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Decision Analysis and Benefit Evaluation of Ridesharing Behavior in Bus Lanes Based on Cumulative Prospect Theory

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Abstract: Sharing dedicated bus lanes with ridesharing private vehicles plays a positive role in improving road traffic efficiency and alleviating traffic congestion. This study investigates the willingness to adopt ridesharing and analyzes the factors influencing ridesharing decisions. Under the scenario of opening dedicated bus lanes to private ridesharing vehicles, a ridesharing decision-making model for dedicated bus lanes is established based on cumulative prospect theory. We analyze the impact of the bus-lane-sharing strategy on travelers' ridesharing decisions and traffic flow structure. In addition, a bus lane operational efficiency evaluation model based on the combined weighting–TOPSIS method is constructed. Using the principle of maximum closeness, the operational efficiency of bus lanes is evaluated through a case study in a specific area of Nanchang City. The research results indicate that the closeness degree is 0.3720 without the bus-lane-sharing strategy, while the minimum closeness degree is 0.3744 and the maximum closeness degree is 0.3749 when the bus-lane-sharing policy is implemented. Therefore, the implementation of the bus-lane-sharing strategy demonstrates better operational efficiency compared to scenarios without sharing strategies. Additionally, when the number of ridesharing vehicles is relatively small and their capacity is large, travel costs are significantly reduced, and the overall road operational efficiency is improved. This study provides important reference values and practical significance for alleviating traffic congestion, improving the utilization efficiency of road resources, and formulating bus-lane-sharing policies.

Keywords: dedicated bus lanes; ridesharing travel; cumulative prospect theory; decision analysis; operational efficiency

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1. Introduction

Traffic congestion is one of the most common challenges faced by modern cities. Public transportation not only alleviates traffic congestion but also reduces air pollution and promotes urban sustainable development. Promoting the use of public transportation has become a widely recognized strategy for achieving sustainable urban mobility, and the implementation of dedicated bus lanes is one of the key measures for prioritizing public transit development.

The establishment of dedicated bus lanes ensures the smooth operation of public transit vehicles and enhances the attractiveness of public transportation. However, the allocation of road space to bus lanes reduces the resources available for private vehicles, restricting their movement and exacerbating the conflict between urban road capacity and traffic demand. To address this issue, some scholars have proposed the concepts of Dynamic Bus Lanes (DBLs) and Intermittent Bus Lanes (IBLs). As a management approach for dynamically allocating road resources, IBLs/DBLs have been extensively studied by researchers both domestically and internationally. Mashrur, S.M. et al. proposed a scheme combining Intermittent Bus Lanes (IBLs) with Transit Signal Priority (TSP), and the research results showed that it could reduce average delays by 40 s [1]. Othman K. studied the effectiveness of Dynamic Bus Lanes (DBLs) in improving the performance of bus corridors under different traffic demand levels and bus frequencies [2]. Guorong Zheng et al. proposed an optimization model that considers the coordination of Intermittent Bus Lanes and signal timing at downstream intersections, maximizing the capacity of general vehicles and reducing delays at intersections for non-transit vehicles [3]. Hongzhao Dong et al. proposed a dynamic time-slice strategy to implement an effective bus lane policy [4]. Chenxin Zhao explored a new method of implementing the Intersection-Based Intermittent Bus Approach (IBA) to achieve lane sharing and bus priority at intersections [5]. Yingying Lin proposed a method to first determine the IBL capacity allowed for regular vehicles and then use it as a cap on the total borrowing volume to implement a bus lane control strategy, improving road capacity [6]. Feng Qiu et al. developed a computer simulation and analytical model to quantitatively study the impacts of IBLs on traffic density distribution, traffic speed, and traffic capacity along road segments [7]. H.B. Zhu proposed a two-lane traffic model with Intermittent Bus Lanes to investigate the characteristics of urban traffic flow [8]. Dingxin Wu et al. introduced a three-lane cellular automaton model with open boundary conditions to analyze the effects of lane-changing behavior, lane usage, and the bus dispatch interval and clearance time on the capacity of BLIP (Bus Lane with Intermittent Priority) roads [9]. Xiaolan Xie et al. constructed an integrated optimization control model with the objective of minimizing the total travel time on road segments. The study results demonstrated that intermittent-priority bus lanes with open times not only ensured bus priority but also expanded the right of way for regular vehicles [10]. The above studies primarily focus on Dynamic Bus Lanes (DBLs) and Intermittent Bus Lanes (IBLs), exploring their impact on bus lanes. By analyzing factors such as lane usage, lane-changing behavior, departure frequency, and bus signal priority, this research evaluates the role of DBLs/IBLs in achieving carpooling and ridesharing within bus lanes, thereby improving traffic conditions.

