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Analysis of Factors Influencing the Willingness to Accept Carbon Inclusion Market Based on Structural Equation Modeling——Taking Xi'an City as an Example

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Abstract

The purpose of this paper is to investigate the willingness of Xi'an residents to accept carbon benefits, using a combination of principal component analysis and structural equation modeling. First, the data were collected from 16 questions using a five-point scale, and after confirming that the data were suitable for principal component analysis by KMO and Bartlett's test of sphericity, five principal components were extracted, with a cumulative variance explained rate of 87.116%, which realized dimensionality reduction and retained the key information. Second, structural equation modeling was used to construct the model with cognitive situation and decision-making behavior as latent variables. It was found that the perception of the carbon inclusion program's effect on carbon emissions significantly affects the cognitive situation, the greatest impact on satisfaction is whether participants are willing to promote the Carbon for All program, and the use of the carbon inclusion platform by people around us has the greatest impact on the practice situation. This study provides a basis for in-depth understanding of residents' willingness to accept carbon benefits, as well as a reference for the promotion and development of carbon benefits.

Keywords: carbon inclusive market, principal component analysis, structural equation modeling

1. Introduction

With the increasing global attention to environmental protection and sustainable development, carbon inclusion, as an innovative low-carbon incentive mechanism, aims to achieve the goal of reducing carbon emissions by encouraging residents to participate in low-carbon behaviors. The promotion and application of Carbon P&P is of great significance in the process of promoting green development in Xi'an. However, residents' willingness to accept carbon inclusion is affected by a variety of factors, and the influencing mechanism behind it is complicated[1].

Currently, research on residents' willingness to accept carbon benefits has gradually gained attention, but the existing studies are still insufficient in terms of the comprehensiveness and depth of the influencing factors. In order to gain a more comprehensive and in-depth understanding of Xi'an residents' willingness to accept carbon benefits, this paper applies principal component analysis to identify the main factors, and then uses structural equation modeling to measure the error and the complex relationship between the variables, to more accurately explore the causal paths between the latent variables, and to provide a strong support for revealing the influencing mechanism of residents' willingness to accept carbon benefits.

2. Research Design

2.1 Data Preprocessing

A total of 1,692 original questionnaires were collected, with 273 items of missing data and 48 items of abnormal data. The key variable "I have a clear understanding of the concept of carbon inclusion programs" had 12 missing items, so this paper used median interpolation to fill in, and the rest of the data with a large number of missing values and data that deviated beyond three times the standard deviation were appropriately excluded. The final number of data available was 1,383.

2.2 Factor Extraction

2.2.1 Quantification of Questionnaire Topics

After gaining an in-depth understanding of Carbon P&P, we proposed 16 questions on the evaluation of residents' willingness to accept Carbon P&P based on the current status and development of Carbon P&P. In order to subsequently facilitate the clustering and analysis of the questions, we quantified the 16 questions and analyzed them as follows:

Table 1. Xi'an residents' rating of the extent to which they choose the carbon inclusive market

Variable	Visible variable
x1	I have a clear understanding of the concept of carbon inclusion programs
x2	I believe that the Carbon P&G program is effective in reducing carbon emissions.
x3	I believe that carbon inclusion programs have a positive impact on environmental protection
x4	I would like to participate in the Carbon Inclusion Project
x5	I think carbon inclusion programs should be promoted
x6	I would like to take the time to learn about the Carbon Inclusion Program
x7	I or my family have started using the Carbon P&P platform
x8	I would like to recommend the use of the Carbon P&P platform by
x9	I am more satisfied with the current use of the Carbon P&P platform
x10	I receive promotional incentives for carbon inclusive projects.
x11	When people around me use the Carbon P&G platform it affects my willingness to participate
x12	People around us often share carbon inclusion related policies in social software
x13	I would like to take the initiative to respond to the government's call to participate in the Carbon P&G program.
x14	I agree with the choice of carbon inclusive projects as a way to reduce carbon footprints
x15	I think the Carbon P&G program is more environmentally friendly than traditional carbon reduction methods.
x16	I would like to call on people around me to use the Carbon P&G platform.

