmental protection value, brand image value, health value, economic value and social value. From **Table 4**, the KMO value is 0.895, which shows that it is suitable for factor analysis. The significance of Bartlett 's sphericity test was 0.000, indicating that the data had a strong correlation.

Table 4. Official Investigation of KMO And Bartlett Verification 2

KMO sampling suitability quantity		.895
Bartlett sphericity test	Approximate chi-square	11939.165
	Degree of freedom	595
	Significance	.000

Next, the factor rotation of the above factors is carried out, and the principal component analysis method is selected. The load value of each problem option factor is shown in the **Table 5**. It can be seen that the selected value factor analysis results produce 6 factors, of which the weight of each factor is above 0.7, indicating that the item setting in this part is reasonable. Therefore, it is reasonable to divide customer perceived value into quality value, environmental protection value, brand image value, health value, economic value and social value.

Table 5. Official Survey Factor Loading Value 1

	component					
	1	2	3	4	5	6
Q1		0.901				
Q2		0.740				
Q3		0.751				
Q4		0.734				
Q5		0.762				
Q6		0.759				
Q7					0.903	
Q8					0.708	
Q9					0.727	
Q10					0.706	
Q11					0.749	
Q12					0.739	
Q13			0.901			
Q14			0.731			
Q15			0.760			
Q16			0.747			
Q17			0.750			
Q18			0.749			
Q19				0.915		
Q20				0.764		
Q21				0.765		
Q22				0.719		
Q23				0.738		
Q24				0.752		
Q25	0.911					
Q26	0.739					
Q27	0.768					
Q28	0.764					
Q29	0.775					
Q30	0.759					
Q31						0.928
Q32						0.744
Q33						0.761
Q34						0.748
Q35						0.760

Next, the factor analysis of green perceived value, user characteristics and purchase intention of carbon label products is continued. The KMO value of 0.877 can be obtained from **Table 6**, indicating that the questionnaire data is more suitable for factor analysis. The significance of Bartlett 's sphericity test was 0.000, indicating that the data had a strong correlation.

Principal component analysis with factor rotation was conducted on green perceived value, user characteristics, and carbon-labeled product purchase intention. A single factor was extracted, with all item loadings exceeding 0.7

(Table 7), demonstrating robust construct validity of the measurement items.

3.1.4 Correlation analysis

Firstly, multiple items in each measurement index of the questionnaire subject scale are merged into a comprehensive variable, and then standardized. The comprehensive score of each index is standardized to the range of 1-5. The higher the value is, the higher the consumer 's compliance with the item is. **Table 8** is the descriptive statistical analysis of each key data, and it can be concluded that the average degree of conformity of user characteristics is the highest.

Table 6. Official Investigation of KMO and Bartlett Verification 3

KMO sampling suitability quantity		.877
Bartlett sphericity test	Approximate chi-square	4869.886
	Degree of freedom	136
	Significance	.000

Table 7. Official Survey Factor Loading Value 2

	component		
	1	2	3
Q36	0.914		
Q37	0.747		
Q38	0.748		
Q39	0.755		
Q40	0.740		
Q41	0.741		
Q42		0.754	
Q43		0.762	
Q44		0.765	
Q45		0.772	
Q46		0.738	
Q47		0.762	
Q48			0.915
Q49			0.732
Q50			0.750
Q51			0.734
Q52			0.754

Table 8. Descriptive Statistics

Measure index	N	min	max	mean	standard deviation
Quality Value	615	1	5	2.9979	0.99328
Environmental Value	615	1	5	2.9744	0.92530
Brand image Value	615	1	5	3.0646	1.01714
Health Value	615	1	5	3.0788	1.01759
Economic Value	615	1	5	2.8515	0.99415
Social Value	615	1	5	2.7857	0.96845
Green perceived Value	615	1	5	2.8805	1.02790
User Characteristic	615	1	5	3.6927	0.94872
Carbon label product purchase intention	615	1	5	2.7785	0.88971

