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RESEARCH ON THE DIFFERENTIATION OF URBAN RESIDENTS' LOW-CARBON TRAVEL INTENTIONS

Summary. The literature on low-carbon travel (LCT) of urban residents regards urban residents as homogeneous individuals and lacks quantitative delineation of the disparities in LCT intentions among different residents. Therefore, this study aims to use Chinese cities as cases to comprehensively investigate the influencing factors and interaction mechanisms of the LCT intentions of urban residents in different regions with different characteristics. First, based on the theory of planned behavior, this study comprehensively considers the inner psychological factors and external factors, selects five psychological latent variables and designs a questionnaire to obtain the LCT intentions data in cities of Shenzhen and Xi'an in China. Secondly, according to the LCT intention data, the residents of Shenzhen and Xi'an are divided into three classes: low intention, medium intention, and high intention. Finally, structural equation models are constructed for different classes of urban residents to investigate the key factors influencing their choices of LCT. The findings indicate that the influencing factors and influencing mechanisms of LCT intentions vary among residents of different intention classes. For residents with low and high intentions, acceptance attitude and subjective norms are the key factors affecting the LCT intentions; for residents with medium intentions, policy perception is the key factor.

1. INTRODUCTION

With rapid economic development, urban permanent population density and urbanization rates have been increasing, and the travel demand has increased dramatically. The number of vehicles has increased drastically – for example, in China, the national motor vehicle ownership reached 435 million by the end of 2023, which has brought a series of urban problems. Relevant data show that the carbon emissions of small passenger cars in urban transportation in China (including metropolitan areas) account for about 40% of the total emissions in the transportation sector. Increasing carbon emissions not only seriously affects the living environment of residents but has also become an issue of concern to the international community. Given the serious energy and environmental problems, China has proposed the dual-carbon goals of achieving a carbon peak by 2030 and carbon neutrality by 2060. Urban transportation, as an important source of energy consumption and carbon emissions, is a key area for achieving the dual-carbon goals.

The decarbonization of urban transportation can primarily be achieved through three key aspects: technological decarbonization, institutional decarbonization, and structural decarbonization. Among them, technological decarbonization measures encompass the promotion of new energy vehicles and the

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enhancement of energy utilization efficiency. Institutional decarbonization measures involve improving market mechanisms and implementing decarbonization policies. And structural decarbonization is mainly based on the change of residents' travel structure. The change in travel structure is the main reason for the change in urban transportation carbon emissions. Compared to the previous two measures, structural decarbonization represents a more direct and effective means. However, as decision-makers involved in carbon emissions in the urban transportation system, residents are both active participants and an unstable factor. Therefore, identifying the key factors influencing the low-carbon travel (LCT) choices of residents is crucial for guiding the travel structure towards low-carbon options and ultimately achieving transportation decarbonization.

Previous research has predominantly utilized the theory of planned behavior as a framework for investigating the LCT intentions of residents [1]. The theory of planned behavior is effective in explaining behavior, positing that the more positive one's perceived behavioral control (PBC), acceptance attitude (ATT), and subjective norms (SN), the stronger their behavioral intention [2]. PBC refers to the cognition of the ability to perform a certain behavior, and ATT refers to an overall positive or negative evaluation of performing a certain behavior. SN are the social pressure one feels when planning to perform a particular behavior. Behavioral intention refers to the subjective probability of performing a certain behavior. Studies have shown that PBC, ATT, and SN have significant positive effects on LCT intentions [3-5]. With the deepening of the research, it has been found that residents' LCT intentions are not only affected by internal factors but also closely related to the external environment of LCT [6-7].

