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Determinants of Sustainable Energy Use Behavior: Evidence from Perceived Risk and Value Thresholds

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Abstract
The Chinese government recognizes the importance of transforming residents' lifestyles and energy consumption patterns for achieving its "dual carbon goals." Therefore, the government is vigorously promoting residential solar photovoltaic power generation in order to transition from traditional fossil fuels to renewable energy sources such as solar power. China, especially in its western regions, is a society based on interpersonal relationships, and residents generally have limited education levels and awareness. This paper constructs a VAM model to investigate the willingness and behavior of community residents in Ningxia to adopt sustainable energy (solar photovoltaic power generation). This paper focuses on the impact of perceived risk and perceived value on the willingness and behavior of residents in Ningxia Hui Autonomous Region, China, regarding sustainable energy use. The results show that perceived risk and perceived value play a significant role in influencing residents' willingness to adopt new energy sources . The findings can provide theoretical support and practical suggestions for local governments to promote new energy initiatives.

Key Words: Sustainable energy use intention ; VAM ; Solar photovoltaic ; SPV

Introduction
Continued greenhouse gas emissions pose multiple risks to humanity, including slow economic development, health damage, water scarcity, frequent extreme weather events, sea-level rise, and the looming threat of global warming. Scientific evidence suggests that China faces greater climate change risks compared to other countries. Underdeveloped and vulnerable regions are more severely affected by climate change. Su Zhaoxian (2021) points out that Ningxia has high energy consumption, high carbon emissions, and low efficiency, and still exhibits a trend of extensive development at the expense of the environment. The Chinese government recognizes the importance of transforming residents' lifestyles and energy consumption patterns for achieving the "dual carbon target" and is vigorously promoting residential photovoltaic power generation to drive the transition from traditional fossil fuels to renewable energy sources such as solar energy. However, according to the International Renewable Energy Agency (IRENA) 2020 renewable energy installed capacity statistics, by the end of the year, the global total renewable energy power generation was approximately 2537

gigawatts, accounting for only about one-third of the global total installed capacity. Li et al. (2021) point out that the penetration rate of solar photovoltaic panels remains very low.

In view of the above issues, this paper explores the key factors influencing the willingness and behavior of Ningxia community residents to adopt sustainable energy solar photovoltaic power generation (SPV). Using the VAM model, a questionnaire survey was conducted to conduct an in-depth analysis of the factors influencing Ningxia community residents' adoption of sustainable energy solar photovoltaic power generation (SPV).

1. Model construction of this study

2.1 Descriptive Analysis

The decision to adopt sustainable energy is a complex process involving many factors. Numerous studies have explored public acceptance of sustainable energy products from multiple dimensions, including self-efficacy theory, social cognitive theory, theory of rational behavior, and theory of planned behavior. This study focuses on consumer behavior and uses the Value Acceptance Model (VAM) to construct its theoretical framework.

The VAM theory explains residents' perceived value and decision-making regarding photovoltaics, focusing on how perceived value (benefits minus costs) determines adoption intention. Compared to TAM/TPB, it focuses more on the trade-off between economic and non-economic values, making it suitable for analyzing photovoltaic adoption behavior driven by economic factors such as subsidy reduction and installation costs. It also serves as the core theoretical support for the "perceived value" variable in research. Perceived gains include economic value (benefits, electricity cost savings), functional value (stable power generation), social value (environmental image), and emotional value (satisfaction with green living); perceived losses include economic costs (installation and maintenance costs), psychological costs (perceived risks, information asymmetry), and time costs (installation and maintenance time). Overall, perceived value (gains and losses) influences adoption intention , which in turn affects actual behavior. The framework of the research model is shown in Figure 1 .

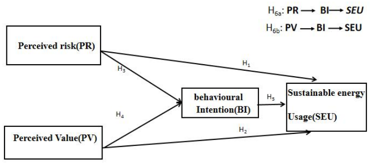

Figure 1 : Conceptual Framework

2.2 Research Hypotheses

2.2.1 Effect Perceived Risk (PR) towards behavioral Intention and Sustainable energy Usage

Perceived risk and its impact on consumers ' consumption intention and behavior attracted the attention of scholars decades ago.