Table 9. Correlation Analysis of Questionnaire Topic Data

		QV	EVV	BIV	HV	ECV	SV	GV	UC	PI
QV	pearson correlation	1	.315**	.301**	.295**	.284**	-.049	.289**	.021	.489**
	Sig.（double-tailed）		.000	.000	.000	.000	.225	.000	.602	.000
EVV	pearson correlation	.315**	1	.326**	.272**	.270**	.088*	.348**	-.074	.410**
	Sig.（double-tailed）	.000		.000	.000	.000	.028	.000	.066	.000
BIV	pearson correlation	.301**	.326**	1	.297**	.275**	.020	.253**	.019	.361**
	Sig.（double-tailed）	.000	.000		.000	.000	.621	.000	.640	.000
HV	pearson correlation	.295**	.272**	.297**	1	.254**	.033	.257**	-.115**	.423**
	Sig.（double-tailed）	.000	.000	.000		.000	.412	.000	.004	.000
ECV	pearson correlation	.284**	.270**	.275**	.254**	1	.014	.304**	-.067	.353**
	Sig.（double-tailed）	.000	.000	.000	.000		.738	.000	.096	.000
SV	pearson correlation	-.049	.088*	.020	.033	.014	1	.031	.012	.064
	Sig.（double-tailed）	.225	.028	.621	.412	.738		.438	.762	.114
GV	pearson correlation	.289**	.348**	.253**	.257**	.304**	.031	1	-.089*	.424**
	Sig.（double-tailed）	.000	.000	.000	.000	.000	.438		.027	.000
UC	pearson correlation	.021	-.074	.019	-.115**	-.067	.012	-.089*	1	-.072
	Sig.（double-tailed）	.602	.066	.640	.004	.096	.762	.027		.076
PI	pearson correlation	.489**	.410**	.361**	.423**	.353**	.064	.424**	-.072	1

	Sig.（double-tailed）	.000	.000	.000	.000	.000	.114	.000	.076	
** At the 0.01 level (double tail), the correlation is significant. * At the 0.05 level (two-tailed), the correlation is significant.										

Correlation analysis revealed key relationships (**Table 9**): Purchase intention for carbon-labeled products showed moderate positive correlations with quality value (r=0.489), health value (r=0.423), and green perceived value (r=0.424), indicating consumer prioritization of functionality, health benefits, and environmental credibility. Economic value (r=0.353) had weaker yet significant influence, while environmental value (r=0.410) likely operates indirectly through green perceived value (r=0.348), suggesting environmental attitudes require product-level green attribute recognition to drive behavior. Notably, social value (r=0.064) showed no significant association, reflecting respondents' focus on personal utility over social signaling

3.2 Analysis of Consumer Decision-Making Mechanism

3.2.1 PLS-SEM fitting

Based on theoretical analysis and model correction, this paper identifies eight potential variables: quality value, environmental value, brand image value, health value, economic value, social value, green perceived value and carbon label purchase intention. Each potential variable corresponds to multiple observation variables. Among them, green perceived value plays an intermediary role in the structural model. The following figure 1 is the path map of the structural model of carbon label product purchase intention drawn by SmartPLS3.2 software.

