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Research Paper

Who is more willing to use shared autonomous vehicles in first-mile-last-mile? A heterogeneity study on carbon incentive policy from China

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ABSTRACT

Encouraging and motivating travelers to opt for more efficient and low-carbon last-mile transportation options is a crucial strategy for increasing the share of public transportation. This study aims to under-stand travelers' preferences for the new travel mode combination of "shared autonomous vehicles + subway" and to explore effective incentive policies to encourage heterogeneous population with di-verse demographics to adopt this mode. Grounded in social cognitive theory, the study establishes a structural equation model encompassing four latent variables: low-carbon knowledge, low-carbon habits influenced by policy incentives, external environmental factors, and low-carbon travel intention, to analyze the factors influencing individual transportation mode choice. Prospect theory is proposed to calculate prospect values rather than utility values, and a discrete choice model is constructed to estimate the risk preference coefficients of various traveler types under different incentive measures, facilitating a comparison of the effectiveness of these incentives. The findings indicate that residents of mega-cities and low-income groups are more responsive to policy incentives and more inclined to choose the combined transportation mode. In mega-cities, travelers show a higher preference for public transportation recharge rewards, whereas cash rewards are more attractive to travelers in second-tier cities and low-income groups. High-income groups exhibit a stronger preference for commodity shop-ping vouchers. Incorporating these insights into the incentive measures of decarbonization platforms will enhance the promotion and adoption of the combined transportation mode.

1. Introduction

During the process of urbanization, issues such as traffic congestion, environmental pollution, and inefficient use of land and road resources have become increasingly prevalent. Numerous studies have highlighted transportation emissions as a

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significant contributor to air pollution (Liu and Liu, 2023). Consequently, the development of intensive and cost-effective public transportation has garnered significant attention in the field of urban transportation, as increasing the share of public transportation is considered a viable solution to urban challenges (Zhao et al., 2019). However, in countries like China, the proportion of motorized travel modes in public transport has declined by approximately 11% in the past five years, indicating a decline in the appeal of public transportation at the demand-side (Adnan et al., 2019). One major factor contributing to the lack of attractiveness of public transportation is its limited level of service, particularly concerning the ''first mile and last mile (FMLM)'' problem in urban rail transit (Adnan et al., 2019). Travelers often face significant time, energy, and opportunity costs when accessing or departing from a subway station, thereby increasing the overall cost of utilizing public rail transit. Addressing the FMLM problem holds promise for enhancing the sharing of public transportation (Fig. 1).

In recent years, significant progress has been made in autonomous driving technology, driven by advancements in artificial intelligence, particularly in recognition, decision-making, and detection capabilities. As a result, manufacturers of fully self-driving cars and related companies have confidently entered the phase of product testing (Gurumurthy et al., 2020). Concurrently, shared transportation services have also witnessed continuous advancements, with platforms gradually improving and shared transportation becoming a popular mode of mass transportation (Yeung et al., 2019). These developments have contributed to the rising popularity of Shared Autonomous Vehicles (SAVs), which encompass on-demand services (where customers book vehicles in real-time), reservation services (where customers book vehicles in advance), and hybrid services (a combination of the two) (Santhanakrishnan et al., 2020). SAVs are considered relatively environmentally friendly and offer a more comfortable and flexible mobility experience compared to most existing public transportation feeder modes (Grahn et al., 2023). Consequently, scholars regard SAVs as a reliable solution to the metro FMLM problem (Wang et al., 2020).

The mode share of public transportation is ultimately determined by the traveler's own decision behavior. Travelers are frequently still hesitant to choose a travel mode, despite the fact that SAV has several advantages in terms of applicability (Haboucha et al., 2017). Many nations, including China and the UK, have placed a strong emphasis on carbon reduction incentives based on personal carbon accounts and have begun to implement phased and regional policy promotion initiatives to encourage tourists to choose low-carbon modes of transportation. Such incentives have demonstrated their efficacy in raising the appeal of services within the sharing economy (Ma et al., 2019; Bandura, 2001). Since SAV access to the metro is expected to be used to promote individual carbon reduction incentives as a form of transit for travelers (Yap et al., 2016).

In recent years, research on incentives to promote low-carbon behaviors and the purchase of low-carbon mobility products (e. g. electric vehicles) has increased due to carbon reduction targets. However, the implementation and diffusion of these incentives face challenges, such as high costs and low acceptance by travelers (Fuso Nerini et al., 2021). Citizens' attitudes towards low-carbon incentives may vary due to self-interest (Long et al., 2021). Current research on low-carbon travel incentives focuses on incentive strength and public acceptability (Wang et al., 2023a,b). However, there is limited attention given to the impact of policy instruments on different travelers, i.e., the influence of traveler heterogeneity on policy effects.

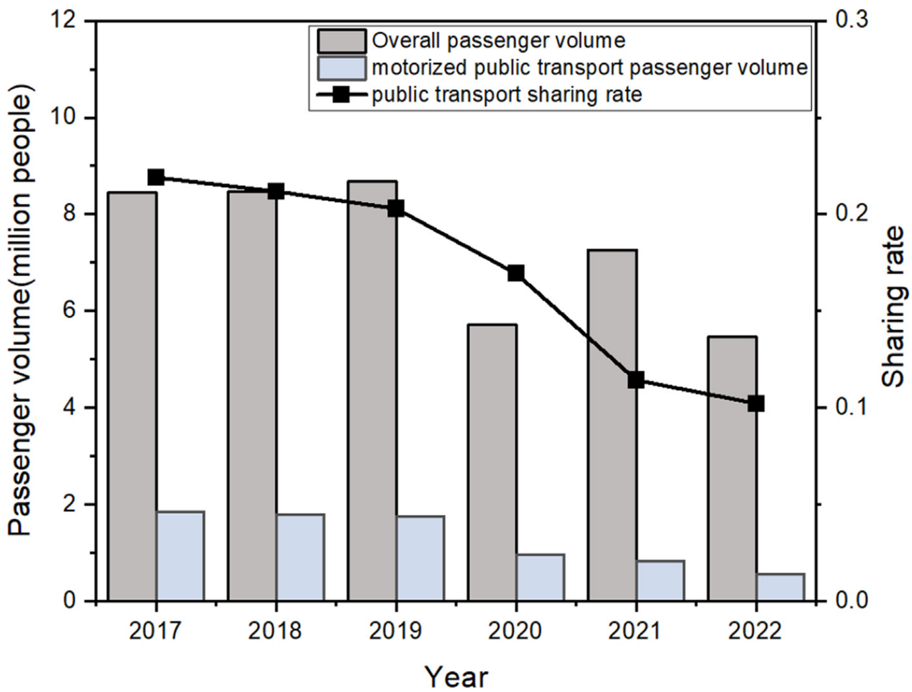


Fig. 1. China's public transport data in recent years.

Furthermore, research on travelers' choice of Shared Autonomous Vehicles (SAVs) as a feeder mode in the context of FMLM is still in its early stages. Although many studies have discussed travelers' preference for SAVs (Pettigrew et al., 2019; Jing et al., 2019; Gurumurthy & Kockelman, 2020; Magassy et al., 2023; Krueger et al., 2016), policy incentives have not been considered, and the impact of individual carbon reduction incentives on promoting the use of SAVs as feeder trips remains unclear. While some studies have mentioned management and policy recommendations (Ansariyar et al., 2023; Zhou et al., 2020), they mainly rely on preference analysis and generalizations, lacking strong guidance. The current discussion on SAV usage preference based on traveler heterogeneity mainly focuses on the convenience they can provide to the elderly population (Hao et al., 2023; Sun et al., 2020; Zandieh & Acheampong, 2021).

In order to fill the existing research gaps, the main objective of this paper is to understand the willingness of travelers to choose the combination of 'SAV + metro' under specific travel scenarios with different attributes of various incentives, and to put forward targeted policy recommendations to encourage travelers to choose the combination of travel modes. This paper aims to achieve these objectives by making the following key contributions:

(1) Based on Social Cognitive Theory (SCT), a structural equation model was established to explore the role of low-carbon habits (including individual participation in carbon reduction incentives) on travelers' choice of travel mode behavior.
(2) A comparative study was conducted on travelers with different income levels and living cities, examining the weights of various costs considered when choosing a travel mode, i.e. the importance placed on the economic, environmental, and comfort aspects of travel modes.
(3) A discrete choice model was established based on Prospect Theory, quantitatively studying the impact of various incentives on the heterogeneous residents' choice of travel mode by calibrating the risk preference coefficients in Prospect Theory, providing targeted recommendations for promoting carpooling in the FMLM scenario.