External environmental factors refer to the external factors that have impact on the LCT choices of urban residents, mainly covering the urban built environment, public transport service level, and government policies. Among these factors, the urban built environment, such as population density, terrain, and climate, has been formed and is not easy to change, which is usually not taken into account in research. Scholars mostly take a certain region as a case to explore the influence of government policies and public publicity on LCT intentions [8-9], such as bus fare subsidies and tax reforms. The findings indicate that effective LCT policies can moderately influence residents' intentions to choose LCT modes [10]. However, the impact of government policies and public publicity on residents' LCT choices is closely related to their recognition and acceptance. Existing studies rarely consider the impact of external factors and psychological perceptions on residents' choice of LCT.

In addition, current studies regard urban residents as homogeneous individuals, and it remains ambiguous whether the influence on residents in different regions with different characteristics varies. Therefore, this study comprehensively considers the internal factors and government policy factors to explore the differentiations of LCT intentions and analyze the key factors influencing the choice of LCT by various urban residents.

In summary, this study aims to take Chinese cities as cases to clarify the influencing factors of urban residents' LCT intentions and the interaction mechanism. Through analyze the key factors motivating different residents to choose LCT and put forward specific suggestions to promote the transformation of urban residents' travel structure to low-carbon.

2. DATA COLLECTION AND VERIFICATION

2.1. Questionnaire design

This study obtained LCT data from urban residents through an online questionnaire survey, including residents' socioeconomic attributes and inherent psychological attributes of LCT. Five psychological latent variables – PBC, SN, ATT, low-carbon travel intention (LCTI), and policy perception (PP) – were selected and measured by a five-point Likert scale. Respondents were asked to rate how strongly they agreed with the items, with 1–5 indicating strongly disagree to strongly agree.

In April 2022, data on the LCT intentions of residents in the cities of Shenzhen and Xi'an in China were collected through online questionnaires. A total of 1,206 questionnaires were issued and recovered, of which 500 valid questionnaires were collected in Shenzhen and 505 valid questionnaires were collected in Xi'an, totaling 1,005, with a response rate of 83%. The statistical results of the samples show the consistency of the sample data with the actual population distribution of Shenzhen and Xi'an, which confirms the representativeness of the sample data to a certain extent.

In order to ensure the effectiveness of the subsequent modeling analysis, this study uses reliability and validity analysis to test the reliability of the sample data. Confirmatory factor analysis is employed to test the rationality of the questionnaire setting.

The reliability analysis primarily employs Cronbach's alpha coefficient as the assessment indicator, with a coefficient exceeding 0.7 indicating high reliability. Validity analysis mostly takes Kaiser-Meyer-Olkin (KMO) as the assessment indicator, with a coefficient greater than 0.5 indicating good validity. Based on the results in Table 1, both Cronbach's alpha coefficient and KMO meet the required standards. The composite reliability (CR) and average variance extracted (AVE) are commonly utilized as assessment indicators for confirmatory factor analysis. A CR exceeding 0.6 is generally considered to be consistent, while an AVE surpassing 0.5 is typically considered a valid assessment indicator reflecting latent variables effectively. It can be seen from the CR and AVE results shown in Table 1 that CR and AVE of all latent variables meet the criteria.

Table 1
Assessment indicator results of questionnaire survey data in the cities of Shenzhen and Xi'an in China

	Shenzhen				Xi'an			
Latent variable	Cronbach's alpha coefficient	KMO	CR	AVE	Cronbach's alpha coefficient	KMO	CR	AVE
SN	0.876	0.827	0.88	0.64	0.884	0.840	0.89	0.66
ATT	0.919	0.901	0.92	0.70	0.922	0.901	0.92	0.70
PBC	0.916	0.900	0.92	0.69	0.920	0.897	0.92	0.70
PP	0.932	0.929	0.93	0.69	0.938	0.935	0.94	0.71
LCTI	0.898	0.849	0.90	0.68	0.905	0.850	0.90	0.70

In conclusion, the questionnaire data can be utilized to model and analyze the differentiations of urban residents' LCT intentions from the aspect of the validity of sample data through testing.