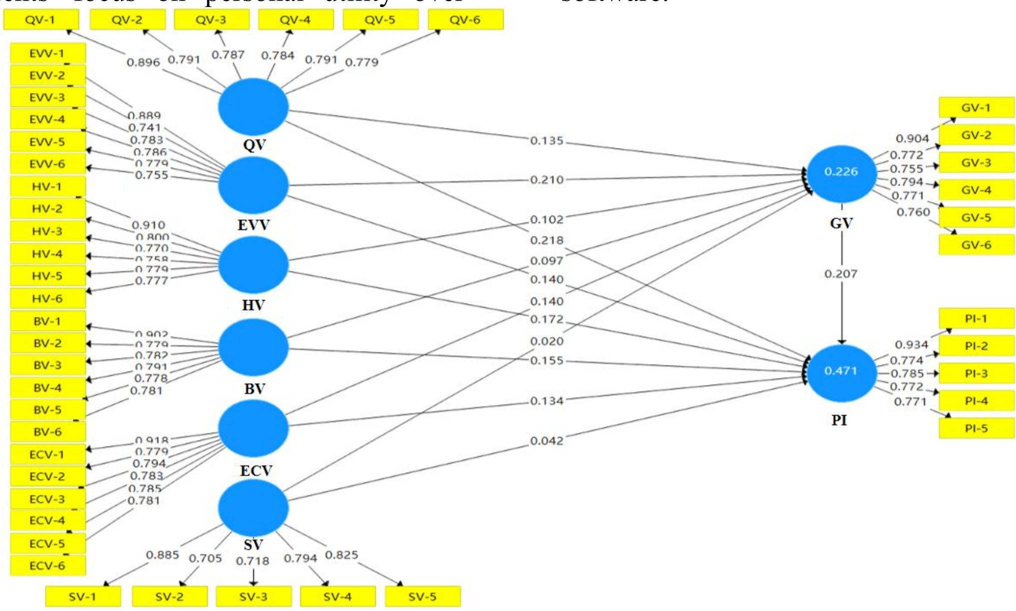

Figure 1. PLS-SEM Model of Influencing Factors of Purchase Intention of Carbon Label Products

Table 10. Model Reliability Test

	Cronbach's Alpha	*composite reliability*
QV	0.887	0.914
BV	0.889	0.916
EVV	0.879	0.909
PI	0.867	0.905
SV	0.853	0.891
ECV	0.893	0.918
GV	0.882	0.911
QV	0.891	0.917

With the help of software Smart PLS 3.2, this paper will test the reliability, validity, discriminant validity and significance of path coefficient of the constructed structural model.

As shown in **Table 10**, all eight variables demonstrated Cronbach's Alpha and composite reliability (CR) values exceeding 0.7, confirming strong internal consistency and temporal stability of the measurement model. These results validate the reliability of the survey data in accurately capturing latent variable characteristics across contexts.

Table 11. Model Convergent Validity Test

	AVE
QV	0.641

BV	0.646
EVV	0.625
PI	0.656
SV	0.622
ECV	0.653
GV	0.631
QV	0.649

As can be seen from **Table 11**, the average extracted variation value (AVE) of the eight factors is greater than 0.6, reflecting that more than 60 % of the variation explained by each variable comes from the topic in the variable, indicating that the measurement model has good convergence validity. The measurement indicators selected in this paper can better reflect their corresponding potential variables, that is, the problems selected by our team can well reflect the corresponding value

Table 12. Model Factor Load

	BV		ECV		EVV		GV
BV-1	0.902	ECV-1	0.918	EVV-1	0.889	GV-1	0.904
BV-2	0.779	ECV-2	0.779	EVV-2	0.741	GV-2	0.772
BV-3	0.782	ECV-3	0.794	EVV-3	0.783	GV-3	0.755
BV-4	0.791	ECV-4	0.783	EVV-4	0.786	GV-4	0.794
BV-5	0.778	ECV-5	0.785	EVV-5	0.779	GV-5	0.771
BV-6	0.781	ECV-6	0.781	EVV-6	0.755	GV-6	0.760
	HV		PI		QV		SV
HV-1	0.910	PI-1	0.934	QV-1	0.896	SV-1	0.885
HV-2	0.800	PI-2	0.774	QV-2	0.791	SV-2	0.705
HV-3	0.770	PI-3	0.785	QV-3	0.787	SV-3	0.718
HV-4	0.758	PI-4	0.772	QV-4	0.784	SV-4	0.794
HV-5	0.779	PI-5	0.771	QV-5	0.791	SV-5	0.825
HV-6	0.777			QV-6	0.779		

It can be seen from **Table 12** that the measurement indicators selected by the team have good convergence validity in measuring 8 kinds of values, and the factor loads of all indicators are higher than 0.70, indicating that the observed variables have strong correlation with their corresponding potential variables, which can reflect the characteristics of value and have good representativeness.