2. Literature review

2.1. Passenger preferences for SAVs

With the development of autonomous driving technology, the public's willingness to use, pay for, and purchase autonomous vehicles has become an important research topic. Numerous studies have investigated the behavioral characteristics of travelers, household and demographic factors, familiarity with autonomous driving technology, and how attributes of the built environment affect the willingness to use autonomous vehicles (Saeed et al., 2020; Koppel et al., 2022). Research has also delved into how people's attitudes towards multitasking during travel (Malokin et al., 2019) and their personal driving styles (Lee et al., 2023) influence the choice of autonomous driving modes during commuting. However, comparative analysis shows that research results on traveler preferences are inconsistent. Contrary to the expectations of some researchers, not all studies consistently show a clear preference or resistance towards using autonomous driving services, as travelers' usage preferences are greatly influenced by travel scenarios.

Shared autonomous vehicles (SAVs), as an important application scenario of AVs, have always been a focus of many studies. Research has shown that, in addition to demographic characteristics (Zhou et al., 2020) and socioeconomic factors (Wang et al., 2021a,b), the increase in waiting time and travel costs associated with shared services is also an important determining factor for passengers to adopt autonomous vehicles (Yao et al., 2022). Many studies believe that SAVs are an ideal solution to the "last mile" problem in the public transportation industry (Khaloei et al., 2021; Mo et al., 2021; Schaller, 2021). However, there is still relatively limited research on the preferences of travelers for choosing SAVs in this scenario, with most studies still focusing on factors influencing choice behavior.

In the research conducted so far, a part of it has focused on elucidating the correlation between traveler personal characteristics, travel attributes, and the willingness to use Shared Autonomous Vehicles (SAVs), with a particular emphasis on analyzing data from the Revealed Preference (RP) questionnaire. Other studies have investigated the willingness of travelers to choose SAVs in specific travel environments by analyzing data from the Stated Preference (SP) questionnaire. Researchers have carefully designed scenarios such as commuting (Haboucha et al., 2017; Etzioni et al., 2021), leisure travel, and different travel distances (Cordera et al., 2022) to explore travelers' subtle preferences for SAVs. These surveys comprehensively analyze the extent of different populations' preferences for SAVs in various travel situations. However, few studies have considered the impact of carbon reduction incentive policies on travelers' willingness to choose SAVs. Without designing experiments and incorporating incentive measures as variables into the experimental scenarios, it is difficult to determine whether carbon reduction incentive policies have a positive effect on travelers' willingness to choose SAVs.

2.2. Theory and models in travel mode choice behavior

In the field of traveler behavior research, the most common types of research models are individual choice models represented by discrete choice models and aggregate models represented by SEM models.

In terms of studying travel mode choice behavior, discrete choice models are one of the most mature and widely used models. Currently, due to the difficulty in obtaining empirical data related to Shared Autonomous Vehicles (SAVs), most researchers prefer to use Stated Preference (SP) or Revealed Preference (RP) surveys to collect data and fit questionnaire results using various discrete choice models. These models mainly include the Multinomial Logit (MNL) model (Andrei et al., 2022; de Clercq et al., 2022) and the Mixed Logit model (Cordera et al., 2022; Zhou et al., 2020; Hamadneh and Esztergár-Kiss, 2022). These discrete choice models have good explanatory power and are suitable for studying travelers' travel intentions in new situations.

However, most of these models only use utility maximization theory combined with logical models, and generally assume that travelers are fully rational and have a clear understanding of the costs of various travel modes. This fails to reflect the psychological state of travelers when faced with new things. In other words, utility maximization theory cannot explain travelers' risk preferences for new combinations of travel modes under incentive mechanisms. Some researchers have incorporated prospect theory into discrete choice models, replacing objective utility with prospect value, to improve the accuracy of model predictions (Ma et al., 2019), providing research ideas for this study.

In addition to using discrete choice models to fit travelers' choice behavior, many researchers have attempted to explore factors influencing travel mode choice behavior using various methods. The factors influencing traveler decision-making are complex and diverse, and these factors can also interact with each other. Traditional discrete choice models are difficult to capture these factors. Therefore, some researchers have tried to use improved logic models or alternative methods. For example, using agent-based models (Lokhandwala and Hua, 2020), Decision Field Theory (DFT) and Random Utility Theory (Gabe and Hyland, 2020), or multitask learning deep neural networks (Wang et al., 2020), etc. These models sometimes play an important role in studying factors related to traveler choice behavior.

Structural equation models have also played an important role in studying factors related to traveler choice behavior. Especially in recent years, researchers have paid more attention to the influence of psychological latent variables on traveler travel mode choice behavior. Scholars have established structural equation models to clarify various latent variables that influence travel behavior to support choice behavior research. It improves the shortcomings of discrete choice models that only consider the influence of travel mode attributes and fail to reflect the influence of personal feelings and attitudes (Si et al., 2019). Many researchers have established structural equation models based on the Theory of Planned Behavior to explore the influence of subjective norms, attitudes, and perceived behavioral control on travel mode choice (Zhang et al., 2022; Zhang et al., 2019; Liu et al., 2017). The research found that psychological factors such as perceived behavioral control and sensitivity to changes in travel utility can influence traveler choice behavior. In the existing literature related to the intention of choosing Shared Autonomous Vehicles (SAVs), researchers believe that factors such as service quality, perceived usefulness, and perceived ease of use of SAVs can influence traveler choice behavior. However, the impact of carbon reduction incentives on traveler behavior has not been reflected in the research, and more research involves restrictive measures such as private car restrictions (Liu et al., 2017). When selecting latent variables related to low-carbon literacy, researchers include variables such as personal low-carbon awareness and low-carbon knowledge in the model. Interestingly, the research results show that the influence of low-carbon knowledge on travel mode choice is limited and weak (He et al., 2024), and the influence of low-carbon awareness on changing travel mode choice is also small and indirect (Liu et al., 2017).

However, the current research focuses more on the definition and division of latent variables in terms of individual cognition and intention, neglecting the impact of external environmental policy changes on travelers. Therefore, in order to incorporate the influence of individual carbon reduction incentives on travel mode choice into the model, a more suitable theoretical model is needed as support, which includes both individual decision mechanisms and the impact mechanism of external environmental changes on individual decisions.

2.3. Incentives policies for low-carbon travel behaviors

Low-carbon incentive policies have been implemented for some time in various countries. From the perspective of incentive effects, the positive impact of incentive policies on promoting the purchase of new energy vehicles (Wang et al., 2019; Wang et al., 2021a,b) and the use of shared transportation modes (Basili & Rossi, 2019; Akyelken et al., 2018) has been affirmed. It particularly emphasizes the potential of low-carbon incentives in encouraging public transportation (Shao et al., 2023). Specifically, the influence of incentive policies on travelers' shift from private car usage to public transportation usage is significant (Jiang et al., 2023). The establishment of various carbon accounts, carbon point settings, and exchanges are all aimed at incentivizing public transportation use. In terms of incentive design, multiple studies suggest that a combination of policy measures is more likely to be accepted, and it is proposed that different measures should be used to incentivize travelers with different attributes (Akyelken et al., 2018; Wang et al., 2021a,b). Some studies have also proposed comprehensive types of policy measures and policy formulation principles (Ma et al., 2019; Wang et al., 2021a,b), but they mostly provide a macro framework and do not directly guide the design of specific incentive measures.

Unfortunately, almost all analyses have treated travelers as a whole group, neglecting the fact that the same incentive policies may have different effects on different types of travelers. Research has shown that factors such as income level, gender, and age can influence the effectiveness of incentive measures on travelers, but it is currently unclear how exactly these factors impact the effectiveness (Chen et al., 2022).

2.4. Summary

In summary, in terms of research content, there are already quite a few references available for exploring travelers' preferences for Shared Autonomous Vehicles (SAV). However, there are relatively few articles that study this in the FMLM scenario. Moreover, during the research process, they generally overlook the influence of external policy incentives on travelers' mode choice behavior and do not incorporate external incentive mechanisms as variables in the research scenario. Additionally, in the related research on incentive mechanism design, the heterogeneity of travelers' socio-economic attributes and low-carbon habits is not adequately considered, which may result in incentive mechanisms that lack targeting and waste policy implementation costs.

In terms of research methods, when constructing SEM, there is rarely an inclusion of policy incentives as a factor in the model, nor is there much consideration of social external factors. When establishing the Logit model, using utility maximization theory can lead to an inability to reflect travelers' risk attitudes towards new things.