High-Occupancy Vehicle (HOV) lanes are an effective measure to alleviate traffic congestion, improve the utilization of dedicated bus lanes, and increase the occupancy rate of passenger cars. Scholars have conducted in-depth research on this topic. Maxime C. Cohen et al. studied the impact of HOV lanes on commuter carpooling behavior and concluded that HOV lanes can influence commuters' travel decisions [11]. Christopher Breiland et al. analyzed the operational efficiency of single-occupant hybrid vehicles using HOV lanes and found that this policy had no significant impact on the operation of HOV lanes in the studied area [12]. Dahlgren's research results indicated that the effectiveness of HOV lanes in promoting carpooling and public transit use depends on the travel time difference between HOV lanes and general-purpose lanes [13]. Bulteau et al. studied carpooling behavior and suggested that residents in economically underdeveloped regions are more inclined to choose carpooling [14]. Chen et al. found that people traveling short distances are more likely to carpool [15]. Zhong L. utilized the bottleneck model to analyze carpooling behavior during the morning peak and concluded that HOV lanes play a positive role in promoting carpooling [16]. The above studies primarily focus on HOV lanes, exploring their impact on carpooling behavior and traffic efficiency. Researchers have used various methods to investigate how factors such as travel time difference, economic conditions, and travel distance influence the effects of HOV lanes on carpooling and traffic efficiency.

To better evaluate the operational efficiency of dedicated bus lanes, numerous scholars, both domestically and internationally, have conducted extensive research using various methods from different perspectives. Jaiswal A utilized the Delphi method and opinion surveys combined with correlation analysis to establish a public transit satisfaction evaluation model, aiding decision-makers in improving public transit services [17]. Wufeng Qiao et al. comprehensively and objectively evaluated the traffic benefits of dedicated bus lanes by adopting the Delphi method and the gray relational analysis method to construct an integrated weighting model for indicators, enabling the assessment of bus lane traffic benefits [18]. Yin et al. evaluated the punctual reliability of transit systems based on station schedules and operational times, assessing various reliability indicators [19]. Saharidis optimized bus transition stops from a passenger perspective, aiming to minimize passenger waiting times by applying a mixed-integer linear programming model [20]. Xinhuan Zhang et al. used a combination of the Analytic Hierarchy Process (AHP), entropy weighting, and fuzzy comprehensive evaluation methods to assess the operational efficiency of public transit, improving the accuracy of passenger satisfaction evaluation and the scientific and objective nature of indicator weighting [21]. Chunyao Deng adopted the AHP to construct an evaluation indicator system, utilizing G1 weighting, entropy weighting, and additive integration methods for subjective and objective weighting, providing a simple and practical evaluation method that enhances evaluation accuracy [22]. Saharidis and colleagues also focused on minimizing passenger waiting times and optimized bus transition stops using a mixed-integer linear programming model [23]. Zhang et al. developed an optimization model for designing branch bus networks with limited-stop routes, taking into account passenger demand patterns across different routes and passenger allocation to determine the optimal bus frequencies and limited-stop service patterns [24]. Miller et al. considered factors such as construction funding, passenger corridors, and management systems as research indicators, aiming to maximize overall system operational efficiency to identify the most cost-effective bus lane schemes [25]. P. Vedagiri and colleagues incorporated survey data and introduced other influencing factors to develop a mode-choice model, identifying the key factors driving shifts from private cars to public transit based on actual and predicted data and analyzing the impact of dedicated bus lanes on transit operational efficiency [26]. Masoud F et al. established a systematic evaluation model for the design and operational management benefits of bus lanes, evaluating and comparing different implementation schemes to provide references for encouraging investment in dedicated bus lanes [27]. Current research mainly evaluates the benefits of bus-only lanes from the perspectives of satisfaction, reliability, and operational costs of the public transit system, but it has not sufficiently considered the economic costs of travelers and the environmental impacts of their trips.

Most of the aforementioned studies analyze the carpooling incentives of shared strategies from the perspectives of time differences and cost differences between different travel modes. Additionally, they investigate travelers' preferences for choosing carpooling based on factors such as travel periods, economic levels, and travel distances. However, these studies are predominantly conducted within the framework of rational decision-making, without adequately considering the bounded rationality of travelers during the decision-making process. In reality, people's travel decisions are not entirely rational, and neglecting the bounded rationality of decision-makers could result in significant deviations between analytical results and real-world conditions. Therefore, it is essential to account for individual bounded rationality when studying carpooling decision-making behavior in the context of dedicated bus lanes.