3. ANALYSES OF POTENTIAL CLASSES OF LCT INTENTIONS

In order to investigate the differentiations of urban residents' LCT intentions and propose tailored LCT recommendations. This study constructed potential class models based on survey data from the cities of Shenzhen and Xi'an in China to determine the optimal number of classes and analyze the characteristics in different classes.

3.1. Class number determination

To ensure the reliability and effectiveness of the data, residents with similar LCT intentions were classified by identifying the scores of observed variables for each latent variable, and probabilities for each class were determined. The Akaike information criterion (AIC), Bayesian information criteria (BIC), sample size-adjusted BIC (aBIC), entropy, Lo-Mendell-Rubin, and bootstrapped likelihood ratio test are typically used to determine the optimal number of classes. Smaller values of AIC, BIC, and aBIC being preferable, entropy values exceeding 0.8 indicating that the classification accuracy exceeds 90%. And significant Lo-Mendell-Rubin and bootstrapped likelihood ratio test values implying that K-class models are superior to K-1 class models. The potential classification results of residents' LCT intentions in Shenzhen and Xi'an are presented in Table 2.

As shown in Table 2, the AIC, BIC, and aBIC all decrease as the number of classifications increases, indicating an improvement in model fit. The bootstrapped likelihood ratio test suggests that increasing the number of classes may not diminish model significance, while Lo-Mendell-Rubin loses statistical significance after the third class, suggesting no further improvement in model fit. Additionally, entropy shows no significant change after the third class. Therefore, this study proposes dividing urban residents' LCT intentions in Shenzhen and Xi'an into three classes.

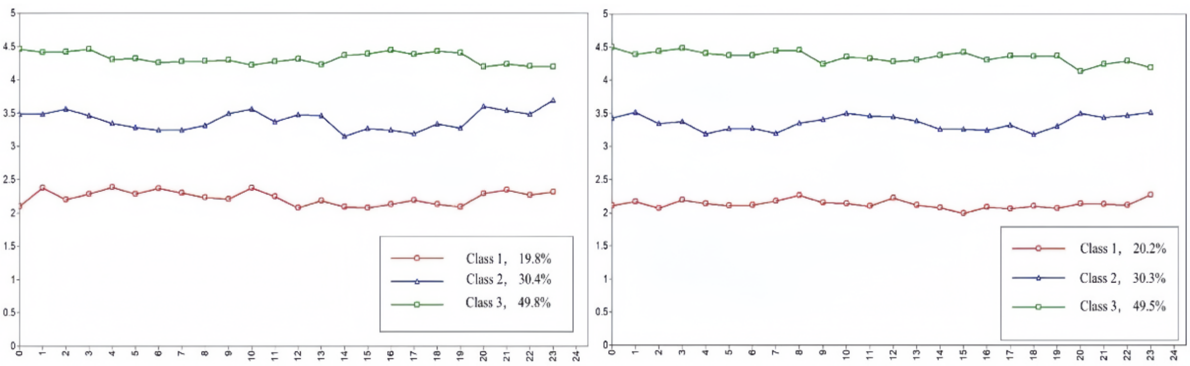
Table 2

Potential classification results of residents' LCT intentions in the cities of Shenzhen and Xi'an in China

City	Class number	AIC	BIC	aBIC	Entropy	Lo-Mendell-Rubin	Bootstrapped likelihood ratio test	Class probabilities
Shenzhen	1	38,793.897	38,996.198	38,843.843	--	--	--	--
	2	33,832.090	34,139.756	33,908.049	0.976	0	0.000	0.320/0.680
	3	32,851.311	33,264.343	32,953.285	0.945	0.003	0.000	0.198/0.304/0.498
	4	32,288.370	32,806.770	32,416.360	0.953	0.347	0.000	0.190/0.200/0.138/0.472
	5	31,972.130	32,595.900	32,126.140	0.955	0.093	0.000	0.180/0.104/0.184/0.420/0.112
	6	31,676.240	32,405.370	31,856.250	0.952	0.513	0.000	0.114/0.078/0.104/0.108/0.412/0.184
Xi'an	1	39,815.540	40,018.320	39,865.960	--	--	--	--
	2	34,260.210	34,568.600	34,336.890	0.972	0.000	0.000	0.325/0.675
	3	32,970.520	33,384.530	33,073.470	0.956	0.000	0.000	0.202/0.303/0.495
	4	32,487.780	33,007.400	32,616.990	0.955	0.636	0.000	0.196/0.145/0.194/0.465
	5	32,176.020	32,801.250	32,331.480	0.953	0.197	0.000	0.172/0.097/0.194/0.402/0.135
	6	31,881.130	32,611.980	32,062.860	0.953	0.455	0.000	0.112/0.087/0.105/0.176/0.382/0.137