3. Methodology

This chapter first introduces the questionnaire design and provides a statistical description of the socioeconomic attributes of the survey respondents. Then, based on social cognitive theory, a structural equation model is established to explore how policy incentives influence the choice of low-carbon travel modes by travelers. Furthermore, based on prospect theory, a travel mode choice model is constructed to fit the choice results of travelers, with the objective of minimizing the probability calculation error. The risk preference coefficient α is calibrated to reflect the risk preferences of different types of travelers towards different incentive measures (Fig. 2).

3.1. Survey design and implementation

This study utilized an online questionnaire as the primary data collection method. Following the design of each section of the questionnaire, it was distributed to a sample of 20 undergraduate and graduate students. Feedback was gathered from the participants, and based on their suggestions, improvements were made to the layout and descriptions of the questionnaire items. After conducting a validity screening process, a total of 442 valid questionnaires were obtained for the study. The questionnaire survey consisted of three parts: a survey gathering respondents' basic information, a survey measuring their willingness towards low-carbon travel using a scale, and a survey assessing their willingness to choose low-carbon travel under specific scenarios.

3.1.1. The statistical power of the hypothesis tests

This study employed simple random sampling to determine the sample size, with the calculation process as follows:

$$n = \frac{Z^2 p(1-p)}{e^2} \tag{1}$$

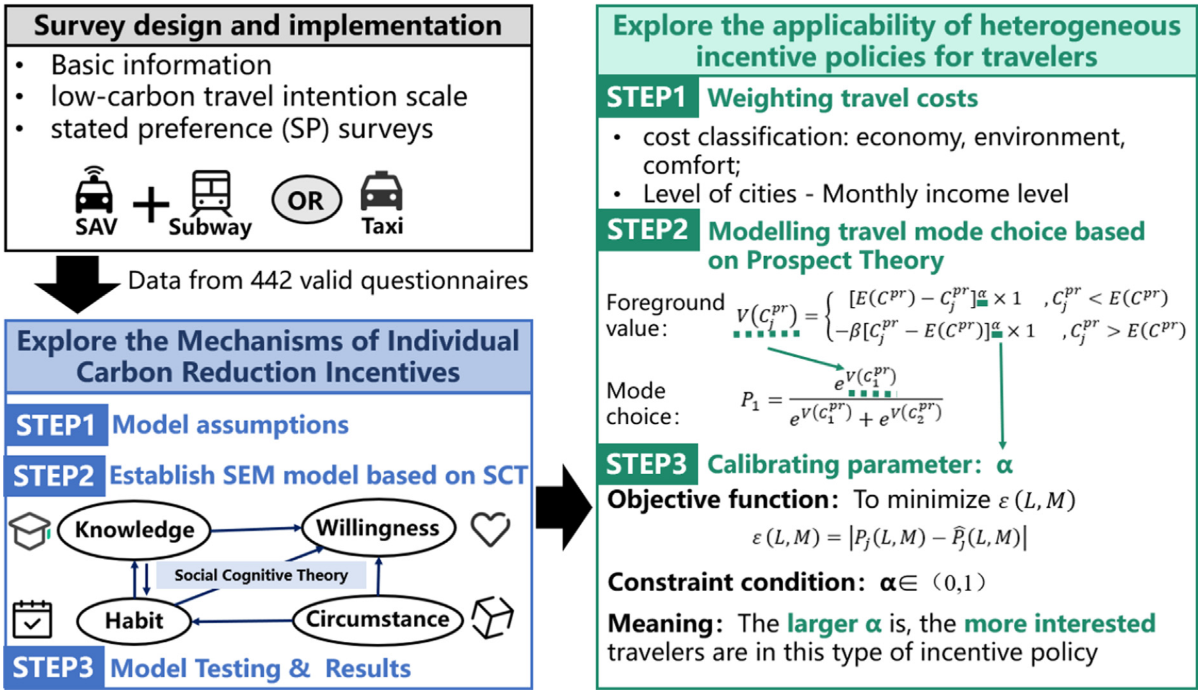


Fig. 2. Research framework.

n represents the minimum required sample size.
p is the proportion of the indicator, and when it is typically taken as 0.5, the estimated value of the sample variance $p(1-p)$ is maximized, yielding a more conservative sample size.
e is the precision, which refers to the allowable error range in the survey; in this study, the allowable error range is set at 5%.
Z is the confidence level, a 95% confidence level corresponds to a confidence value of 1.96.

The calculation revealed that this study needs to obtain at least 384 questionnaires to draw valid conclusions. Additionally, some studies (Hair et al., 2009) have indicated that when constructing a structural equation model with seven or fewer constructs and a required factor loading of no less than 0.45, a minimum of 300 samples is necessary. Therefore, the number of samples needed for this study should be between 384 and 500. Furthermore, considering the potential existence of invalid questionnaires during the collection process, the initial number of questionnaires that this study needs to acquire should exceed 420 but be less than 500.

3.1.2. Basic information investigation

This section ai ms to collect nine key pieces of information regarding the respondents. These include age, gender, monthly income level, city of residence classification, education level, occupation type, possession of a driver's license, ownership of a private car, and the number of family members.

3.1.3. Survey on low carbon travel intention and its influencing factors

To examine the process and mechanism of how carbon reduction incentive policies affect individual travel mode choices, this study developed a low-carbon travel intention scale. The scale comprises both existing items and novel items that assess travelers across four dimensions: low-carbon knowledge, participation in carbon reduction policies, situational factors, and low-carbon travel intention. Table 1 presents the references for the questionnaire items used in this scale.

3.1.4. Travel scenario design for stated preference (SP) surveys

The travel scenarios for this study were designed as follows:

– Travel starting point: Chengdu Tea Culture Park.
– Travel end point: Jinjiang Campus of Chengdu Vocational and Technical College.
– Travel time: During the morning peak on weekdays.
– Mode of travel options: Online taxi or SAV (Shared Autonomous Vehicle) + subway + SAV (Fig. 3).

The travel fares and travel times used in the two travel modes are based on actual situations.

3.2. Exploring the mechanisms of individual carbon reduction incentives

3.2.1. Social cognitive theory

Bandura's (Bandura, 2001) Social Cognitive Theory (SCT) has been widely used across research fields in validating individual behavior. It emphasizes that individual behavior, subject cognition and social environment are dynamically interacting. Among them, subjective cognition is divided into two components: self-efficacy and outcome expectations.

Table 1
Variables and their corresponding items.

Latent variable	Code	Observed variable (item)
Low carbon knowledge	KNO1	I know which behaviors are low-carbon behaviors
	KNO2	I know the importance of low carbon behavior
	KNO3	I know how to do low carbon behavior
	KNO4	I know what the carbon inclusion mechanism is
Low carbon habits	HAB1	I turn off the lights when I leave the room
	HAB2	In my daily life, I generally don't use disposable items or non-renewable resources
	HBA3	I often manage my low-carbon travel points
	HAB4	I often redeem my low-carbon travel points for rewards
	HAB5	I often introduce and show low-carbon travel points and their redemption function to my family and friends
Circumstances factors	CIR1	If there are policy incentives, I would like to use public transport more
	CIR2	If there is positive information in the media, I will be willing to use public transport more
	CIR3	If the people around me are advocating low-carbon travel, I will be willing to use public transportation more
Low-carbon travel willingness	WIL1	In order to reduce traffic congestion, I am willing to participate in green travel
	WIL2	When choosing a travel mode, I will consider whether the mode is low-carbon
	WIL3	I will support the low-carbon travel policy advocated by the state
	WIL4	I would like to encourage my family and friends to choose low-carbon travel modes

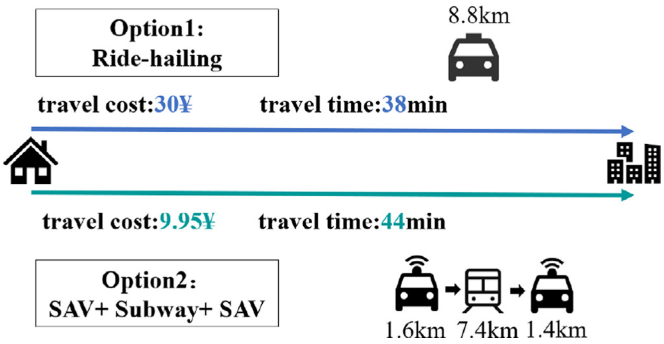


Fig. 3. Research scene design diagram.

3.2.2. SEM modeling

To investigate the decision-making process of travelers' mode choice under carbon reduction incentive policies, this study incorporates four key variables based on the Social Cognitive Theory (SCT): low-carbon knowledge, low-carbon habits, low-carbon travel intention, and situational factors, corresponding to outcome expectations, self-efficacy, individual behavior, and social environment in the SCT theoretical framework. As shown in Fig. 4, a structural equation model (SEM) is constructed to examine the relationships among these variables (Fig. 4).