In the past, scholars have conducted a comprehensive review of consumers' risk perception . Numerous studies have shown that perceived risk affects consumers' intention to use [products/services] (Chen et al., 2012; Marakanon & Panjakajornsak, 2017; Wang et al., 2019; Han Chenchen & Zhang Hongmei, 2022; Li Chuang et al., 2021; Liu Ruyi, 2020; Shao Peng et al., 2020; Yin Jielin et al., 2019) . Chen et al. (2012) pointed out that individuals' risk perception and intention of electric vehicles are negatively correlated. That is, if consumers believe that buying electric vehicles will bring financial pressure for later maintenance and upkeep, personal safety concerns caused by driving failures, and the time cost of charging, then their intention to buy electric vehicles will also decline . Marakanon and Panjakajornsak (2017) showed that perceived risk and customer trust have a direct impact on customer loyalty. Wang et al. (2019) mentioned that There is a significant positive correlation between perceived risk and public acceptance . A large number of studies have shown that perceived risk affects consumer usage (Tanveer et al., 2021; Qiu Huanguang et al., 2020) . Tanveer et al. (2021) The results show that perceived risk has a negative impact on consumers' WTA solar photovoltaics.

Therefore, this paper makes the following assumptions:
H_1 : There is a relationship between perceived risk and sustainable energy use .
H_3 : There is a relationship between perceived risk and behavioral intention .

2.2.2 The Relationship Between Perceived Value and Behavioral intentions to Use Sustainable Energy

The study of perceived value and its impact on consumers ' consumption intention and behavior has attracted the attention of scholars decades ago. A large number of studies have shown that perceived value affects consumers' attitudes and behaviors (Chen et al., 2012; Gârdan et al., 2023; Muhammad Irfan, 2021; Wang et al., 2019; Woodruff, 1997; Zeithaml, 1988; Li Lulu et al., 2022; Yuan Xiangling, 2022; Zhang Penggui, 2018; Zhao Min & Wang Lu, 2019; Zhong Kai, 2013) . Chen et al. (2012) pointed out that perceived value is si gnificantly correlated with purchase intention, and Gârdan et al. (2023) also pointed out that the intention to consume renewable energy is strongly influenced by other latent structures. Wang et al. (2019) pointed out that perceived benefits are correlated with public acceptance. Li Lulu et al. (2022) believed that perceived value affects consumers' acceptance of their willingness to buy a house, and combined consumer choice theory with deci d ing theory to propose a value-based mobile Internet adoption model (VAM). In VAM, consumers' willingness to adopt mobile Internet can be explained by perceived value. Shaw and Sergueeva (2019) It was found that perceived value affects consumer willingness in mobile commerce contexts. (Liu Fang and Li Hanwei, 2023) proposed that value can be perceived during exchange, use or experience and affect consumer behavior. Perceived value helps predict the behavioral outcomes of individuals in the field of social marketing (Yuan Xiangling, 2022) .Zhong Kai (2013) proposed that utilitarian value affect individuals' willingness to repurchase in online contexts. Nguyen et al. (2024) found that perceived value affects consumer willingness in mobile commerce contexts. Individuals' acceptance of Internet financial management platforms belongs to financial service consumption behavior. Previous studies have shown that individuals' perceived value affects their willingness to consume, individuals' willingness to adopt will be affected by the perceived value of financial technology platforms. Roy and Mohapatra (2022) suggests macro forces that hinder adoption , a finding that could be directly related to the low adoption rate of SPV in India. Even with a general level of awareness and knowledge about alternative energy sources, the average consumer is still not fully aware of the details associated with installations that could complement existing sources of electricity.

There are also literature that Muhammad Irfan (2021) pointed out that consumers' beliefs about the benefits of SPV have no significant impact on their willingness to adopt SPV. Therefore, this paper makes the following assumptions:
H_2 : perceived value has a positive impact on sustainable energy use.

H_4 : perceived value has a positive effect on behavioral intention.