This paper adopts a "five-point scale" to set up questionnaires to examine the acceptance level of carbon credit among Xi'an residents, with a total of 16 questions and scores of 1, 3, 4, and 5 according to the scores of "strongly disagree", "not agree", "neutral", "relatively agree", and "strongly agree", respectively, A total of 16 questions were set up and scored according to "strongly disagree", "not quite agree", "neutral", "quite agree", and "strongly agree", which were scored as 1, 2, 3, 4, and 5, respectively.

Table 2. KMO and Bartlett's test results

KMO value		0.932
Bartlett's test of sphericity	Approximate chi-square	1767.418
	df	120
	P	0.000***

The KMO value amounted to 0.932, which is higher than the desirable value of 0.9, showing strong correlation between the variables. In the Bartlett's test of sphericity, the approximate chi-square value of 1767.418, with 120 degrees of freedom and significance of 0.000<0.05, rejected the hypothesis of independence of the variables, indicating that the variables are significantly associated with each other. Therefore, this dataset is suitable for principal component analysis, which can effectively extract the main components and optimize the variable structure.

2.2.2 Principal Component Factor Analysis

After the preliminary organization of the original collection data, the covariance matrix of the 16 types of evaluation questions was solved by the principal component analysis of SPSS software, and then by calculating the eigenvalues and eigenvectors corresponding to each question, in order to derive the magnitude of the cumulative contribution rate, and finally, the linear combination of the evaluation variables was utilized for the evaluation of the questionnaire's survey respondents[2].

The results are shown below:

Table 3. Total Variance Explained

Ingredient	Characteristic root	Explanation of variance (%)	Cumulative variance explained (%)
1	11.144	69.65	69.65
2	1.058	6.61	76.259
3	0.836	5.225	81.485
4	0.479	2.994	84.478
5	0.422	2.637	87.116
6	0.313	1.954	89.069
7	0.288	1.798	90.868
8	0.274	1.714	92.581
9	0.246	1.537	94.118
10	0.206	1.288	95.406
11	0.185	1.155	96.561
12	0.165	1.031	97.592
13	0.129	0.806	98.398
14	0.111	0.693	99.091
15	0.091	0.566	99.657
16	0.055	0.343	100

According to the results, the first principal component explains 69.65% of the variance with an eigenvalue of 11.144, and the eigenvalue and the percentage of variance decreases with the increasing number of the principal components, to the 16th principal component, the cumulative variance reaches 100%, which covers all the variance of the original variables. The cumulative variance explained by the first five principal components in this paper is 87.116%, which means that these five principal components can retain most of the information of the original variables, and can achieve the purpose of dimensionality reduction and retaining the key information as much as possible.

Table 4. Component matrix

Name	Ingredient 1	Ingredient 2	Ingredient 3	Ingredient 4	Ingredient 5
X1	0.782	0.215	0.134	0.102	0.089
X2	0.453	0.326	0.189	0.117	0.093
X3	0.601	0.683	0.542	0.126	0.107
X4	0.198	0.531	0.487	0.403	0.342
X5	0.212	0.557	0.619	0.135	0.124
X6	0.385	0.429	0.408	0.248	0.571
X7	0.327	0.396	0.582	0.189	0.156
X8	0.291	0.268	0.653	0.365	0.163
X9	0.408	0.142	0.521	0.647	0.512
X10	0.224	0.319	0.493	0.428	0.335
X11	0.196	0.098	0.467	0.609	0.058
X12	0.373	0.276	0.342	0.591	0.192
X13	0.252	0.257	0.418	0.273	0.505
X14	0.335	0.241	0.196	0.557	0.428

X15	0.119	0.126	0.375	0.242	0.751
X16	0.307	0.213	0.254	0.128	0.573

According to each principal component feature, this paper categorizes X1, X2, X3 as cognitive situation, X4, X5, X6 as decision-making behavior, X7, X8, X9 as usage, X10, X11, X12 as subjective norms, and X13, X14, X15, X16 as willingness to accept.