Drawing from existing research on the relationships between these variables, the following hypotheses are proposed:

H1: Low-carbon knowledge positively influences participation in carbon reduction incentive policies.
H2: Low-carbon knowledge positively influences low-carbon travel intention.
H3: Participation in carbon reduction incentives positively influences willingness to travel low-carbon.
H4: Situational factors positively influence low-carbon travel intention.
H5: Situational factors positively influence participation in carbon reduction incentive policies.

3.3. Modelling of approach selection based on prospect theory

In this study, travelers are firstly classified based on their monthly income levels and city class of residence. This classification takes into account the variations in reference points for travelers residing in different city classes and the differences in monetary costs and congestion costs based on their income levels. By calculating the subjective perceived travel costs and the corresponding reference point travel costs for different types of travelers, the value function and decision weight function are derived. These calculations further determine the prospect values associated with two travel options.

In the final analysis, the probability of mode choice for a specific population group is determined by replacing the traditional utility value with the prospect value. The Logit model is employed to calculate the probability of mode choice, which is then compared with the actual probability obtained from the questionnaire data. Through this comparison, the risk preference parameter is calibrated to refine the estimation of mode choice probabilities.

3.3.1. Weighting of travel cost components

In this study, travelers are classified based on their monthly income level and the city tier they reside in. This classification takes into account the differences in reference points for travelers residing in different city tiers, as well as the variations

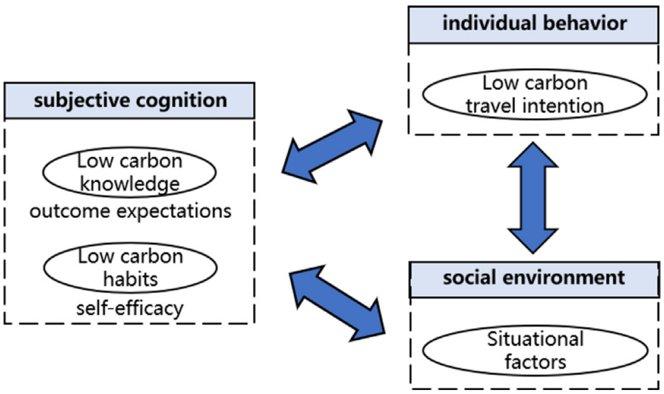


Fig. 4. Structural equation model based on social cognitive theory.

in monetary costs and congestion costs based on their income levels. These two categorization dimensions were chosen because they are more observable and representative of how respondents reflect on incentives in different living environments. By calculating the subjective perceived travel costs and corresponding reference point travel costs for different types of travelers, value functions and decision weighting functions are derived. These calculations further determine the prospect values associated with the two travel options.

In the final analysis, prospect values are used instead of traditional utility values to determine the mode choice probabilities for specific population groups. The mode choice probabilities are calculated using a Logit model and then compared with the actual probabilities obtained from questionnaire data. Through this comparison, risk preference parameters are calibrated to improve the estimation of mode choice probabilities.

For individual travelers, time and cost are two important factors influencing travel costs, followed by considerations of comfort and safety during the travel process. This study defines the subjective perceived travel costs of the two modes of transportation as a weighted combination of travel monetary costs, travel environmental costs, and train overcrowding costs. These components reflect the economic, environmental, and comfort aspects of the travel modes, and the weights depend on the cognitive judgments of individual travelers, which will be obtained through a questionnaire survey.

$$C^{pr} = w_1 \cdot \left(C_{11}^{pr} + C_{12}^{pr}\right) + w_2 \cdot C_2^{pr} + w_3 \cdot C_3^{pr} \tag{2}$$

In the equation:

C^{pr} represents the subjective perception of travel cost for travelers;
$C_1^{pr\prime}$ represents the monetary cost of travel, C_{11}^{pr} represents the time cost of travel; w_1 represents the weight of monetary cost, ranging from 0 to 1;
C_2^{pr} represents the environmental cost of travel; w_2 represents the weight of environmental cost, ranging from 0 to 1;
C_3^{pr} represents the congestion cost of travel; w_3 represents the weight of congestion cost, ranging from 0 to 1;

The time cost and ticket cost are obtained from real data of the research scenario, and the time cost is calculated based on the theory of time value and the monthly income level of the travelers; the environmental cost is calculated by converting the CO_2 emissions of the two travel modes; the congestion cost is obtained by referring to the income level classification table of the travelers. After calculating the travel costs of each component, there are significant numerical differences, which can easily lead to errors in the model selection results. Therefore, it is necessary to standardize them. The min–max method is used, and the calculation method is as follows:

$$C_i^{pr} = \frac{C_i^{pr\prime} - min}{max - min} \quad (i = 1, 2, 3) \tag{3}$$

In the equation:

C_i^{pr} represents the standardized cost of the i type of travel;
$C_i^{pr\prime}$ represents the original cost of the i type of travel;
max represents the maximum value among all travel mode costs in this category;
min represents the minimum value among all travel mode costs in this category.

According to the questionnaire data, the importance of the three factors, namely, cost, environmental friendliness, and comfort, in choosing modes of transportation can be obtained. The weights of different components of the cost are calculated by averaging the weights according to the level of the residential city and the monthly income level, which will be used as reference points for calculation.

3.3.2. Calculate the reference point

Calculate the standardized costs of different transportation modes for all travelers using data from Tables 2 and Table 8, which will provide a reference point for different categories of travelers. The calculation method is as follows:

$$E\left(C^{pr}\right) = \sum_i \rho_i \left(\sum_i w_i C_{ij}^{pr}\right) \tag{4}$$

where

$E\left(C^{pr}\right)$—reference point value for travelers;
ρ_i—share rate of mode j, obtained from the statistical yearbook of the research scenario;
w_i—weight of cost for the i category of travelers, i = {1,2,3};
C_{ij}^{pr}—cost of mode j for the i category of travelers.

Table 2
Statistics on basic traveler information.

Basic information	Classification	Classification standard	Unit	Number of people	Rate
Sex	Male			195	44.12%
	Female			247	55.88%
Household size	Small size	1–2	person	36	8.14%
	Middle size	3		246	55.66%
	Large size	More than 4		160	36.20%
Monthly income level	Low-income groups	Less than 2,000	RMB	138	28.28%
	Medium and low-income groups	2000–5000		84	2.94%
	Middle-income groups	5001–8000		64	19.00%
	Middle and high income groups	8000–10000		87	23.98%
	High-income groups	More than 10,000		27	25.79%
Education level	Junior high school and below			13	2.94%
	High school (junior college)			25	5.66%
	Bachelor's Degree (College)			343	77.60%
	Master's Degree and Above			61	13.80%
City Classification	Mega-city	More than 10 million		49	11.09%
	Metropolis	5–10 million		30	6.79%
	Type I Large Cities	3-5 million		240	54.30%
	Type II Large Cities	1–3 million		123	27.83%
Age	Teenagers	Less than 25	year	137	31.00%
	Young and middle-aged people	25–40		76	17.19%
	Middle-aged and elderly people	41–60		222	50.23%
	Elderly people	Older than 60		9	2.04%
Driver's license	Yes			347	78.51%
	No			95	21.49%
Private family car	No car family	0	car	61	13.80%
	Single-car family	1		255	57.69%
	Two-car family	2		107	24.21%
	Multi-car family	3 and over		19	4.30%
Nature of Occupation	Government Employee			56	12.67%
	Corporate Employee			104	23.53%
	Full-time student			135	30.54%
	Others			147	33.26%
Total	All participant in a survey			442	100%

3.3.3. Value calculation of prospect

Based on the foundation of prospect theory, the value function is determined by the subjective perception of travel cost and the reference point. For an individual making a travel decision, when the subjective perception of travel cost C_j^{pr} for the chosen option j is smaller than the reference point $E(C^{pr})$, they should gain a profit; otherwise, they would experience a loss. The value of profit and loss is weighted by the decision weight function to obtain the prospect value. In this study, there is only one situation for the mode choice made by the traveler in the research scenario, with a probability of 1. The prospect value for choosing mode j can be obtained as follows:

$$V\left(C_j^{pr}\right) = \begin{cases} \left[E\left(C^{pr}\right) - C_j^{pr}\right]^{\alpha} \times 1, & C_j^{pr} < E\left(C^{pr}\right) \\ -\beta\left[C_j^{pr} - E\left(C^{pr}\right)\right]^{\alpha} \times 1, & C_j^{pr} > E\left(C^{pr}\right) \end{cases} \quad (5)$$

where

$V^{+}\left(C_j^{pr}\right)$— Prospect value of travelers choosing travel mode j;

C_j^{pr}—Subjective perceived travel cost of mode j, with weights for various costs determined by questionnaire data rather than classification.