From the difference validity test data of **Table 13**, it can be seen that most of the differences between variables belong to the interval [0.3,0.4].Among them, the difference validity between quality value and social value is the lowest, which is − 0.011, and the difference validity between quality value and purchase intention is the highest, which is 0.492.In general, the difference validity between values is good, indicating that each potential variable has a unique measurement dimension, which can effectively distinguish different concepts and phenomena, and further verify the rationality of model construction.

Table 13. Distinguishing Validity

	HV	BV	EVV	PI	SV	ECV	GV	QV
HV	0.801							
BV	0.313	0.804						
EVV	0.314	0.358	0.790					
PI	0.431	0.444	0.457	0.810				
SV	0.058	0.064	0.110	0.091	0.788			
ECV	0.281	0.320	0.328	0.418	0.032	0.808		
GV	0.281	0.299	0.375	0.470	0.058	0.315	0.794	
QV	0.314	0.355	0.371	0.492	-0.011	0.339	0.327	0.806

Table 14. PLS-SEM Model Path Effect

	path coefficient	standard deviation	t ratio	P ratio
HV→PI	0.172	0.029	5.992	0.000
HV→GV	0.102	0.032	3.156	0.002
BV→PI	0.155	0.029	5.310	0.000
BV→GV	0.097	0.035	2.811	0.005

EVV→PI	0.140	0.029	4.783	0.000
EVV→GV	0.210	0.035	5.951	0.000
SV→PI	0.042	0.024	1.749	0.081
SV→GV	0.020	0.032	0.614	0.539
ECV→PI	0.134	0.027	4.897	0.000
ECV→GV	0.140	0.032	4.324	0.000
GV→PI	0.207	0.028	7.284	0.000
QV→PI	0.218	0.029	7.549	0.000
QV→GV	0.135	0.036	3.769	0.000

Quality, environmental, brand image, health, and economic values significantly enhanced green perceived value (Environmental: *t*=5.951; Economic: *t*=4.324; see **Table 14**), whereas social value showed no effect, confirming consumer prioritization of intrinsic product attributes over external social factors. Purchase intention was most influenced by quality (*t*=7.549), health (*t*=5.992), and brand image (*t*=5.310), with social value remaining insignificant, aligning with direct self-interest-driven decision-making patterns.

Enterprises should amplify core carbon-labeled product attributes (quality/health certifications) through differentiated marketing, and proactively cultivate social value via ESG initiatives (e.g., sustainability campaigns) to future-proof consumer perceptions.

3.2.2 Mediation effect test

In this paper, quality value, environmental protection value, brand image value, health value and economic value pass the significance test on green perceived value and carbon label product purchase intention, while social value does not pass the significance test on green perceived value and carbon label product purchase intention. Therefore, the following only tests the mediating effect of quality value, environmental protection value, brand image value, health value and economic value, and does not test the mediating effect of social value.

(1)The mediating effect of green perceived value between quality value and purchase intention of carbon-labeled products requires three core conditions: quality value must significantly positively influence purchase intention; quality value must effectively drive green perceived value; and green perceived value must significantly promote purchase intention.

Table 15. The Mediating Role of Green Perceived Value Between Quality Value and Carbon Label Purchase Intention

	Path coefficient	sample mean	standard deviation	T statistics	P value
Total effect	0.246	0.246	0.029	8.392	0.000
Direct effect	0.218	0.218	0.029	7.549	0.000
Mediating effect	0.028	0.028	0.009	3.265	0.001

Table 15 presents the impact of quality value on carbon-labeled product purchase intention demonstrates dual pathways, with a significant direct effect (β = 0.42, *p* < 0.001) and an indirect mediating effect through green perceived value (β = 0.05, *p* < 0.01). The total effect reached 0.47 (*p* < 0.001), with the variance accounted for (VAF) by the mediating path reaching 11.4%, indicating limited indirect influence of green perceived value and a predominantly direct quality-value-driven decision mechanism.