2.3 Factor Structure and Path Analysis of Willingness to Accept

2.3.1 Structural Equation Design

According to question 19 of the questionnaire, 16 observed variables were used as explicit variables, while 5 corresponding latent variables were selected based on the results of the factor analysis. The model consists of two parts: measurement model and structural model[3].

Measurement equation: used to describe the relationship between latent variables and observed variables. The equation is divided into reflecting the relationship between the latent variable ξ and the observed variable x, and the relationship between the latent variable η and the observed variable y.

$$x = \Lambda_x \xi + \delta \ (1)$$

where x is a vector of observed variables; Λ_x is a factor loading matrix reflecting the degree of influence of the latent variable ξ on the observed variable x; and ξ is an exogenous latent variable δ is the error term of the observed variable x.

$$y = \Lambda_y \eta + \varepsilon \ (2)$$

where y is the vector consisting of the observed variables; Λ_y is the factor loading matrix, capturing the extent to which the latent variable η acts on the observed variable y; η is the endogenous latent variable; and ε is the error term for the observed variable y.

Structural equations: used to characterize the relationship between latent variables

$$\eta = B\eta + \Gamma\xi + \zeta \ (3)$$

where η is the vector of endogenous latent variables; B is the relationship matrix between the endogenous latent variables, reflecting the interactions between the endogenous latent variables; Γ is the matrix of exogenous latent variables on the endogenous latent variables, reflecting the role of the exogenous latent variable ξ on the endogenous latent variable η; ξ is the vector of exogenous latent variables; and ζ is the residual term of the structural equation, representing the part of the model that is not explained by the model.

2.3.2 Model Building

In this paper, five items, namely cognitive situation, subjective norms, decision-making behavior, willingness to choose, willingness to accept and use, are used as latent variables. When deciding whether or not to accept and promote carbon inclusive projects or activities, residents first need to have a basic cognition of carbon footprints and carbon inclusive, decide whether or not to participate in carbon inclusive based on the cognitive situation of carbon inclusive, and then decide to participate in the carbon inclusive project before they have an After determining to participate in the Carbon P&P program, you should then have an in-depth understanding of the Carbon P&P platform, related policies, etc., and finally decide on your choice.

Table 5. Setting of latent and manifest variables

Latent variable	Visible variable	Hypothetical content
Cognitive situation A	I have a clear understanding of the concept of carbon inclusion programs(A1)	Positive effect on satisfaction
	I believe that the Carbon P&G program is effective in reducing carbon emissions (A2)	Positive effect on satisfaction
	I believe that carbon inclusion programs have a positive impact on environmental protection(A3)	Positive effect on satisfaction
	I would like to participate in the Carbon Inclusion Project(B1)	Positive effect on satisfaction

Decision-making behavior B	I think carbon inclusion programs should be promoted(B2)	Positive effect on satisfaction
	I would like to take the time to learn about the Carbon Inclusion Program(B3)	Positive effect on satisfaction
Utilization C	I or my family have started using the Carbon P&P platform(C1)	Positive impact on practice
	I would like to recommend the use of the Carbon P&P platform by(C2)	Positive impact on practice
	I am more satisfied with the current use of the Carbon P&P platform(C3)	Positive impact on practice
Subjective norm D	I receive promotional incentives for carbon inclusive projects(D1)	Positive impact on practice
	When people around me use the Carbon P&G platform it affects my willingness to participate(D2)	Positive impact on practice
	People around us often share carbon inclusion related policies in social software(D3)	Positive impact on practice
Willingness to accept E	I would like to take the initiative to respond to the government's call to participate in the Carbon P&G program. (E1)	Positive impact on practice
	I agree with the choice of carbon inclusive projects as a way to reduce carbon footprints(E2)	Positive impact on practice
	I think the Carbon P&G program is more environmentally friendly than traditional carbon reduction methods(E3)	Positive impact on practice
	I would like to call on people around me to use the Carbon P&G platform(E4)	Positive impact on practice

Before running this structural equation model, this paper initially sets the initial value of the factor loading between the latent variables and their observed variables as 1, and also sets 0.1 as the initial variance for the error term of each observed variable. In determining the initial path coefficients of the causal paths between the latent variables, this paper sets the initial value with reference to theories or previous studies, and finally determines it to be 0.7, and sets a reasonable initial variance for the residual term of the endogenous latent variables to be 0.5. After verifying that the data obeys normality, it is estimated by using the great likelihood estimation method.