3.2. Model analysis results

The LCT intentions of urban residents in the cities of Shenzhen and Xi'an in China were divided into three classes. The horizontal coordinate is the measurement item, and the comprehensive coordinate is the estimated mean of the score. The estimated mean scores of each class of urban residents' LCT intentions on the measurement variables are shown in Fig. 1.



a) Shenzhen b) Xi'an

Fig. 1. The mean scores of each class of urban residents' LCT intentions on the measured variables

As can be seen from Fig. 1, among urban residents in Shenzhen and Xi'an, class 1, defined as low intention, exhibits the lowest scores on each measurement variable of LCT intentions. Class 2, defined as medium intention, demonstrates intermediate scores on each measurement variable of LCT intentions. Class 3, defined as high intention, shows the highest scores on each measurement variable of LCT intentions. Furthermore, the estimated mean scores of LCT intentions for urban residents within the same class in Shenzhen and Xi'an exhibit minimal differences across each measurement variable. Further, with each class as an independent variable and the score of each latent variable as the dependent variable. F-test was conducted to explore whether each latent variable had a significant impact on each class. The results are shown in Table 3.

Table 3
Comparison of latent variables in different classes between the cities of Shenzhen and Xi'an in China

Variable	Shenzhen					Xi'an				
	Low intention	Medium intention	High intention	F	η^2	Low intention	Medium intention	High intention	F	η^2
	99 people	152 people	249 people			102 people	153 people	250 people		
SN	2.25±0.57	3.51±0.63	4.43±0.45	603.15 **	1.12	2.13±0.58	3.41±0.58	4.45±0.42	787.12 **	1.29
ATT	2.33±0.86	3.28±0.87	4.29±0.62	257.64 **	0.94	2.16±0.75	3.25±0.81	4.41±0.48	461.21 **	1.25
PBC	2.23±0.79	3.48±0.86	4.26±0.59	285.75 **	0.95	2.14±0.82	3.45±0.77	4.30±0.59	351.57 **	1.09
PP	2.11±0.64	3.25±0.69	4.40±0.48	578.81 **	1.28	2.06±0.74	3.25±0.77	4.37±0.53	473.97 **	1.29
LCTI	2.31±0.89	3.59±0.88	4.21±0.66	210.38 **	0.82	2.15±0.85	3.50±0.89	4.21±0.70	245.77 **	0.97

Note: ** indicates significance at the 5% level.

Overall, the F value of each latent variable reaches a statistical significance level, indicating that each latent variable exerts a significant influence on each class. Furthermore, there are no significant differences in the mean scores of LCT intentions for all classes of residents in Shenzhen and Xi'an on each latent variable. The high intention exhibits the highest scores on SN, ATT, PBC, PP, and LCTI, followed by the medium intention and then the low intention. This finding also supports the naming of three classifications to some extent.

4. ANALYSIS OF THE LCT INTENTIONS OF URBAN RESIDENTS BASED ON A STRUCTURAL EQUATION MODEL

Based on the aforementioned analysis, the classification of urban residents' LCT intentions in the cities of Shenzhen and Xi'an in China is consistent. Consequently, data from the same class in both cities are amalgamated to establish structural equation models for exploring the influencing factors and their influencing mechanisms affecting these three classes of residents' LCT intentions.