In summary, this paper constructs a carpooling decision-making model for dedicated bus lanes based on cumulative prospect theory (CPT). As a theoretical model in behavioral economics, CPT fully considers the bounded rationality of individual behavior and uses a psychological framework to analyze travelers' preferences and decision-making behavior in carpooling, thereby making travel decisions more aligned with real-world scenarios. Through this model, this paper examines the impact of bus-lane-sharing strategies on travelers' carpooling decisions and the resulting changes in traffic flow structure after the strategy's implementation. In terms of traffic efficiency evaluation, this study establishes a comprehensive evaluation system encompassing traffic, economic, and ecological benefits. Multiple evaluation indicators are selected to construct a traffic operational efficiency evaluation model based on a combined weighting–TOPSIS approach. The CRITIC method and G1 method are used to determine the objective and subjective weights of the indicators, integrating stakeholders' perceptions and objective facts. The concept of minimizing deviation is introduced to determine the combined weights. Using the TOPSIS method, multiple indicators are comprehensively assessed to provide a holistic evaluation of the operational efficiency of dedicated bus lanes. The structure of this study is as follows: A survey on carpooling willingness is conducted, and the survey data are analyzed to gain an in-depth understanding of residents' awareness of carpooling and the factors they are most concerned about. Section 2, based on cumulative prospect theory (CPT), establishes a carpooling decision-making model for dedicated bus lanes and analyzes the impact of bus-lane-sharing strategies on travelers' carpooling decisions and the structure of traffic flow. This provides a reference for formulating optimized bus lane policies. Section 3 evaluates the operational efficiency of dedicated bus lanes by selecting evaluation indicators that cover traffic, economic, and ecological benefits. A dedicated bus lane operational efficiency evaluation model is constructed. Using a specific case study of a region in Nanchang City, a comprehensive evaluation of the operational efficiency of dedicated bus lanes is conducted, providing a scientific and comprehensive evaluation method for future research on the operational efficiency of bus lanes.

2. Carpooling Decision-Making Analysis for Dedicated Bus Lanes

2.1. Design of Carpooling Willingness Survey Questionnaire

Travel decision-making is a complex process influenced by various factors, such as travel cost, travel time, travel purpose, accessibility, and individual characteristics of travelers. Under the shared dedicated bus lane strategy, analyzing travel decisions requires considering the impact of these factors on the benefits of carpooling. Therefore, a survey questionnaire is designed to provide a basis for the development of the decision-making model and the evaluation of benefits. The questionnaire includes content on travelers' personal attributes, travel process information, and their perception of carpooling on dedicated bus lanes. The survey scenarios focus on curbside or median dedicated bus lanes that are open to multi-passenger private vehicles. The questionnaire will emphasize the travel characteristics of different population groups, their perceptions of dedicated bus lanes, and the factors influencing their travel decisions. The survey questionnaire is presented in Table 1.

Table 1. Summary of carpooling willingness survey.

	Survey Content	Option Settings
Personal characteristics	Age	Less than 18; 18–22; 22–30; 30–60; More than 60
	Gender	Male; Female
	Monthly income level	Less than CNY 2000; CNY 2000–3500; CNY 3500–5000; CNY 5000–8000; More than CNY 8000
	Driving experience	Less than 0 years; 0–2 years; 2–5 years; 5–10 years; More than 10 years
	Household car ownership	None; 1 car; 2 cars; More than 2 cars
	Commuter count	1 person; 2 people; 3 people; More than 3 people
Travel characteristics	Mode of transportation	Private car; Public transit; Taxi; Non-motorized vehicle; Walking; Other
	Travel distance	Less than 2 km; 2–5 km; 5–10 km; 10–15 km; More than 15 km
	Travel cost	Less than CNY 2; CNY 2–5; CNY 5–15; CNY 15–25; More than CNY 25
	Time of travel	0:00–7:00; 7:00–9:30; 9:30–17:00; 19:30–24:00
	Traffic congestion level	Very congested; Somewhat congested; Neutral; Relatively smooth; Very smooth
	Travel time flexibility	Very flexible; Somewhat flexible; Neutral; Somewhat fixed; Very fixed
Cognitive attributes of carpool lanes	Do you agree that the driving speed on bus lanes is faster than on regular lanes	Strongly agree; Somewhat agree; Neutral; Disagree; Strongly disagree
	Who would you be willing to choose as a carpool partner?	Family; Friends; Colleagues; Neighbors; Strangers with similar travel needs
	Desired information or services from the carpool platform	Ridesharing price; Ridesharing route; Estimated time of arrival; Audio recording and route tracking; Channel for feedback and ratings after ridesharing
	Do you have safety concerns about carpooling?	Strongly agree; Somewhat agree; Neutral; Disagree; Strongly disagree
	Are you familiar with the local policies regarding bus lanes?	Very Familiar; Somewhat Familiar; Neutral; Unfamiliar; Completely Unfamiliar
	Through which channels do you usually get the latest road information?	Social media; Traditional media channels; Navigation app alerts; Told by friends
	Would you carpool if bus lanes were available on your route	Very willing; Somewhat willing; Neutral; Unwilling; Completely unwilling
	Acceptable detour time	Less than 5 min; 5–10 min; 10–20 min; 20–30 min; More than 30 min
	Reasons for willingness to carpool	1. It reduces travel costs and meets daily commuting needs. 2. Wily and friends expect to carpool using bus-exclusive lanes. 3. When vehicle supply is insufficient or restricted by traffic policies. 4. Carpooling can meet commuting demands. 5. It can save social resources and reduce environmental pollution. 6. It can alleviate traffic congestion. 7. It can provide a relatively convenient travel experience in certain scenarios.