2.2.3 The Relationship Between Behavioral intentions and Sustainable Energy Use

The concept of intention falls under the realm of psychology. Fishbein and Eisen's theory of rational action defines behavioral intention as the subjective probability that an individual will take a specific action. From this perspective, purchase intention is the subjective probability that a consumer is willing to buy a certain product. To predict consumer behavior, we must first understand consumers' purchase intentions. Although having a purchase intention does not necessarily mean that a consumer will actually make a purchase, the occurrence of a purchase is necessarily based on the existence of that intention. Purchase is an action, while intention is a psychological activity; purchase intention refers to the thought process surrounding the purchase, and a positive purchase intention will lead to the occurrence of the purchase. He Yewei (2017) defines the intention to purchase new energy vehicles as the consumer's plan and willingness to purchase new energy vehicles. Furthermore, the impact of community residents' attitudes and perceptions on the development of renewable energy has been discussed for many years abroad. Colenbrander, Gouldson, Roy et al. (2017) used a low-carbon community in Kolkata, India as an example to explore the degree of coordination between social, economic, and climate goals. The study concluded that, if implemented as planned, Kolkata's energy bill could be reduced by 8.5% and greenhouse gas emissions by 20.7% by 2025; however, the development of low-carbon communities will increase social operating costs and bring significant economic costs. However, if residents cooperate with the government, these social costs can be reduced to some extent. Building on the original impact of government and businesses on residents' low-carbon behavior, Chen (2020) further pointed out that residents themselves are the main actors in the transformation of low-carbon communities and focused more on how residents' own behavior affects the construction of low-carbon communities. Other studies have also found a correlation between public energy projects and positive attitudes towards related energy technologies, highlighting the importance of trust between communities and project developers. An encouraging finding of Roy (2022) is the relationship between behavioral intentions and conversion behavior. The results showed that if consumers are persuaded to adopt solar technology , they are more likely to switch from their existing household power source to an alternative power source. The stronger the convenience and practicality experience of electric vehicles, the more positive their attitude towards purchasing them (Chen , 2020).

Iuliana Petronela Gârdan and Gârdan (2023) indicate that consumer attitudes toward renewable energy consumption are strongly influenced by other underlying factors, with perceived utility, perceived risk , and environmental concerns being the most decisive. Consumers' behavioral intentions and actual consumption behaviors toward renewable energy are increasingly clearly reflected in their preferences for different types of renewable energy technologies. In the process of accepting renewable energy technologies, people gradually become aware of the negative environmental impacts of using traditional "brown" energy sources, such as noise and air pollution, climate change and biodiversity loss in some areas, declining living standards and safety due to rising energy prices and insufficient energy supply, and the emergence of other traditional energy sources. Therefore, people's acceptance of new technologies in the energy sector, as well as the risks and benefits they bring, influence the expression and updating of personal norms, thereby affecting consumption and acceptance behavior. The research of Roy et al. (2021) found that the willingness to use solar energy has a

positive impact on energy conversion behavior.
Based on the above evidence, this paper proposes a hypothesis based on the role of mediating variables.
H_5 : There is a relationship between behavioral intentions and sustainable energy use ;

2.2.4 The mediating role of behavioral intentions
According to the 2021 Global Climate Status Report, climate change caused by human activities poses a severe challenge to the sustainable development of the global economy. How to reduce carbon dioxide emissions and improve carbon emission efficiency has become an important issue of common concern to countries around the world. The Intergovernmental Panel on Climate Change (IPCC) Special Report on Global Warming of 1.5°C points out that the impacts of climate change are more severe than expected, and the pace of climate action should not be slowed down (Leiman, A; Ma, H, 2021).

This paper argues that behavioral intention is not only an important variable in the relationship between individual variables and behavior, but also a mediating variable. Existing research shows that the evidence for behavioral intention as a mediating variable is mainly reflected in the following aspects: its core logic is that "antecedent variables (such as perceived risk, perceived value, etc.) influence behavioral intention, and thus influence sustainable energy use behavior."