4.1. Model construction

As a method for confirmatory analysis, the structural equation model is employed to validate the proposed hypothesis paths. This study first formulates a hypothesis regarding the influence among the latent variables of the three classes of residents' LCT intentions by collating and summarizing the existing research outcomes. Subsequently, the structural equation models of the three classes of residents' LCT intentions were constructed to verify the hypothesized path and quantify the impact level. Following existing studies [11-14], the low-, medium-, and high-intention structural equation models were constructed, as depicted in Fig. 2.

The commonly used fit indicators for structural equation models include absolute fit statistics and parsimonious fit statistics. The absolute fit statistics include root mean square error, goodness of fit index, incremental fit index, Tucker-Lewis index, and comparative fit index. Parsimonious fit statistics include the parsimony goodness of fit index, parsimony normed fit index, and chi-square freedom ratio. The fitness test results for each hypothesis model with the observed data are presented in Table 4. A comparison of the fitting values of common fitting indicators with standard values revealed that all models exhibit strong fitting effects.

4.2. Model analysis results

To ensure good model adaptation, factor load analysis was conducted for the three structural equation models. Each factor load is positive and significant, indicating that each observed variable affects the construction of the latent variable. The factor load reflects the relative importance of each observed variable to the corresponding latent variable and the greater the absolute value, the higher the degree of correlation. The results of the factor load analysis for the three structural equation models are presented in Table 5.