α—risk attitude coefficient of decision maker, Kahneman and Tversky experimentally calibrated this parameter as 0.88, which needs to be calibrated by itself. In this study, a larger α means that travelers are more sensitive under that incentive policy, while the policy has a greater impact on that type of travel group. For a class of people, a larger alpha data calibration result means that this class of people is more likely to be influenced by policy to change their choice behavior;

β—The loss aversion coefficient reflects the sensitivity of the decision maker to losses. A value greater than 1 indicates a higher sensitivity to losses. In previous experiments, Kahneman and Tversky calibrated this parameter to be 2.25.

In the transportation mode choice model, the utility values have been replaced by the foreground value results to obtain the probabilities of different attribute travelers choosing mode 1 (ride-hailing) and mode 2 (SAV connecting subway) for travel.

$$P_1 = \frac{e^{V_1}}{e^{V_1} + e^{V_2}} \tag{6}$$

where

P_1—Probability of travelers choosing to travel by online car.
V_1—Prospect value of travelers choosing to travel by SAV.
V_2—Probability of travelers choosing SAV to connect to the subway.

3.3.4. Estimation of risk preference parameters

According to prospect theory, the parameter α takes values within the range of (0,1). Using an exhaustive method with a step size of 0.01, we search for the estimated values of the parameter through iteration. The absolute difference between the true value P_j and the predicted value $\widehat{P}_j$ of the survey results is considered as the model's error. We use the model error as an overall evaluation index, and the optimal parameter results should minimize the model error, that is, the model fitting results are closest to the reality. The model error is calculated as follows:

$$\varepsilon(L, M) = \left| P_j(L, M) - \widehat{P}_j(L, M) \right| \tag{7}$$

where

$\varepsilon(L, M)$—The error of the traveler's choice model with the city of residence class L and the monthly income level M;
$P_j(L, M)$—The actual probability that a traveler with a city of residence class L and a monthly income level M chooses mode j to travel;
$\widehat{P}_j(L, M)$—The predicted probability that a traveler with a city of residence class L and a monthly income level M will choose mode j to travel.

4. Results and discussions

4.1. Questionnaire data collection and analysis

A total of 442 valid questionnaire data were collected in this study, which satisfies the statistical needs with the random sampling error range taken as 5%. The social attributes of travelers include gender, age, monthly income level, ownership of private cars and driver's licenses, and the grade of the city of residence, etc. The above indicators were statistically analysed (Table 2).

Questionnaire survey data show that the ratio of men to women among the respondents is close to 4:5, with slightly more women than men; the age of the respondents is concentrated in the range of less than 25 years old as well as 41–60 years old, which account for 32% and 48% of the sample overall, respectively; there are 76 people aged 25–40 years old, which account for 17.19% of the overall, and there are 9 people aged 60 years old or above, which account for 2.04% of the overall; in terms of the level of monthly income, the only cost of living accounted for 28.28%, 106 of 5001–8000 yuan, accounting for 23.98%, and 114 of more than 8000 yuan, accounting for 25.79%; 12.67% of the sample were government employees, 23.53% were enterprise employees, 30.54% were students, and other occupations accounted for 33.26%; in terms of educational attainment, 86.2% of them had a bachelor's degree or below, and master's degree or above accounted for 13.8%; 11% of the respondents are from first-tier cities in China, 6.79% live in new first-tier cities, 54.30% live in second-tier cities, and 27.83% live in third-tier cities and below; 78% of the respondents have a driver's license, and more than half of the respondents have one or more private cars at home to use.

Further analysis based on the basic information of the respondents found that for the non-student group accounted for 68% of the total sample, of which 34% and 37% of the total sample had a monthly income level of 5,000–8,000 yuan and 8,000 yuan or more, and the vast majority of the student group was in a no-income status.

Overall, the data from this survey can support a study that categorizes travelers along two dimensions: income level and city class of residence.

4.2. SEM model test results

The observed variables in the questionnaire correspond to each latent variable. To assess the model's reliability, validity, and fitness, reliability tests, validity tests, and model fit evaluations were conducted for each variable in this study.

Table 3 presents the standard loadings, Cronbach's α, combined reliability (CR), and average variance extracted (AVE) for each factor. The results indicate that all four variables have Cronbach's α values exceeding 0.7 and CR values exceeding 0.8, indicating high reliability. The standard loadings for the factors are all above 0.5, and the AVE values are all greater than 0.5, indicating good model validity (Table 4).

Overall, the KMO value of the model is 0.876, greater than 0.8, and the significance in the Bartlett's test is less than 0.05, with an approximate chi-square value of 4477.352, making it very suitable for factor analysis. Factor analysis results are shown in Table 5.

The cumulative variance contribution rate of the four factors reaches 82%, which can fully reflect the original data. The number of factors extracted through orthogonal rotation is 4, which is consistent with the assumptions in the model, has good structural validity, and there is no problem of multicollinearity (Table 6).

Initially, the fitness metrics of the model in this study did not meet the desired requirements. How-ever, the deviation from the required range was minimal. After careful observation, the path relation-ships between the residual terms e10 and e11, e11 and e14, e11 and e15, and e3 and e11 were added. The adjusted model fitness indexes are presented in Table 6, and all the fitness indexes of this model now meet the recommended value requirements. (e1, e2, e3... etc. are the residual terms that construct the structural equation model is defined as the gap between the observed data and the data predicted by the model, indicating the portion of the variance that the model fails to explain.).

According to the fit indices in the table, the overall fit of the SEM model in this study is good, with indices such as RMSEA and CFI meeting the recommended value requirements.

To delve deeper into the impact of carbon reduction incentives on different types of travelers, this study conducts a differentiated outcome analysis by categorizing respondents based on their income level and city class of residence. The aim is to examine whether there are significant differences in the coefficients of key variables among various groups of travelers with different attributes. This analysis allows for a more comprehensive understanding of how carbon reduction incentives influence different segments of the surveyed population.

4.3. Results of travel cost and weighting calculations

In this study, the personal perceived travel cost of a traveler is defined as comprising monetary cost, congestion cost, and environmental cost. The monetary cost includes both time cost and fare cost. The time cost incorporates the concept of time value and is calculated using the classification of the traveler's income level. The congestion cost is determined based on the results of classifying the monthly income level, referring to existing research findings. Table 2 presents the respective structures for calculating the travel costs associated with the two travel modes (Table 7).

To examine the incentive effects of various carbon reduction incentive policies on different types of travelers, this study introduces four policy types: cash rewards, commodity coupons, public transportation top-ups, and public welfare project assistance. These policy types are based on actual cases found in existing application platforms.

The weights of the various components of the travelling cost for each type of traveler, based on different income levels and classes of city of residence, are calculated as follows (Table 8):

4.4. Interpretation of path coefficients for SEM models

See Fig. 5 and Table 9.

(1) The analysis shows that there is no significant relationship between the current low carbon habits of travelers and the low carbon habits of those who participate in carbon reduction incentives. The p-value of the standardized path coefficient between these two variables is 0.392, which is greater than 0.05 and not statistically significant.

Table 3
Reliability and validity test results of model variables.

Latent variable	Variable of observation	Standard load	Cronbach's α	CR	AVE
Low carbon knowledge	KNO1	0.887	0.863	0.88	0.7105
	KNO2	0.770			
	KNO3	0.867			
Low carbon habits	HAB3	0.872	0.930	0.924	0.803
	HAB4	0.925			
	HAB5	0.890			
Situational factor	CIR1	0.856	0.902	0.866	0.682
	CIR2	0.827			
	CIR3	0.794			
Low-carbon travel willingness	WIL1	0.757	0.885	0.8575	0.602
	WIL2	0.697			
	WIL4	0.811			
	WIL5	0.831			

Table 4
KMO Measure and Bartlett's Test of Sphericity Results.

Item		Value
KMO Measure of Sampling Adequacy		0.876
Bartlett's Test of Sphericity	Approximate Chi-square	4477.352
	Degrees of Freedom	78
	Significance	0.000

Table 5
Total variance explained.

Component	Initial Eigenvalues			Extraction Sum of Squared Loadings			Rotation Sum of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.456	49.662	49.662	6.456	49.662	49.662	2.873	22.098	22.098
2	1.922	14.781	64.443	1.922	14.781	64.443	2.833	21.791	43.889
3	1.372	10.556	74.999	1.372	10.556	74.999	2.545	19.578	63.467
4	1.033	7.178	82.177	1.033	7.178	82.177	2.432	18.710	82.177
5	0.445	3.425	85.602						
6	0.348	2.675	88.277						
7	0.319	2.454	90.731						
8	0.303	2.330	93.061						
9	0.250	1.920	94.981						
10	0.238	1.831	96.812						
11	0.183	1.406	98.218						
12	0.122	0.937	99.154						
13	0.110	0.846	100.000						

Table 6
Comparison table of the modified model fitness index and its recommended values.