Based on high perceived value, residents develop a strong intention to install photovoltaic (PV) systems, such as actively consulting PV installation companies, comparing installation plans, and calculating the return on investment (Ali et al., 2020) . Driven by this strong intention, they ultimately complete the signing, installation, and daily use of PV panels, achieving self-consumption and grid connection of surplus electricity. If residents only perceive the value of PV panels but lack a clear intention to install them (e.g., due to a lack of renovation plans), this cannot be converted into actual installation. Behavioral intention is the key bridge between perceived value and actual use (Balta-Ozkan et al., 2015) . Users perceive air source heat pump water heaters as having high initial purchase costs (economic risk), low heating efficiency in winter (functional risk), high maintenance technical requirements, few after-sales service outlets (service risk), large installation space requirements, and poor adaptability (usage risk), resulting in a high overall perceived risk. Based on this high perceived risk, users have a very low willingness to purchase sustainable energy , such as foregoing understanding product parameters, directly excluding this option, and instead choosing traditional gas/electric water heaters. Due to a lack of purchase intention, no purchase or use of the air source heat pump water heater occurred. The mediating effect is evident: even if the energy-saving value (perceived value) of the air source heat pump water heater objectively exists, high perceived risk inhibits behavioral intention, severing the conversion of perceived value into actual use. If perceived risk can be reduced (e.g., by offering free installation or nationwide warranty), it will increase users' sustainable energy use , thereby promoting purchase behavior (Jain et al., 2022) . Optimization through policy/market mechanisms can simultaneously enhance perceived value, reduce perceived risk, strengthen behavioral intention, and thus promote use . A study by Wall et al. (2021) on Thai consumers shows that antecedent variables such as awareness of renewable energy and beliefs about its benefits influence adoption behavior through the mediating variable of behavioral intention (i.e., the "awareness → intention → behavior" chain). Without the mediating role of behavioral intention, the direct association between antecedent variables and behavior will be significantly weakened.

Therefore, this paper makes the following assumptions:
H_{6a} : Behavioral Intention mediates the relationship between Perceived risk and Sustainable Energy Usage ;
H_{6b} : Behavioral Intention mediates the relationship between Perceived Value and Sustainable Energy Usage ;

2. Questionnaire design and data collection

This study collected information on the willingness and behavior of Ningxia community residents regarding the use of sustainable energy, solar photovoltaic power generation, through a questionnaire survey. The reliability and validity of the model were analyzed using SPSS statistical software, and the goodness of fit and hypotheses were tested using AMOS 26.0. The questionnaire consisted of two parts: basic information about Ningxia community residents and information related to their willingness and behavior regarding the use of sustainable energy, solar photovoltaic power generation. The scales for assessing the willingness and behavior regarding the use of sustainable energy, solar photovoltaic power generation, included perceived value (PV, 6 items), perceived risk (PR, 6 items), willingness to use (BI, 6 items), and sustainable energy use behavior (SEU, 6 items). These indicators were measured using a 5-point Likert scale, where 1 indicates "strongly disagree" and 5 indicates "strongly agree".

3. Data Statistics and Analysis

3.1 Descriptive Analysis

A total of 410 questionnaires were collected for this analysis, of which 403 were valid, resulting in a valid response rate of 98.29%. Specifically, in terms of gender distribution, there were 147 females and 256 males, accounting for 36.48% and 63.52% of the total population, respectively. In terms of age distribution, there was little difference in the number of participants across age groups. Regarding education level, there were 147 females and 256 males, representing 36.48% and 63.52% of the total population, respectively. In terms of age, the number of participants in each age group was 147 and 256, representing 36.48% and 63.52% of the total population, respectively. In terms of education level, the majority of respondents (236 people, 58.56%) have a high school education or below . In terms of monthly income, RM4,001 to RM6,000 is the most common, with 184 people (45.66%). In terms of occupation, the majority are farmers and self-employed individuals, with 194 and 165 people respectively, accounting for 48.14% and 40.94%. In terms of information source, the number of people from different channels is not significantly different.

Table 1. Descriptive analysis of different dimensions

Name	Sample size	average value	Standard deviation	Skewness	Kudo
PR	403	3.455	0.813	- 0.426	0.03
PV	403	3.17	0.768	0.018	- 0.417
BI	403	3.435	0.807	- 0.356	0.209
SEU	403	3.622	0.674	- 0.694	0.447

Chart 1 shows that the average scores for perceived risk , perceived value , behavioral intention, and sustainable use were 3.455, 3.17, 3.435, and 3.622, respectively, slightly higher than the median of 3. This indicates that respondents' overall evaluations of the scale items tended to be positive, with no excessively high or low scores.

To further examine whether the data conforms to a normal distribution, this paper refers to the criteria proposed by Kline (1998), namely, an absolute skewness of less than 3 and an absolute kurtosis of less than 10. The calculation results show that the skewness and kurtosis of each item in this study's scale meet the above criteria, indicating that the data distribution does not have significant skewness or abnormal kurtosis. This result shows that the distribution of the scale data basically conforms to a statistically normal distribution.