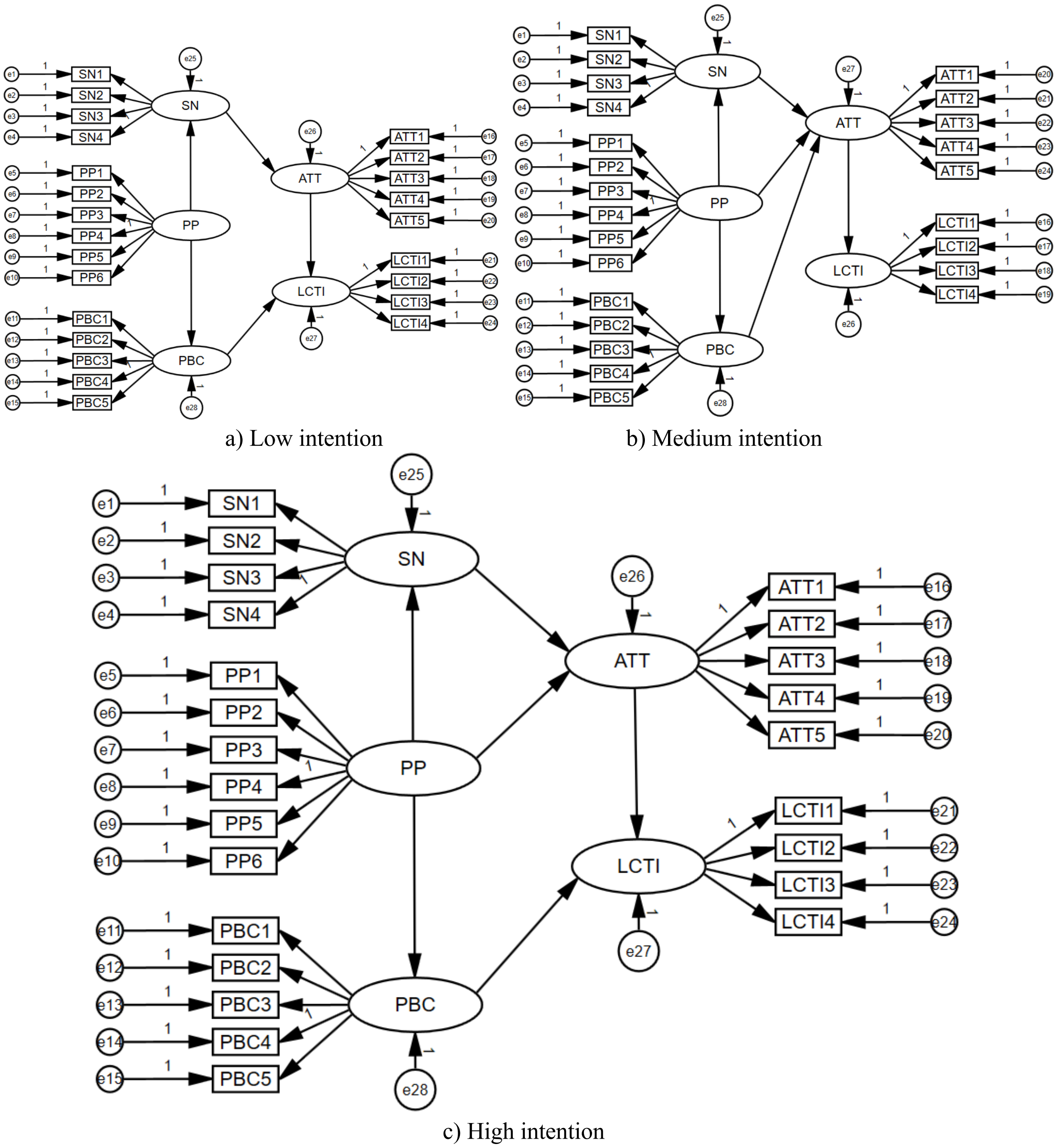


Fig. 2. Structural equation models for three classes of urban residents' LCT intentions

As can be seen from Table 5, the factor load coefficients of all measurement items are all greater than 0.4, indicating that the models have strong explanatory ability. In addition, the factor load coefficient is essentially the contribution degree of observed items to latent variables. The sensitivity of residents to each observed item can be found by comparing the standardized factor load coefficient. The specific analysis is as follows.

Table 4

Fitting indicators results of structural equation models for three classes of urban residents' LCT intentions

Fit indicator		Standard value	Fitted value		
			Low intention	Medium intention	High intention
Absolute fit statistics	Root mean square error	<0.05	0.020	0.026	0.028
	Goodness of fit index	>0.90	0.901	0.928	0.947
	Incremental fit index	>0.90	0.989	0.976	0.960
	Tucker-Lewis index		0.987	0.973	0.954
	Comparative fit index		0.988	0.976	0.959
Parsimonious fit statistics	Parsimony goodness of fit index	>0.50	0.885	0.779	0.855
	Parsimony normed fit index	>0.50	0.773	0.870	0.778
	Chi-square freedom ratio	1-3	1.078	1.206	1.400

Table 5

Results of factor load analysis of three structural equation models

Latent variable	Measured variable	Measured variable content	Standardized factor load coefficient		
			Low intention	Medium intention	High intention
SN	SN1	Relatives and friends think I should travel with low carbon.	0.40	0.55	0.45
	SN2	The government/society advocates LCT.	0.64	0.47	0.43
	SN3	I will choose LCT because my relatives and friends choose LCT.	0.59	0.49	0.52
	SN4	I will choose LCT because the government advocates LCT.	0.40	0.49	0.43
PP	PP1	I support restricting the use of motor vehicles.	0.75	0.67	0.61
	PP2	I support mandatory policies such as purchase limits and fuel consumption limits.	0.73	0.58	0.53
	PP3	I support incentives such as tax incentives for fuel-efficient vehicles and financial subsidies for replacing old vehicles with new ones.	0.73	0.62	0.55
	PP4	I support the national incentive policy for LCT.	0.69	0.66	0.62
	PP5	I think low-carbon policies can change the way people travel.	0.80	0.68	0.67
	PP6	I think a low-carbon policy is meaningful for the country to achieve the dual-carbon goal.	0.75	0.64	0.61
PBC	PBC1	The promotion of shared bikes has made it easier for me to choose LCT.	0.76	0.69	0.60
	PBC2	The development of public transport has made it easier for me to choose LCT.	0.77	0.67	0.59
	PBC3	The increase in taxi fares makes me more inclined to choose LCT.	0.75	0.67	0.64
	PBC4	The restriction of car purchases and the increasing cost of car use make me more inclined to choose LCT.	0.69	0.70	0.71