Index of fit	Recommended value	Value of fit	Whether it meets the requirements
χ^2	No recommended value, the smaller the better	173.399	Yes
GFI	>0.9	0.949	Yes
AGFI	>0.8	0.915	Yes
RMSEA	<0.08	0.065	Yes
IFI	>0.9	0.977	Yes
CFI	>0.9	0.977	Yes
NFI	>0.9	0.965	Yes

Table 7
Travel costs perceived by travelers.

Type of cost	Property classification	SAV + subway	Taxi	Bus
Cost of ticket	No classification	9.95	30.00	2.00
Environmental costs	No classification	6.28	18.16	2.18
Cost of crowding	No fixed income	1.58	0.00	6.85
	0–2000	1.58	0.00	6.85
	2–5000	2.12	0.00	9.20
	5–8000	2.47	0.00	10.71
	>8000	3.19	0.00	13.87
Cost of time	No fixed income	0.00	0.00	0.00
	0–2000	5.72	5.07	7.80
	2–5000	19.36	17.16	26.40
	5–8000	36.08	31.98	49.20
	>8000	77.44	68.64	105.60

(2) The results of the study show that participation in carbon emission reduction incentive policies can enhance the low carbon knowledge of tourists, which indirectly affects their low carbon travel willingness. The standardized coefficients of these two paths are 0.956 and 0.312 respectively, which are both statistically significant.
(3) The results indicate that external situational factors have a significant impact on travelers' habit of developing the habit of participating in carbon reduction incentives. The standardized path coefficient for this relationship is 0.895, indicating a strong positive correlation between situational factors and participation.

Table 8
Weights of various types of travel costs for heterogeneous passengers.

Residential City Level	Income Level	Economic Weight	Environmental Weight	Comfort Weight
Mega-City	No fixed income	0.5086	0.1614	0.33
	0–2000 yuan	0.22	0.29	0.27
	2000–5000 yuan	0.4675	0.165	0.3675
	5000–8000 yuan	0.3383	0.5167	0.145
	Above 8000 yuan	0.438	0.212	0.35
Metropolis	No fixed income	0.525	0.1541	0.3209
	0–2000 yuan	0.62	0.08	0.3
	2000–5000 yuan	0.82	0.18	0
	5000–8000 yuan	0.355	0.18	0.465
	Above 8000 yuan	0.25	0.2267	0.5233
Type I Large City	No fixed income	0.48	0.2267	0.2933
	0–2000 yuan	0.335	0.3	0.365
	2000–5000 yuan	0.336	0.37	0.294
	5000–8000 yuan	0.3382	0.3857	0.2762
	Above 8000 yuan	0.2742	0.3469	0.3789
Type II Large City	No fixed income	0.4871	0.2282	0.2846
	0–2000 yuan	0.4588	0.27	0.2713
	2000–5000 yuan	0.256	0.4485	0.2955
	5000–8000 yuan	0.3121	0.3615	0.3264
	Above 8000 yuan	0.2171	0.5147	0.2682

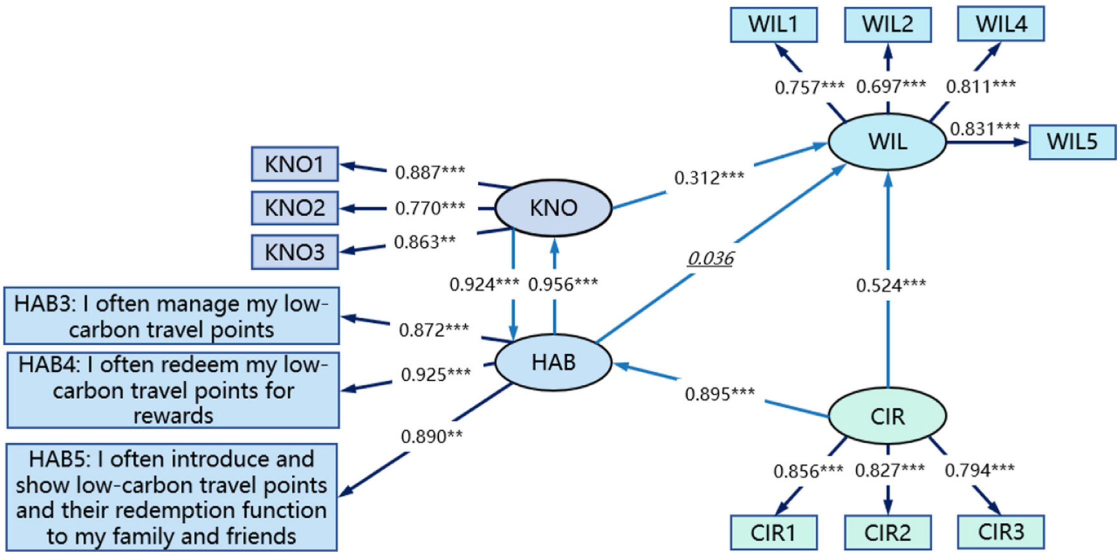


Fig. 5. Structural Equation Model result diagram.

Table 9
Results of structural equation modeling and group difference analysis.

Type of traveler	Path of relationship	Standardized path coefficient	*P*	Conclusion
All the travelers	Low carbon habits ← Situational factors	0.895	***	Accept
All the travelers	Low carbon habits ← Low-carbon knowledge	0.924	***	Accept
All the travelers	Low carbon travel intention ← Low-carbon knowledge	0.312	***	Accept
All the travelers	Low-carbon knowledge ← Low-carbon habits	0.956	***	Accept
All the travelers	Low carbon travel intention ← Situational factors	0.524	***	Accept
All the travelers	Low carbon travel intention ← Low-carbon habits	0.036	0.392	Not to accept
High-income travelers	Low carbon travel intention ← Situational factors	0.621	***	Accept
Middle and high-income travelers	Low carbon travel intention ← Situational factors	0.814	***	Accept
Low-income travelers	Low carbon travel intention ← Situational factors	0.919	***	Accept
Travelers without fixed income	Low carbon travel intention ← Situational factors	0.914	***	Accept

(4) When considering group differences, the empirical analysis shows that compared to the middle- and high-income groups, the low-income group and the student group with no fixed income are more receptive to policy advocacy, and therefore have a higher level of participation in carbon reduction incentives. The standardized coefficients for these two paths are 0.919 and 0.914, respectively, indicating that these groups have higher policy acceptance.
(5) It is worth mentioning that the reliability and validity of using the participation degree of travelers' carbon reduction incentives to measure the latent variable of low-carbon habits is very high.

The results of the model are generally consistent with the SCT theory.

4.5. Heterogeneous traveler preferences

Based on questionnaire data, the subjective perception weights of various components of travel costs for travelers were summarized, as shown in the Fig. 6.