The causal path diagram is shown below:

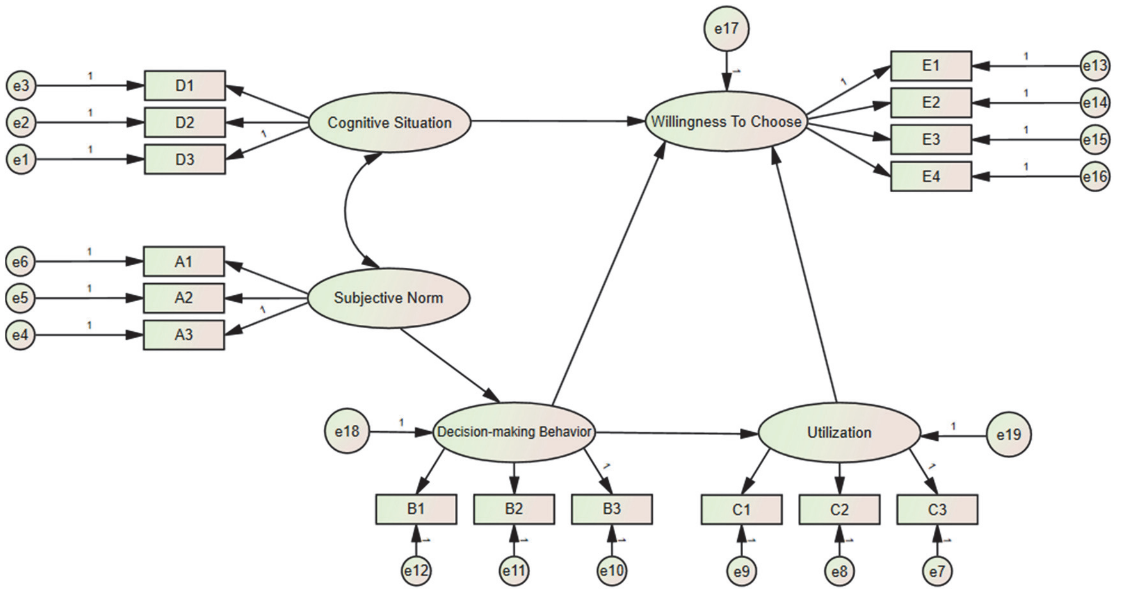

Figure 1. Causality path diagram

In this paper, a goodness-of-fit test for structural equations is conducted with the purpose of determining the degree of fit between the theoretically constructed structural equation model and the actual observed data. Only when the model passes the goodness-of-fit test and is proven to fit the data well, the theoretical architecture and analysis results have a high degree of scientific validity and reliability. Different types of model fit indices can be tested from absolute fit index, relative fit index, and goodness-of-fit index related indicators.

Table 6. Structural equation modeling tests

Norm	Numerical value	Recommended values
CMIN	370.521	No
P	0.000	<0.05
CMIN/DF	3.734	1-3 is excellent, 3-5 is good
GFI	0.884	>0.9
AGFI	0.840	>0.9
NFI	0.898	>0.8
TLI	0.907	>0.8
PCFI	0.762	>0.5
RMSEA	0.085	<0.05 is excellent, <0.09 is good

CMIN was 370.521 with a p-value of 0.000, indicating that the model was significantly different from the data; CMIN/DF was 3.734, which was in the good range. However, the GFI and AGFI are 0.884 and 0.840 respectively, slightly lower than the ideal value of 0.9. The NFI is 0.898 and the TLI is 0.907, close to the good level. the PCFI is 0.762, which meets the requirement of greater than 0.5, and the RMSEA is 0.085, which belongs to the good but not excellent. Some of the indicators show that there is still room for improvement in the fit, but overall, the model is close to good in some of the indicators.