	PBC5	It is easy for me to choose LCT.	0.72	0.74	0.64
ATT	ATT1	I think LCT is good for easing traffic congestion.	0.71	0.73	0.60
	ATT2	I think LCT can reduce energy consumption.	0.73	0.67	0.61
	ATT3	I think LCT can promote the realization of the dual-carbon goal.	0.72	0.73	0.64
	ATT4	I think LCT is good for health.	0.74	0.70	0.60
	ATT5	I think LCT promotes a positive way of life in line with the social value orientation.	0.69	0.72	0.66
LCTI	LCTI1	I would like to make public transport my preferred mode of travel.	0.72	0.72	0.69
	LCTI2	I prefer public transport to cars for daily travel.	0.73	0.75	0.66
	LCTI3	For short distances, I prefer to walk or cycle.	0.76	0.74	0.72
	LCTI4	I would like to recommend LCT to others.	0.77	0.74	0.71

For residents with low intention, SN2 makes the greatest contribution to SN, indicating that such residents are more sensitive to government or social advocacy. PP5 makes the greatest contribution to PP, indicating that such residents pay more attention to the impact of policies on lifestyle. PBC2 makes the greatest contribution to PBC, indicating that such residents pay more attention to the convenience of public transportation facilities. ATT4 makes the greatest contribution to ATT, indicating that such residents pay more attention to the benefits of LCT for health. LCTI4 makes the greatest contribution to LCTI, indicating that such residents are more willing to recommend LCT to others.

For residents with medium intention, SN1 makes the greatest contribution to SN, indicating that such residents are more sensitive to the publicity of companies and communities. PP5 makes the greatest contribution to PP, indicating that such residents pay more attention to the impact of policies on lifestyle. PBC5 makes the greatest contribution to PBC, indicating that such residents pay more attention to their ability to perform LCT. ATT1 and ATT3 make the greatest contribution to ATT, indicating that such residents pay more attention to the role of LCT in alleviating congestion and promoting energy conservation and emission reduction. LCTI4 makes the greatest contribution to LCTI, indicating that such residents would prefer to use public transport rather than cars.

For residents with high intention, SN3 makes the greatest contribution to SN, indicating that such residents are more sensitive to publicity from relatives and friends. PP5 makes the greatest contribution to PP, indicating that such residents pay more attention to the impact of policies on lifestyle. PBC4 makes the greatest contribution to PBC, indicating that such residents pay more attention to the use cost of cars. ATT5 makes the greatest contribution to ATT, indicating that such residents pay more attention to the significance of LCT to social value. LCTI3 makes the greatest contribution to LCTI, indicating that such residents are more willing to choose LCT for short-distance travel.

Overall, three classes of residents are sensitive to the LCT policies introduced by the government. The residents with low intention are more willing to accept the advocacy of the state and society to choose LCT. Residents with medium and high intentions are more willing to accept the advocacy of friends and relatives to choose LCT. For the residents with low intention, the improvement of public transport can effectively promote LCT, while for residents with high intention, the increase in the cost of car use is the key to promoting LCT. In addition, the residents with low intention pay more attention to the benefits of LCT on physical health, while residents with medium and high intentions are more concerned about the benefits of LCT on social development.

Further, a path analysis was conducted to investigate the causal relationships between latent variables. The path analysis results among the latent variables of LCT intentions for three classes of urban residents are presented in Table 6.