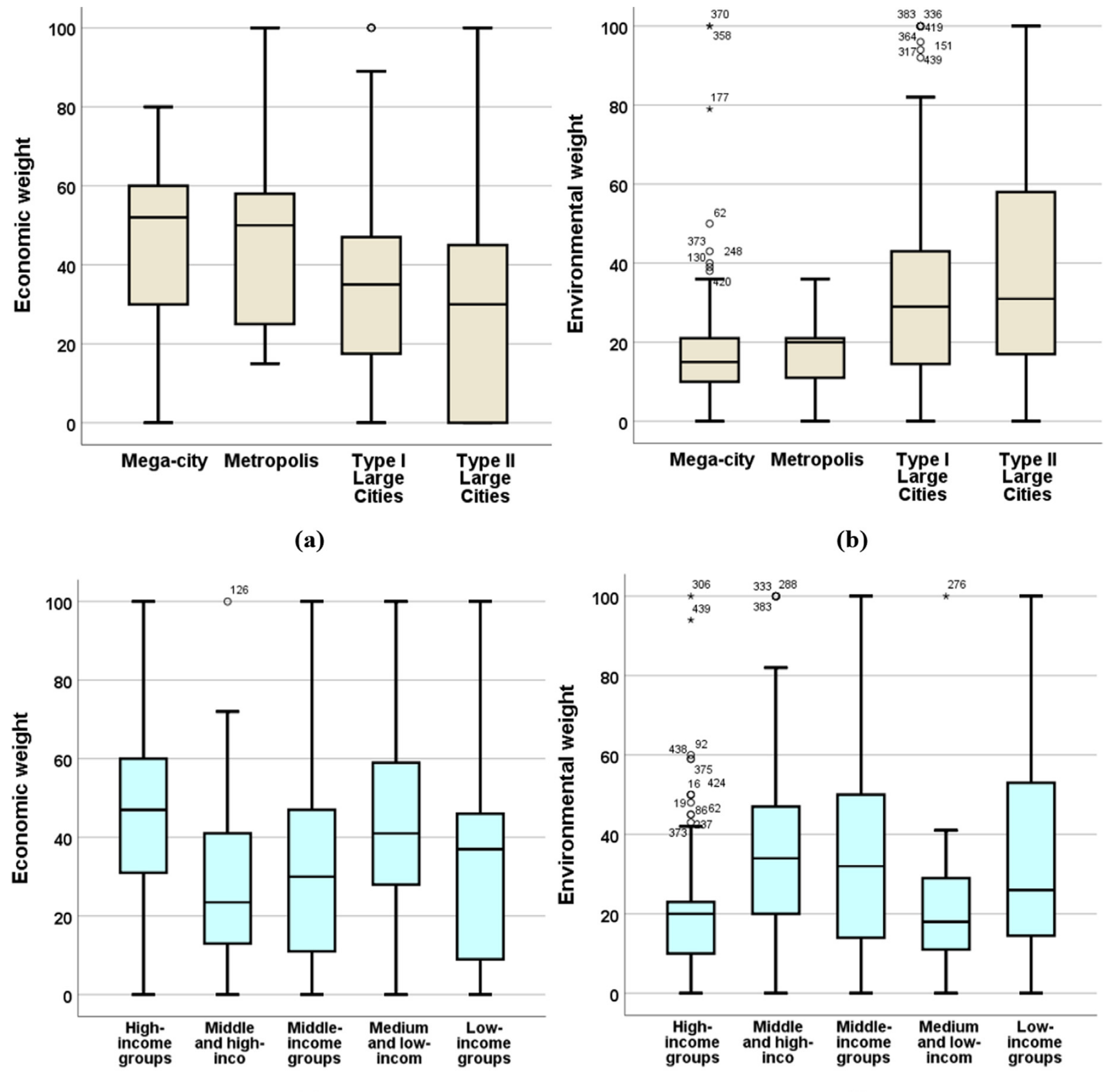


Fig. 6. Preference score chart for different types of travelers' mode choices.

Firstly, comparing travelers from different city levels, it can be observed that residents from higher-level cities pay more attention to the economy of transportation modes, while residents from lower-level cities are more concerned about the environmental friendliness of transportation modes, but the weight data is more dispersed. Residents of mega-cities and large cities generally have less concern for the environmental friendliness of transportation modes, with more concentrated weight distribution.

Secondly, comparing travelers from different income levels, it can be found that the higher the income, the more the travelers focus on the economy of transportation modes and the less they care about the environmental friendliness. Conversely, lower-income travelers pay more attention to the environmental friendliness of transportation modes.

Taking all factors into consideration, it is evident that residents with lower income and lower city levels are more concerned about the environmental friendliness of transportation modes and are more likely to accept low-carbon transportation options.

4.6. Sensitivity analysis for different incentive policies

4.6.1. Robustness verification

To verify that the classification model has good robustness, we divided the data into 5 groups and plotted the ROC curves for each group to verify the robustness of the classification model. Plotting ROC curves on multiple different datasets, if the model shows high AUC values and similar ROC curve shapes on these datasets, it can indicate that the model has good robustness (Table 10 and Fig. 7).

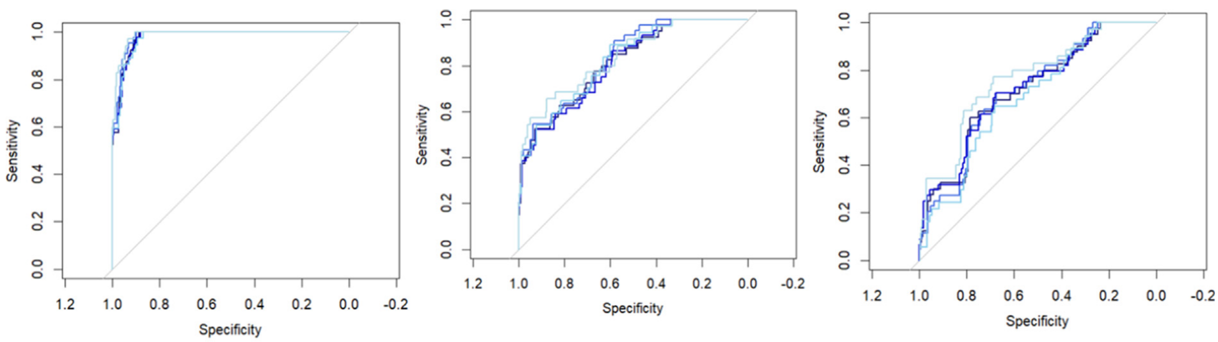
As shown in the figure, the ROC curves drawn for the three core independent variables in the model: C_1^{pr}, C_2^{pr} and $E(C^{pr})$ all have relatively similar shapes. Observing the AUC values in the table also reveals that the AUC values for the same independent variable do not vary significantly across different groups. Combining the ROC curve figures with the AUC calculation results, we can conclude that the discrete choice model has relatively good robustness.

4.6.2. Results analysis

According to the foundation of prospect theory, we can know that when α is larger, it indicates that decision-makers have a greater degree of risk aversion in the context of gains, meaning they are unwilling to take risks when judging the current state as a gain. At the same time, decision-makers have a greater preference for risk in the context of losses, meaning they are more willing to take risks when judging the current state as a loss. To summarize, a larger α in this study means that the traveler is more sensitive under that incentive policy, while the policy brings more impact for that type of travelling group.

Table 10
AUC values for different variables.

	C_1^{pr}	C_2^{pr}	$E(C^{pr})$
All Groups	0.98	0.824	0.722
Group1	0.978	0.816	0.718
Group2	0.983	0.832	0.718
Group3	0.977	0.809	0.724
Group4	0.976	0.826	0.688
Group5	0.987	0.839	0.764



(a)ROC curve corresponding toC_1^{pr} **(b)ROC curve corresponding toC_2^{pr}** **(c)ROC curve corresponding to$E(C^{pr})$**

Fig. 7. ROC Curves for Each Data Group.

(1) For all travelers, the α value is highest for monetary rewards and lowest for rewards related to public transportation. This indicates that travelers are more sensitive to monetary rewards and relatively less sensitive to rewards related to public transportation. This may imply that travelers pay more attention to the monetary return and value of money when making travel decisions, and are more easily attracted by monetary rewards, while they may not be interested in or prioritize rewards related to public transportation (Fig. 8).

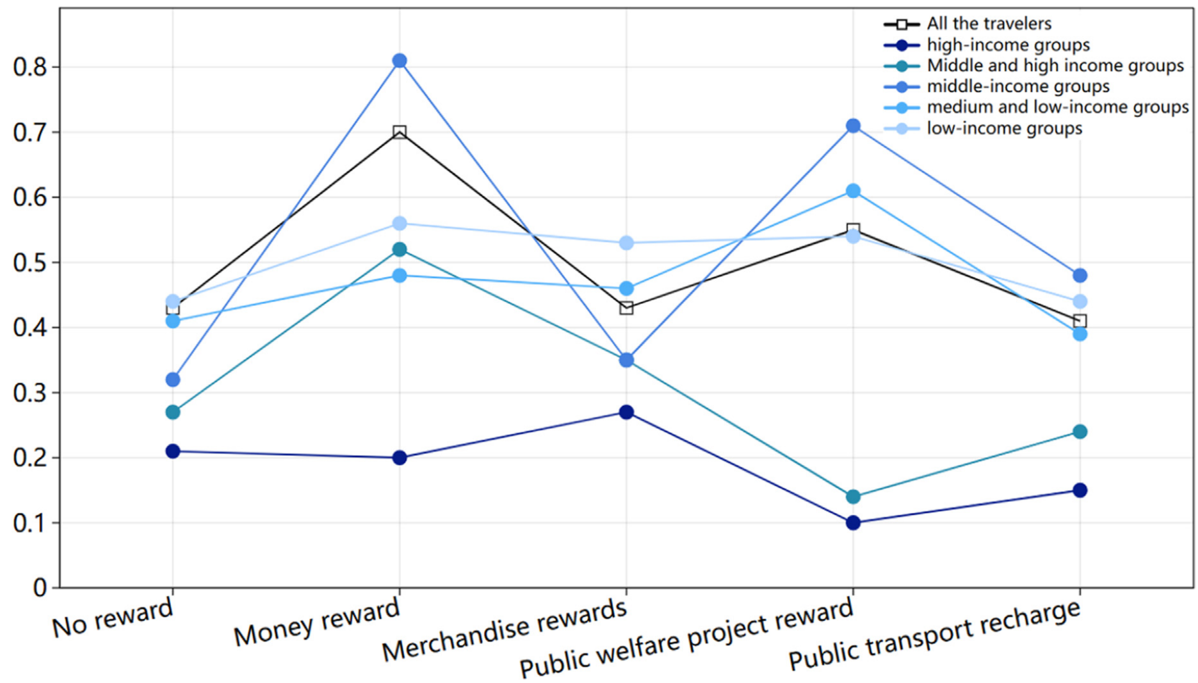


Fig. 8. Different income level travelers' risk preference coefficients for various incentive measures.