Table 7. Convergent validity and reliability tests for each dimension

Pathway relationship			Estimate	AVE	CR
Cognitive situation A3	<---	Cognitive situation A	0.739		
Cognitive situation A2	<---	Cognitive situation A	0.742	0.437	0.764
Cognitive situation A1	<---	Cognitive situation A	0.564		
Decision-making behavior B3	<---	Decision-making behavior B	0.734		
Decision-making behavior B2	<---	Decision-making behavior B	0.766	0.537	0.842
Decision-making behavior B1	<---	Decision-making behavior B	0.727		
Utilization C3	<---	Utilization C	0.591		
Utilization C2	<---	Utilization C	0.703	0.492	0.812
Utilization C1	<---	Utilization C	0.782		
Subjective norm D3	<---	Subjective norm D	0.677		
Subjective norm D2	<---	Subjective norm D	0.797	0.454	0.789
Subjective norm D1	<---	Subjective norm D	0.636		
Willingness to accept E1	<---	Willingness to accept E	0.798		
Willingness to accept E2	<---	Willingness to accept E	0.763	0.582	0.876
Willingness to accept E3	<---	Willingness to accept E	0.724		
Willingness to accept E4	<---	Willingness to accept E	0.758		

Under the premise that the CFA model of the Carbon Market Acceptance Scale (CMA) has a good fit, the convergent validity of the latent variables and the observed variables, AVE and the combined validity, CR, were further examined, and the values of Estimate were mostly positive and in the range of 0.564-0.798, which reflected the positive correlation, while the values of CR were more than 0.7, which indicated that the model's internal consistency and reliability were good. However, the AVE values of “Decision-making Behavior B” and “Acceptance Intention E” are greater than 0.5, which indicates a good convergent validity, while the AVE values of “Cognitive Situation A”, “Usage Situation C” and “Acceptance Intention E” are greater than 0.5, which indicates a good convergent validity. C” and ‘subjective norms D’ are slightly lower than 0.5, and the convergent validity needs to be enhanced. Overall, the convergent validity and reliability of the model are good.

Table 8. Descriptive statistics of the sample

Measurement item	Average value	Standard deviation	Skewness	Kurtosis
Cognitive situation A1	3.45	0.824	-0.232	0.517
Cognitive situation A2	3.81	0.861	-0.626	0.726
Cognitive situation A3	3.93	0.863	-0.85	1.147
Decision-making behavior B1	3.82	0.884	-0.688	0.742
Decision-making behavior B2	3.93	0.854	-0.918	1.488
Decision-making behavior B3	3.88	0.86	-0.65	0.789
Utilization C1	3.86	0.873	-0.585	0.351
Utilization C2	3.89	0.853	-0.61	0.408
Utilization C3	3.62	1	-0.491	-0.168
Subjective norm D1	3.6	0.849	-0.341	0.139
Subjective norm D2	3.79	0.885	-0.715	0.851
Subjective norm D3	3.71	0.851	-0.738	0.938
Willingness to accept E1	3.91	0.79	-0.904	1.848
Willingness to accept E2	3.99	0.848	-0.767	0.972
Willingness to accept E3	3.93	0.873	-0.876	1.226
Willingness to accept E4	3.81	0.847	-0.388	0.118

The mean values of the measurement items range from 3.45-3.93, indicating that, overall, respondents rated the content covered by these items at a moderate to slightly higher level. The standard deviation ranges from 0.824 to 1, indicating that the dispersion of the data for each question is relatively close, i.e., there is not much difference in the dispersion of the respondents' answers. However, the standard deviation for “Usage C3” is 1, which is relatively large, meaning that there is a slight difference in the responses of the respondents for this question. All skewness values are negative, indicating that the data distribution is left skewed, with some small extremes, but the absolute values are not very large, indicating that the degree of skewness is not particularly serious. The kurtosis values vary considerably, with some positive and some negative, indicating that there are differences in the pattern of data distribution for different question items. The kurtosis value of “Decision-making Behavior B2” is 1.488, the data distribution is steeper than the normal distribution, with fewer extreme values; while the kurtosis value of “Usage C3” is -0.168, the data distribution is more gentle than the normal distribution, and the extreme values may be relatively more. In summary, the data are approximately normally distributed and can be used for structural equation modeling.