In summary, from the distribution characteristics of the mean and standard deviation to the test results of skewness and kurtosis, the data in this paper demonstrates high stability and reasonableness, conforming to the basic requirements of a normal distribution. Therefore, the data collected in this study can be used to further explore statistical methods such as regression analysis. This not only provides a reliable data foundation for subsequent causal relationship tests but also provides statistical support for model construction and interpretation.

4.2 Reliability Testing

In statistical analysis, reliability verification is crucial, its core being the testing of the internal consistency of the measurement tool. The alpha coefficient is a typical indicator for measuring the correlation and consistency among items in a questionnaire. Specifically, this coefficient assesses the degree of correlation between item scores to demonstrate whether they collectively and consistently reflect the same concept or trait. The alpha coefficient typically ranges from 0 to 1. The closer the value is to 1, the stronger the internal consistency, meaning the more consistent the item scores. It is generally accepted in the industry that an alpha coefficient exceeding 0.7 indicates good reliability, and exceeding 0.8 indicates very high reliability. According to the data in Table 2 , the alpha coefficients for perceived risk , perceived value , behavioral intention, sustainable energy use , and sustainable Cronbach's alpha are 0.908, 0.874, 0.916, and 0.825, respectively, all above the threshold of 0.7, confirming the high reliability of this study.

Table 2 Reliability Test

Name	Item quantity	Sample size	Cronbach's α coefficient
PR	6	403	0.908
PV	6	403	0.874
BI	6	403	0.916
SEU	6	403	0.825

4.3 Validity testing

Exploratory factor analysis aims to delve into hidden dimensions and factor structures to reveal potential common patterns or latent factors among observed variables. The validity of the analysis can be validated using the KMO test and Bartlett's test of sphericity. The KMO test primarily assesses whether the dataset is suitable for factor analysis. Its core is to measure the correlation between variables to determine the presence of common factors. Ideally, the KMO value should be greater than 0.6; if the KMO value is less than 0.6, it indicates that the data is

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not suitable for factor analysis. On the other hand, Bartlett's test of sphericity focuses on the strength of the correlation between variables; a p-value less than 0.05 indicates that the data is suitable for factor analysis. If these test results do not support factor analysis, it may be necessary to reassess the suitability of the data or consider other analytical strategies. In this case, the KMO value is 0.914 (greater than 0.6), with a significance level of 0.000 (less than 0.001) , as shown in Figure 3 , which confirms that the data is suitable for factor analysis.

Table 3 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.914
Bartlett's Test of Sphericity	Approx. Chi-Square	5089.103
	do	276
	Sig.	.000

Total variance explained refers to the extent to which the selected factors in a factor analysis can explain the variance of the original data. It helps determine how many principal components or factors should be included in the model and helps explain the model's effectiveness. Total variance explained is typically measured using the initial eigenvalues and the sum of squared rotational loadings. First, as shown in Figure 4, regarding the initial eigenvalues, the values greater than 1 are 7.197, 3.584, 2.667, and 1.923, meaning there are four values greater than 1, and all items can be divided into four categories. Second, regarding the sum of squared rotational loadings, the corresponding values are 17.677, 17.308, 15.657, and 13.405, with a total value of 64.046%, higher than 60%. All items can also be divided into four categories.

Table 4 Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Totale	% of Varianc	Cumulative %	Totale	% of Varianc	Cumulative %
1	7.197	29.987	29.987	7.197	29.987	29.987	4.242	17.677	17.677
2	3.584	14.935	44.922	3.584	14.935	44.922	4.154	17.308	34.985
3	2.667	11.113	56.035	2.667	11.113	56.035	3.758	15.657	50.641
4	1.923	8.011	64.046	1.923	8.011	64.046	3.217	13.405	64.046
5	.721	3.005	67.051						
6	.687	2.863	69.914						
7	.631	2.627	72.542						
8	.587	2.446	74.987						
9	.541	2.252	77.240						
10	.504	2.102	79.341						
11	.489	2.036	81.377						
12	.460	1.919	83.296						
13	.448	1.867	85.163						
14	.406	1.692	86.855						
15	.384	1.598	88.453						

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16	.364	1.515	89.969
17	.351	1.462	91.431
18	.336	1.398	92.829
19	.323	1.348	94.177
20	.314	1.310	95.487
21	.296	1.233	96.720
22	. 287	1.197	97.917
twenty-three	. 268	1.118	99.035
twenty-four	. 232	. 965	100. 000

The rotated component matrix reveals the specific structure and interpretation of the latent factors. This matrix visually depicts the interaction between the original observed variables and the latent factors. The rotation process aims to improve factor resolution, making them clearer and more understandable. As shown in Table 5 , the entries for each dimension remain consistent with the initial settings.