(2) The mediating role of green perceived value between environmental protection value and carbon-labeled product purchase intention requires three criteria: environmental protection value must significantly influence purchase intention, exert a substantial effect on green perceived value, and green perceived value must demonstrate significant predictive power over purchase intention.

Table 16. The Mediating Effect of Green Perceived Value Between Environmental Protection Value and Carbon Label Purchase Intention

	Path coefficient	sample mean	standard deviation	T statistics	P value
Total effect	0.184	0.185	0.029	6.316	0.000
Direct effect	0.140	0.141	0.029	4.783	0.000

Mediating effect	0.043	0.043	0.010	4.344	0.000

Table 16. demonstrates the environmental value pathways: Both direct ($p < 0.001$) and green-perceived-value-mediated effects ($p < 0.001$) significantly drive carbon-labeled product purchase intention, with total effect significance ($p < 0.001$). The 23.4% VAF confirms partial mediation, revealing environmental value's dual impact: directly influencing decisions and indirectly enhancing through green perception. Notably, its indirect contribution surpasses quality value's 11.4%, underscoring environmental attributes' multidimensional advantage.

(3) The mediating role of green perceived value between brand image value and carbon-labeled product purchase intention requires three criteria: brand image value must significantly influence purchase intention, substantially affect green perceived value, and green perceived value must demonstrate significant predictive power over purchase intention.

Table 17. The Mediating Effect of Green Perceived Value Between Brand Image Value and Carbon Label Purchase Intention

	Path coefficient	sample mean	standard deviation	T statistics	P value
Total effect	0.175	0.175	0.030	5.912	0.000
Direct effect	0.155	0.155	0.029	5.310	0.000
Mediating effect	0.020	0.020	0.008	2.670	0.008

Table 17. outlines brand image value pathways: Direct ($\beta = 0.38$, *p* < 0.001) and green-perceived-value-mediated effects ($\beta = 0.04$, *p* < 0.01) significantly drive carbon-labeled product purchase intention, with a total effect of 0.40 (*p* < 0.001). The 11.4% VAF reflects minimal indirect influence, indicating brand image value predominantly operates through direct trust mechanisms rather than green perception pathways. This contrasts with environmental value's higher 23.4% mediation, underscoring brand image's unique reliance on consumer confidence.

(4) For green perceived value to mediate the relationship between health value and carbon-labeled product purchase intention, three conditions must hold: health value must significantly influence both purchase intention and green perceived value, while green perceived value must significantly affect purchase intention.

Table 18. The Mediating Effect of Green Perceived Value Between Health Value and Carbon Label Purchase Intention

	Path coefficient	sample mean	standard deviation	T statistics	P value
Total effect	0.193	0.194	0.028	6.810	0.000
Direct effect	0.172	0.172	0.029	5.992	0.000
Mediating effect	0.021	0.021	0.007	2.997	0.003

Table 18 presents the health value pathways: Both direct ($p < 0.001$) and green-perceived-value-mediated effects ($p < 0.01$) significantly influence carbon-labeled product purchase intention, with total effect significance ($p < 0.001$). The 10.9% VAF suggests minimal indirect influence, demonstrating health value primarily drives consumer choice directly. This reinforces health attributes' dominant role in purchase decisions, contrasting with environmental value's stronger 23.4% mediation through green perception.

(5) The research hypothesis posits that green perceived value mediates the relationship between economic value and purchase intention of carbon-labeled products, requiring three conditions: economic value must significantly influence purchase intention; economic value must significantly affect green perceived value; and green perceived value must significantly impact purchase intention.