After running the model through using AMOS, the path coefficient identification was completed and the results are shown in the figure below:

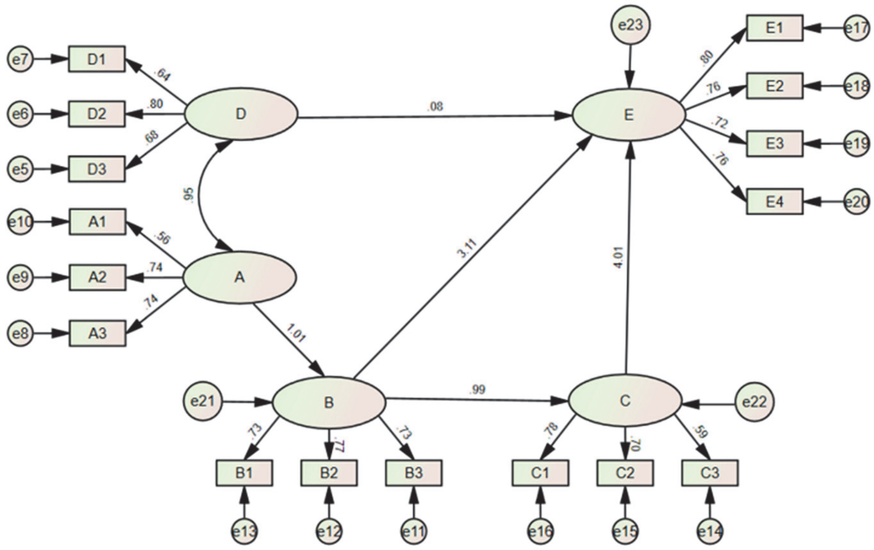

Figure 2. Structural equation diagram for labeling path coefficients

3. Conclusion

The dominant variable with the greatest influence on the cognitive situation is the size of the carbon inclusion program's effect on carbon emissions (A2). In the case of carbon inclusion programs, people's perceptions of their effectiveness in reducing carbon emissions greatly influence the overall cognitive situation. When individuals are convinced that carbon inclusion programs are effective in reducing carbon emissions, they will focus on this core cognition and take the initiative to learn more about the concept of the program, participation methods, and other aspects of the program in order to build a more comprehensive cognitive system. On the other hand, if they are skeptical about the effectiveness of carbon reduction, it is difficult for them to understand the program in depth, and their overall perception will be limited.

The dominant variable that has the greatest impact on satisfaction is whether participants are willing to promote the Carbon for All program (B2) When participants are willing to actively promote the Carbon for All program, it means that not only are they themselves satisfied with the program's rules, its implementation effects, and the environmental and personal benefits it has brought about, but they are also convinced of the value of the program and are willing to share it with others, and such a positive attitude reflects to a large extent the high level of satisfaction they have within themselves. On the other hand, if participants are reluctant to promote the program, it is very likely that they encountered problems during the program experience, such as unclear rules and unattractive rewards, which led to a significant reduction in satisfaction.

The dominant variable that has the greatest impact on practice is the use of the Carbon P&P platform by people around us (D2).Human beings are social animals, and the behavioral demonstration of people around them plays a significant role in the practice of carbon inclusive actions or projects. When seeing friends and family around us actively using the Carbon P&P platform, a sense of group identity and emulation will be created, which will in turn increase their own willingness to participate in the use. This kind of influence based on social relationship is more likely to motivate people to actually use the platform and play a key role in promoting the use of the platform, compared with pure advertising and publicity.

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