Table 5 Rotation component matrix

	Element			
	1	2	3	4
PR 1		.816		
PR 2		.824		
PR 3		.820		
PR 4		.812		
PR 5		.811		
PR 6		.794		
PV 1			.749	
PV 2			.748	
PV 3			.771	
PV 4			.805	
PV 5			.710	
PV 6			.775	
BI1	.801			
BI2	.819			
BI3	.834			
BI4	.809			
BI5	.818			
BI6	.817			
SE U 1				.760
SEU 2				.696
SEU 3				.716
SEU 4				760
SEU 5				669
SEU 6				523

Fit index	Critical value	Current Value	result

Chi-square		349.293	
Degrees of Freedom		246	
Chi-square/degrees of freedom	< 3	1.420	Comply with standards
RMSEA	< 0.10	0.032	Comply with standards
GFI	> 0.8	0.933	Comply with standards
AGFI	> 0.8	0.918	Comply with standards
RFI	> 0.9	0.925	Comply with standards
NFI	> 0.9	0.933	Comply with standards
IFI	> 0.9	0.979	Comply with standards
TLI	> 0.9	0.976	Comply with standards
CFI	> 0.9	0.979	Comply with standards

Confirmatory factor analysis (CFA) is a statistical method used to verify the goodness of fit between a theoretical model and actual data. As shown in the table, all fit indices reached or exceeded the thresholds, indicating that these indices have successfully passed the statistical tests , thus confirming that the model has good fit performance.

4.4 Convergent validity

The standardized loadings of the measurement model were verified to generally exceed the threshold of 0.6, and the observed standard relative error was small, indicating that the model has good accuracy. Furthermore, the critical ratios of all factors exceeded 3.29, and the parameter estimates were significant at the 0.001 significance level, further confirming the significant contribution of each factor to the model's explanatory power, thus verifying the model's high fit.

The average variance extracted (AVE) is a method for assessing the validity of a scale. It aims to quantify the proportion of variance explained by each measurement item within the construct, which relatively includes the portion related to observation error. Its value typically ranges between 0 and 1. A higher AVE value indicates a stronger ability of the measurement items to explain the construct variance; that is, they more effectively reflect the nature of the construct. Generally, an AVE value greater than 0.5 is considered to indicate good validity. On the other hand, composite reliability (CR), as an indicator of model reliability, calculates the proportion of non-error components in the total variance of the measurement items. Similarly, the CR value also ranges between 0 and 1. A higher CR value indicates strong internal consistency among the measurement items. Generally, a CR value greater than 0.7 is considered an acceptable level of consistency. In this study, since both the AVE values were above 0.5 and the CR values were above 0.7, it is sufficient to demonstrate that the scale has good convergent validity.

Table 7 Convergent validity

Factor	Explicit variables	Std. Error	z (CR value)	p	Std. Estimate	AVE	CR
PR	PR 1	-	-	-	0.79	0.623	0.908
PR	PR 2	0.059	17.229	0	0.796		
PR	PR 3	0.061	17.539	0	0.807		
PR	PR 4	0.059	17.095	0	0.791		
PR	PR 5	0.06	16.929	0	0.785		
PR	PR 6	0.06	16.496	0	0.768		

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PV	PV 1	-	-	-	0.719		
PV	PV 2	0.076	13.797	0	0.738		
PV	PV 3	0.075	13.474	0	0.72		
PV	PV 4	0.082	14. 701	0	0.789	0.539	0.875
PV	PV 5	0.083	12.993	0	0.694		
PV	PV 6	0.083	13.862	0	0.742		
BI	BI1	-	-	-	0.803		
BI	BI2	0.058	17. 406	0	0.784		
BI	BI3	0.054	18.254	0	0.813		
BI	BI4	0.057	18.315	0	0.815	0.645	0.916
BI	BI5	0.055	17.935	0	0.802		
BI	BI6	0.054	17.93	0	0.802		
SEU	SEU 1	-	-	-	0.781		
SEU	SEU 2	0.068	12.271	0	0.639		
SEU	SEU 3	0.067	13.15	0	0.682		
SEU	SEU 4	0.066	13.271	0	0.689	0.545	0.826
SEU	SEU 5	0.068	11.74	0	0.613		
SEU	SEU 6	0.055	11.055	0	0.579		