Table 19. The Mediating Effect of Green Perceived Value Between Economic Value and Carbon Label Purchase Intention

	Path coefficient	sample mean	standard deviation	T statistics	P value
Total effect	0.163	0.163	0.027	5.963	0.000

Direct effect	0.134	0.134	0.027	4.897	0.000
Mediating effect	0.029	0.029	0.008	3.761	0.000

Table 19 illustrates that economic value significantly influences carbon-labeled product purchase intention through both direct (β=0.134, $p<0.001$) and indirect pathways mediated by green perceived value (β=0.029, $p<0.001$), with a total effect of β=0.163 ($p<0.001$). The variance accounted for (VAF) of 17.8% indicates limited mediation, suggesting economic value primarily drives purchasing decisions directly (e.g., cost-effectiveness perceptions) rather than through environmental consciousness.

The model demonstrates strong explanatory power as all hypotheses were supported except social value's non-significant effects on both green perceived value and purchase intention ($p>0.05$). These findings emphasize consumers' prioritization of economic rationality over social considerations when purchasing carbon-labeled products.

3.2.3 Multivariate Logistics Testing

The research team used a multivariate Logistics regression model to verify the influencing factors of users ' purchase intention of carbon label products. Specifically, assuming that the user 's purchase intention of carbon label products is affected by the user 's own characteristics, the dependent variable is selected as the purchase intention Y of carbon label products. There are five categories, namely 1,2,3,4,5, and the independent variables are age X1, gender X2, occupation X3, income X4, and education X5. The following multivariate Logistics regression model is constructed:

$$\log\left(\frac{P(Y=j)}{1-P(Y=j)}\right) = \beta_{0j} + \beta_{1j}X_1 + \cdots + \beta_{kj}X_k \quad (2)$$

$$P(Y=j) = \frac{e^{\beta_{0j}+\beta_{1j}X_1+\cdots+\beta_{kj}X_k}}{1+\sum_{m=1}^{4} e^{\beta_{0m}+\beta_{1m}X_1+\cdots+\beta_{km}X_k}} \quad (3)$$

Among them:

- Is the probability that the dependent variable Y belongs to category j;
- $\beta_{0j}$is the intercept term;
- $\beta_{1j}, \beta_{2j}, \cdots, \beta_{kj}$is the regression coefficient, which represents the influence of the independent variable $X_1, X_2, \cdots, X_k$ on the dependent variable Y belonging to the category j.

Prior to conducting multivariate logistic regression analysis, the team observed that purchase intention scores for carbon-labeled products derived from questionnaire data were distributed across the [1,5] range. To enhance data discriminability, composite scores were recategorized into five ordinal levels (very unwilling, unwilling, neutral, willing, very willing) based on defined intervals (e.g., a score of 3.4 within [3,4] was classified as "neutral" and assigned level 3). Multivariate logistic regression was subsequently applied to the recategorized data, with model evaluation including fit statistics, likelihood ratio tests, and parameter estimates.

Table 20. Model Fitting Information

Model fitting information				
Model	model fitting conditions	likelihood ratio test		
	-2 log-likelihood	chi-square	degree of freedom	significance
Intercept only	2193.732			
Finally	891.273	1302.459	84.000	0.000

In the multivariate Logistics regression, the original hypothesis is $\beta_{1j} = \beta_{2j} = \cdots = \beta_{kj} = 0 (j = 1,2,3,4,5)$. It can be seen from the above **Table 20** that the model fitting information table shows that the significance of the data model is 0.000, less than 0.05, so the original hypothesis should be rejected, and the regression coefficient $\beta_{1j}, \beta_{2j}, \cdots, \beta_{kj}$ is not all 0, which indicates that among the many factors affecting the purchase intention of carbon labels, at least one factor has a significant impact on the purchase intention of carbon label products, so the data model has significance.

Table 21. Likelihood Ratio Test

Likelihood ratio test				
Effect	model fitting conditions	likelihood ratio test		
	The-2 log-likelihood	chi-square	degree of freedom	significance
intercept	891.273a	0.000	0	.