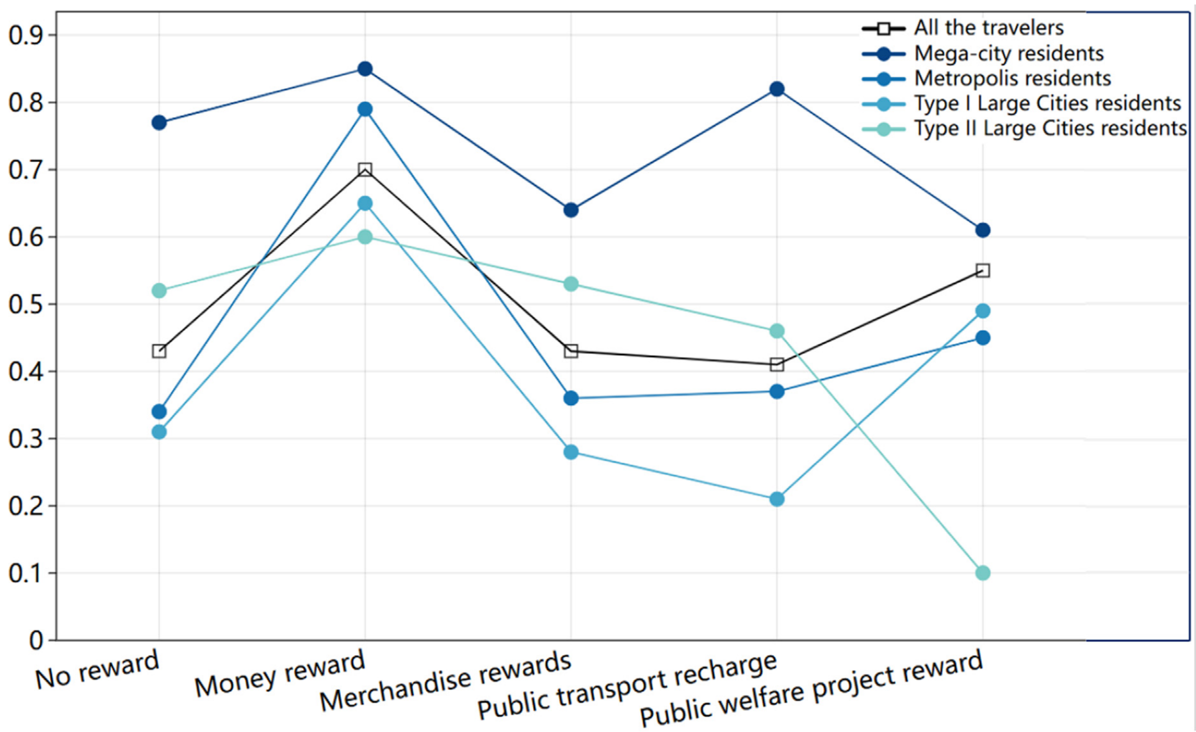


Fig. 9. The risk preference coefficient of various incentive measures for travelers in cities at all levels.

(2) Comparing high-income and low-income groups, it can be found that the α values of the high-income group are generally lower than those of the low-income group, which means that the low-income group is more interested in a series of low-carbon travel incentives, consistent with the discussion results of the structural equation model.

(3) For low-income groups, cash rewards, product rewards, and public welfare project rewards are all incentive measures that they are interested in. We believe that the public transport top-up incentive has the potential to further encourage them to adopt low-carbon travel modes, creating a virtuous cycle.

(4) For middle-income and upper-middle-income individuals, cash rewards are the most interesting incentive measure to them. This group is of a swing nature and every effort should be made to win them over to low-carbon travel options (Fig. 9).

(5) Similarly, compared to residents in large second-tier cities, residents in mega-cities are more interested in a series of low-carbon travel incentives, and they are more willing to accept public transportation recharge rewards, with an alpha value as high as 0.85.

(6) For residents in mega-cities, large first-tier cities, and large second-tier cities, they are most interested in cash rewards, with alpha values of 0.79, 0.65, and 0.6, respectively.

(7) Travelers in less developed cities are very insensitive to the way public transportation is incentivized. We believe that underdeveloped local public transportation infrastructure is the reason. Therefore, for such cities, encouraging low-carbon travel modes also needs to be based on the development of public transportation infrastructure.

5. Conclusions

This study builds a research scenario of commuter travel based on a real scenario, investigates the preference of travelers to choose the combination travel mode of SAV connecting to the subway in the scenario, analyzes the mechanism of individual low-carbon incentive policies on the travel choice behavior by establishing a structural equation model, and draws the following conclusions by constructing a discrete choice model and calibrating the risk aversion coefficients in the theory of moving forward:

(1) The current incentives for low-carbon travel do not directly encourage travelers to choose multimodal transportation, but rather achieve this by increasing travelers' knowledge of low-carbon options. With active promotion and education from external factors such as the government, media, and peers, travelers are more willing to accept personal incentives.
(2) Low-income groups and residents in lower-tier cities are more concerned about the environmental friendliness of their travel methods and are more likely to be guided to choose low-carbon transportation options.
(3) Compared to high-income groups, low-income groups are more likely to accept personal carbon reduction incentives and choose multimodal transportation. This includes student groups without a fixed income, who are most interested in cash incentives.
(4) Residents of mega-cities are more likely to choose multimodal transportation under the encouragement of personal carbon reduction policies. Incentives such as public transportation recharge can more effectively guide them to choose multimodal transportation.

Although objectively speaking, incentive measures are beneficial to travelers, different groups of travelers with different attributes exhibit significantly different attitudes towards the same incentive measures, which can even affect their choice of travel mode. In light of this situation, combined with the SCT theory, we propose the following policy recommendations for personal carbon reduction incentives on relevant platforms:

(1) In low-carbon travel incentive platforms in mega cities, it is recommended to design and promote rewards for public transportation recharge. This recommendation is not only based on the findings of this study, but also supported by the more developed public transportation systems in mega cities.
(2) When it is possible to classify travelers based on their income levels, targeted promotion of low-carbon travel rewards should be implemented. Specifically, cash rewards should be emphasized for lower income groups.
(3) Actively promoting individual carbon reduction incentive policies contributes to more people engaging in low-carbon travel modes, with such promotion being particularly effective for low-income individuals and students.
(4) Regardless of the city level, it is important to actively enhance residents' low-carbon knowledge. According to the SCT theory and the results of this study's model, this will help improve residents' understanding of and engagement in low-carbon travel modes.

It is important to acknowledge the limitations of this study. Firstly, the modeling of structural equations has considered a limited range of influencing factors. To enhance the comprehensiveness of the model results, future research should incorporate psychological latent variables of travelers, such as their acceptance of new technology and motivation to modify established itineraries. The cultural differences of the travelers' regions are also possible factors influencing their behavioral choices, and we hope to have the opportunity to observe and analyze the relationship between regional cultures and travelers' choice behaviors in future studies. Secondly, the sample size of the questionnaire data was limited, allowing for significant categorization of travelers in only two ways. To obtain more robust results, future studies should explore additional dimensions of categorization, including psychological attributes, in addition to basic socio-economic-demographic attributes. Furthermore, targeted stratified sampling should be conducted to ensure reliable sample sizes for each attribute category. This will yield more nuanced and tailored recommendations for individual carbon reduction incentives. Finally, research on the long-term effectiveness and sustainability of behavioral incentive policies is valuable, and we expect to be able to refine it further in future studies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Chenjing Bi: Writing – original draft, Software, Formal analysis, Data curation, Conceptualization. **Ye Li:** Writing – review & editing, Supervision, Data curation, Conceptualization. **Dominique Gruyer:** Writing – review & editing, Supervision, Data curation, Conceptualization. **Meiting Tu:** Writing – review & editing, Supervision, Software, Resources, Methodology, Funding acquisition, Data curation, Conceptualization.

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