4.5 Discriminant Validity

Discriminant validity measures the effectiveness of a measurement tool in distinguishing different concepts or constructs; that is, whether it can effectively distinguish other similar but different constructs. According to the criteria proposed by Fornell and Larcker (1981), discriminant validity can be judged by comparing the mean variance extracted (AVE) of a construct with the squared correlation coefficient between the construct and other constructs. Specifically, the AVE value of each construct should be greater than its squared correlation coefficient with other constructs. This means that a construct should be more correlated with other constructs, thus demonstrating sufficient discriminant validity. If the correlation between a construct and other constructs is too high, there may be a discriminant validity problem. Observing the discriminant validity indicators, the absolute values of the values in the upper row are greater than the absolute values of the values in the lower row, indicating good discriminant validity. In Table 8 , perceived risk , perceived value , behavioral intention, and sustainable energy use are 0.789, 0.734, 0.803, and 0.738, respectively, and the discriminant validity meets the standard.

Table 8 Discriminant Validity

	PR	PV	BI	SEU
PR	0.789			
PV	0.171	0.734		
BI	0.184	0.333	0.803	
SEU	0.358	0.387	0.354	0.738

Note: The diagonal numbers are the square root values of AVE

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4.6 Structural Equation Model

Structural equation modeling (SEM), as a comprehensive statistical analysis technique, is often used to evaluate and validate the applicability of theoretical frameworks and to analyze the interactions between variables in depth. The unique feature of this method is its ability to integrate explicit and implicit factors into a single model, thereby enabling a comprehensive analysis of complex phenomena. The results are as follows:

In BI<--- PR , the standardized regression coefficient is -0.138 , P=0.009<0.01, therefore, the impact of perceived risk on behavioral intention is significant;

In BI <--- PV , the standardized regression coefficient is 0.344, P = 0.000 < 0.001, therefore, the impact of perceived value on behavioral intention is significant;

SEU <---BI , the standardized regression coefficient is 0.228, P=0.000＜0.001, therefore, the impact of behavioral intention on sustainable energy use is significant;

In SEU <--- PR , the standardized regression coefficient is -0.313 , P=0.000＜0.001, therefore, the impact of perceived risk on sustainable energy use is significant;

In SEU <--- PV , the standardized regression coefficient is 0.296, P = 0.000 < 0.001, therefore, the perceived value has a significant impact on sustainable energy use.

Table 9 Results of the structural equation modeling

			Estimate	SE	CR	P	Estimate
BI	<---	PR	0.141	0.054	2.606	0.009	- 0.138
BI	<---	PV	0.349	0.058	6.053	***	0.344
SEU	<---	BI	0.216	0.052	4.127	***	0.228
SEU	<---	PR	0.305	0.052	5.844	***	- 0.313
SEU	<---	PV	0.285	0.056	5.134	***	0.296
PR 6	<---	PR	1				0.768
PR 5	<---	PR	1.035	0.063	16. 347	***	0.785
PR 4	<---	PR	1. 023	0.062	16.498	***	0.791
PR 3	<---	PR	1.074	0.064	16.897	***	0.807
PR 2	<---	PR	1.024	0.062	16.619	***	0.796
PR 1	<---	PR	1.011	0.061	16.474	***	0.79
PV 6	<---	PV	1				0.742
PV 5	<---	PV	0.934	0.07	13.355	***	0.694
PV 4	<---	PV	1.053	0.069	15.231	***	0.789
PV 3	<---	PV	0.874	0.063	13.876	***	0.72
PV 2	<---	PV	0.913	0.064	14.231	***	0.738
PV 1	<---	PV	0.871	0.063	13.849	***	0.719
BI1	<---	BI	1				0.803
BI2	<---	BI	1.003	0.058	17.381	***	0.784
BI3	<---	BI	0.978	0.054	18.228	***	0.813
BI4	<---	BI	1.047	0.057	18.292	***	0.815
BI5	<---	BI	0.985	0.055	17.914	***	0.802
BI6	<---	BI	0.974	0.054	17.906	***	0.802
SEU1	<---	SEU	1				0.781
SEU2	<---	SEU	0.837	0.068	12.258	***	0.639
SEU3	<---	SEU	0.877	0.067	13.134	***	0.682