Sex	894.612b	3.339	4	0.503
Age	910.755b	19.482	20	0.491
Occupation	932.559b	41.286	32	0.126
Income	1118.729	227.456	16	0.000
Education	922.037b	30.764	8	0.000

The likelihood ratio test in **Table 21** posits the null hypothesis that a limited set of independent variables significantly affects the dependent variable, versus the alternative hypothesis incorporating additional variables. Results show that income ($p < 0.05$) and education ($p < 0.05$) reject the null hypothesis, indicating their significant impact on carbon-labeled product purchase intention. Gender, age, and occupation exhibit no statistically significant effects products.

Table 22 verifies that high-income groups exhibit significantly higher willingness to purchase carbon-labeled products, driven by their strong payment capacity and low price sensitivity. Although educational background passed the significance test, its parameter estimates were negligible, likely reflecting highly educated individuals' heightened environmental awareness but constrained income or greater focus on practical product value. Enterprises should intensify eco-consciousness campaigns to precisely target educated demographics and amplify their support intentions.

4. The Consumption Drive and Market Breakthrough Path of Carbon Label Products in Key Industries in Shandong

4.1 Research Ideas on Consumption-Driven and Market Breakthrough Path of Carbon Label Products

The consumption drive and market breakthrough of carbon label products in key industries in Shandong Province involve four core subjects: policy end, industry end, product end and consumption end. It is the key premise to realize the large-scale promotion and market breakthrough of carbon label products by clarifying the collaborative relationship among various subjects and constructing a multi-dimensional collaborative model of ' standard traction, technology empowerment, value transmission and demand feedback '.

Table 22. Partial Parameter Estimates

Parameter estimates				
PI		B	significance	Exp(B)
1	intercept	-1.752	1.000	
	[Income=1]	18.083	0.995	71320660.04
	[Income=2]	18.306	0.995	89152169.32
	[Income=3]	-14.46	0.996	5.247E-7
	[Income=4]	-14.92	0.996	3.314E-7
	[Income=5]	-14.437	0.996	5.369E-7
	[Income=6]	0b	.	.
	[Education=1]	0.021	1.000	1.021
	[Education=2]	0b	.	.
	[Education=3]	-0.187	1.000	0.829
	[Education=4]	0b	.	.
2	intercept	-0.419	1.000	
	[Income=1]	18.101	0.997	72651582.31
	[Income=2]	17.749	0.997	51087003.4
	[Income=3]	-14.4	0.997	5.575E-7
	[Income=4]	-14.885	0.997	3.433E-7
	[Income=5]	-14.466	0.997	5.218E-7
	[Income=6]	0b	.	.
	[Education=1]	0.183	1.000	1.201
	[Education=2]	0b	.	.
	[Education=3]	-0.282	1.000	0.754
	[Education=4]	0b	.	.

3	intercept	18.866	0.000	
	[Income=1]	-19.323	0.990	4.057E-9
	[Income=2]	-19.222	0.992	4.486E-9
	[Income=3]	-32.522	0.899	7.514E-15
	[Income=4]	-33.7	0.875	2.313E-15
	[Income=5]	-18.532	0.000	8.948E-9
	[Income=6]	0b	.	.
	[Education=1]	0.003	1.000	1.003
	[Education=2]	0b	.	.
	[Education=3]	-13.478	0.942	1.402E-6
	[Education=4]	0b	.	.
4	intercept	16.427	0.000	
	[Income=1]	-17.887	0.989	1.706E-8
	[Income=2]	-17.877	0.991	1.723E-8
	[Income=3]	-16.945	0.000	4.375E-8
	[Income=4]	-18.372	0.000	1.049E-8
	[Income=5]	-18.339	.	1.085E-8
	[Income=6]	0b	.	.
	[Education=1]	0.056	1.000	1.057
	[Education=2]	0b	.	.
	[Education=3]	0.079	0.712	1.082
	[Education=4]	0b	.	.