As can be seen from Table 6, for the residents with low intention, ATT exerts a significant impact on LCTI, and SN affects LCTI by influencing ATT, while PP and PBC do not yield significant effects. For such residents, LCT intentions can be increased by improving ATT and SN scores. Therefore, promoting the benefits of LCT, such as health benefits, alleviating traffic congestion, and reducing energy consumption, can improve their acceptance of LCT and guide them to choose LCT actively. Furthermore, the dangers of traffic congestion, air pollution, and energy consumption can be displayed to the public to help residents feel the serious consequences of traditional motorization more directly and guide them to choose LCT.

Table 6

Path analysis results among latent variables of LCT intentions for three classes of urban residents

Hypothetical path	Standardized path coefficient		
	Low intention	Medium intention	High intention
PP → SN	0.070	0.061	0.059
PP → PBC	0.181**	0.272***	0.076
PP → ATT	--	0.381***	0.189***
SN → ATT	0.787***	0.686***	0.543***
ATT → LCTI	0.224***	0.143**	0.252***
PBC →LCTI	0.107	--	0.188***
PBC → ATT	--	0.277***	--

Note: ** indicates significance at the 5% level; *** indicates significance at the 1% level.

For residents with medium intention, ATT exerts a significant impact on LCTI. SN and PBC affect LCTI through influencing ATT, while PP indirectly influences LCTI by influencing ATT and PBC. For such residents, LCT intentions can be increased by improving the scores of ATT, SN, PBC, and PP, among which PP is the main factor. Therefore, the improvement of LCT facilities and the implementation of encouraging policies for public transport can improve the acceptance attitude and perceived behavior control of LCT of such residents, thereby enhancing their LCT intentions. Furthermore, the government can regulate car purchasing and car use through economic measures, such as increasing parking fees, and raising purchase taxes so that urban residents feel that choosing public transport is more favorable.

For residents with high intention, ATT and PBC significantly influence LCTI, and PP and SN indirectly affect LCTI by affecting ATT. For such residents, LCT intentions can be increased by improving the scores of ATT, SN, PBC, and PP, among which SN and ATT are the main factors. The status and outcomes of energy conservation and emission reduction in society can be announced through various kinds of publicity to enhance residents' understanding, and support of LCT. Meanwhile, increasing investment in public transport and enhancing transport infrastructure can improve the convenience and comfort of public transit to enhance the LCT environment of residents. Additionally, a carbon account can be established to enable residents to obtain carbon credits according to LCT scenarios, and receive certain rewards accordingly so that residents can feel the benefits of LCT more intuitively.

Overall, SN and ATT significantly influence the LCT intentions of all three classes of residents. In light of this, communication platforms can be established for LCT publicity activities, symposia, and forums to provide the public with popular science education on green travel knowledge, skills, and practical methods. Furthermore, targeted measures should also be taken for residents with different characteristics of LCT intentions to guide them to choose LCT.

5. CONCLUSIONS

In order to effectively guide urban residents towards LCT, this study employed latent class analysis to identify the group differentiations of residents' LCT intentions. Then constructed structural equation models for different classes of residents with different characteristics of LCT intentions to investigate the factors influencing residents' LCT intentions and their influencing mechanisms, accordingly proposes recommendations to promote residents LCT.

The primary findings of this study are as follows: there are differentiations in the LCT intentions among urban residents, which can be classed into low, medium, and high intention. The influencing factors and influencing mechanisms of LCT intentions of different intention classes are different. For residents with low and high intentions, acceptance attitude and subjective norms are the key factors affecting their LCT intentions, while for residents with medium intention, policy perception is the main factor. Relevant policies and measures can be formulated for different classes of residents to promote LCT. The LCT intentions of residents in different cities tend to be consistent, and the government can develop a series of relevant policies to promote LCT on a pilot basis and promote them across the nationwide. This study used the cities of Shenzhen and Xi'an in China as representative examples respectively, to investigate the disparities in LCT intentions among urban residents, which can offer certain theoretical guidance for the government in mitigating carbon emissions. However, due to the diverse backgrounds and cultures of different cities, there may be variations in the implementation of certain LCT measures, which warrant further investigation.

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