SEU4	<---	SEU	0.879	0.066	13.256	***	0.689
SEU5	<---	SEU	0.802	0.068	11.726	***	0.613
SEU6	<---	SEU	0.61	0.055	11.037	***	0.579

4.7 Hypothesis Testing

The final hypothesis test results are shown in Table 1.0 below :

Table 1 Summary of results under hypothesis 0

Symbol	Assumption	result
H_1	Perceived risk has a significant impact on the use of sustainable energy.	Establish
H_2	Perceived value has a significant positive impact on the use of sustainable energy.	Establish
H_3	Perceived risk has a significant impact on behavioral intentions.	Establish
H_4	Perceived value has a significant positive impact on behavioral intentions.	Establish
H_5	Behavioral intentions have a significant positive impact on the use of sustainable energy.	Establish
H_{6a}	Behavioral intentions play a mediating role in the impact of perceived risk on sustainable energy use .	Establish
H_{6b}	Behavioral intentions play a mediating role in the impact of perceived value on sustainable energy use .	Establish

4.8 Intermediary Inspection

The bootstrap method is a nonparametric method based on repeated sampling used to test for mediation effects. It effectively overcomes the strict requirements of traditional methods (such as the Baron & Kenny method and the Sobel test) on sample size and normality (Pr Pvcher & Hayes, 2008). The core idea of this method is to repeatedly and randomly draw samples from the original dataset (usually 5000 or 10000 times), calculate the mediation effect of each sample (i.e., the indirect effect of the independent variable X on the dependent variable Y through the mediator M), and finally construct confidence intervals (usually 95% or 90%) to determine whether the mediation effect is significant (Efron & Toshiari, 1993). If the confidence interval for the indirect effect does not contain zero, the mediation effect is significant; otherwise, the mediation effect is not significant (MacKinnon et al., 2004).

In Table 1 , the confidence interval for PR => BI => SEU is 0.007-0.051, which does not include 0, so there is a mediating effect; the confidence interval for PV => BI => SEU is 0.035-0.103, which does not include 0, so there is a mediating effect.

Table 1.1 Intermediary inspection

thing	Total effect	Mediation effect value	95% Bootcut Pants	direct effects	Test Conclusion
PR => BI => SEU	0.249***	0.023	0.007 ~ 0.051	0.226***	Some middlemen
PV => BI => SEU	0.295***	0.059	0.035 ~ 0.103	0.236***	Some middlemen

Note: * p<0.05 ** p<0.01 *** p<0.001
Bootstrap type = percentile Bootstrap method

4. Results and Discussion

Structural equation modeling (SEM), as a comprehensive statistical analysis technique, is often used to evaluate and validate the applicability of theoretical frameworks and to analyze the interactions between variables in depth. The unique aspect of this method is its ability to integrate explicit and implicit factors into a single model, thereby enabling a comprehensive analysis of complex phenomena. The results are as follows: In BI <--- PR , the standardized regression coefficient is -0.138 , P = 0.009 < 0.01, therefore, perceived risk has a significant impact on behavioral intention; in BI <--- PV , the standardized regression coefficient is 0.344, P = 0.000 < 0.001, therefore, perceived value has a significant impact on behavioral intention; in SEU <--- BI, the standardized regression coefficient is 0.228, P = 0.000 < 0.001, therefore, behavioral intention has a significant impact on sustainable energy use ; in SEU <--- PR, the standardized regression coefficient is -0.313, P = 0.000 < 0.001, therefore, perceived risk has a significant impact on sustainable energy use; in SEU <--- PV, the standardized regression coefficient is 0.296, P = 0.000 < 0.001, therefore, perceived value has a significant impact on sustainable energy use.

This study has several limitations worth emphasizing. First, it was conducted in the Ningxia Hui Autonomous Region and took into account the region's cultural and traditional factors. These factors differ from those in other regions, therefore caution should be exercised when generalizing the findings to other areas. Another limitation is the relatively small sample size, which may affect the general applicability of the results.

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