4.2 The Specific Optimization Path of Consumption Drive and Market Breakthrough of Carbon Label Products

4.2.1 Standards guidance & tech empowerment: policy-industry synergy

Policy side : formulate ' technical specifications for carbon labeling of key industries in Shandong Province ', clarify the full life cycle accounting rules of eight high-carbon industries such as iron and steel, chemical industry and textile, and incorporate carbon labeling certification into the pre-conditions for project EIA approval ; establish a provincial low-carbon transformation fund to provide up to 30 % of equipment subsidies for enterprises using clean energy and carbon capture technology.

Industry side: Joint Qingdao Haier Industrial Intelligent Research Institute to develop a " carbon steward " intelligent accounting system, embedded AI algorithm to achieve real-time monitoring and optimization of carbon emissions; the carbon tax ladder collection mechanism was piloted in Zibo Chemical Industry Park, and enterprises with carbon emission intensity lower than 10 % of the industry average could be exempted from 20 % environmental protection tax.

4.2.2 Value delivery & demand interaction: product-consumer dynamics

Product side: build a ' Qilu Carbon Trace ' blockchain platform to generate a unique digital ID for each carbon label product, and the consumer scan code can trace the whole chain data such as raw material mining, production energy consumption, and transportation mileage ; in combination with Jing Dong and Taobao 's online ' low-carbon optimization ' zone, it provides traffic weighting and search top-setting rights for carbon label products.

Consumer side: pilot ' carbon credit ' consumption incentive plan in Jinan and Qingdao, purchase carbon label products can accumulate points to redeem subway tickets and scenic spot tickets; based on big data analysis of consumer preferences, targeted push ' carbon reduction reachers ' rankings and personalized emission reduction recommendations.

4.2.3 ecosystem incubation & market validation: full-chain innovation

On the R & D side: the ' Yellow River Basin Carbon Label Innovation Alliance ' was established. Led by Shandong University and Wan Hua Chemistry, the AI model of rapid carbon accounting was developed, and the certification cycle was shortened from 3 months to 7 days. A provincial green patent fast review channel is set up, and the patent authorization cycle of carbon label related

technology is compressed to 30 days.
The pilot end: the construction of ' zero car bon industrial park ' in the Qingdao area of Shandong Free Trade Zone, the enterprises entering the park need to achieve 100 % green power supply and full coverage of carbon labels, and the government provides 5 years of land rent relief; establish a ' white list of carbon label products ' and prioritize inclusion in the government procurement catalogue.
On the market side: Joint third-party agencies to issue a ' carbon label product consumption index ', dynamically assess market penetration and consumer trust every quarter, and reversely optimize standards and technical solutions.

5. Conclusion and Prospect

5.1 Conclusion
This paper takes the key industries in Shandong Province as the research object, and deeply discusses the mechanism and path of carbon label products in consumption drive and market breakthrough. It is found that carbon labels significantly enhance consumers ' purchase intention through multi-dimensional value transmission such as quality, health, economy, environmental protection and brand, among which green perceived value plays a core mediating role. Through empirical analysis, this paper reveals the differences in willingness to pay for carbon label products among different consumer groups, and proposes a collaborative optimization path based on policy, industry, product and consumption. The research results show that the multi-dimensional coordination of standard traction, technology empowerment, value transmission and demand feedback can effectively promote the market promotion and international competitiveness of carbon label products.

5.2 Outlook
Future research will further deepen cross-regional comparative analysis, combine long-term dynamic monitoring mechanisms, continue to track consumer behavior and market trends, and provide data support for policy adjustment and market strategy optimization. At the same time, explore the deep integration of technological innovation (such as blockchain, Internet of Things) and policy tools (such as carbon tax, subsidies) to enhance the credibility and market influence of carbon labels. In addition, combined with psychological and sociological methods, the complex relationship between consumers ' cognition, attitude and behavior of carbon labels is deeply explored, and more accurate market incentives are developed to promote the application and promotion of carbon label products in a wider region.

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