Table 1. *Cont.*

	Survey Content	Option Settings
Cognitive attributes of carpool lanes	Concerns about carpooling	1. It is difficult to easily find carpoolers with the same needs. 2. Unable to complete the trip on time. 3. May cause social discomfort. 4. Carpooling raises safety concerns. 5. Mixed traffic with buses significantly impacts public transportation operations. 6. Mixed traffic with large buses is unsafe.

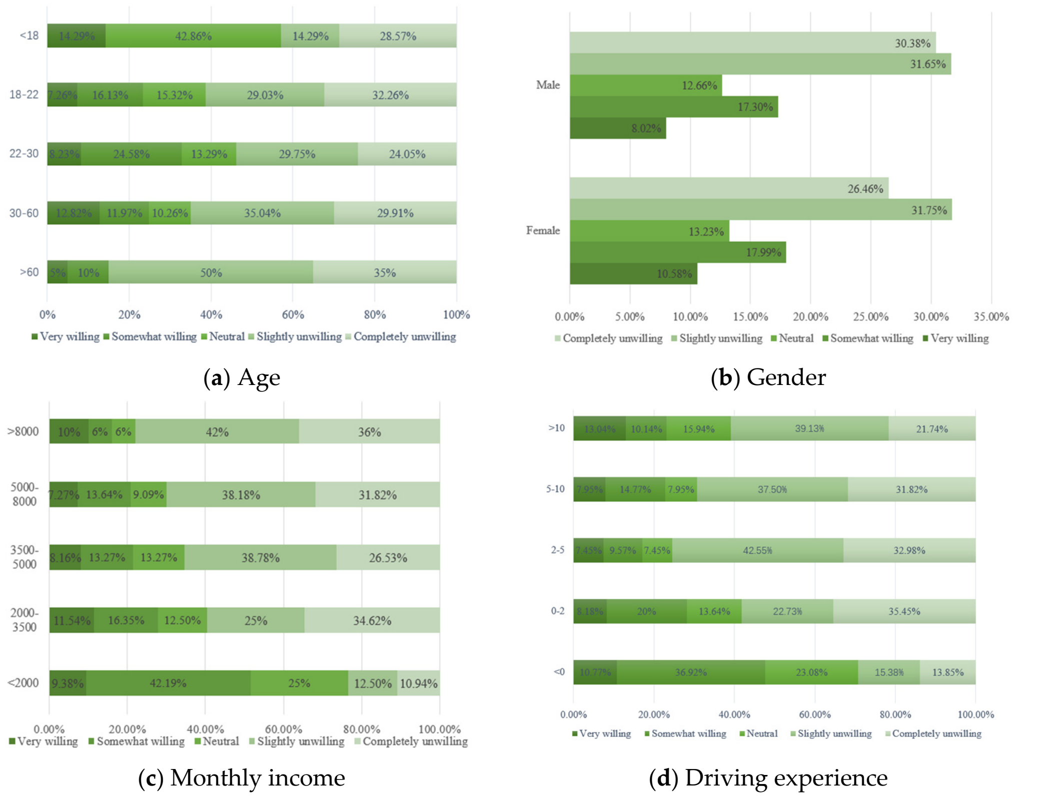
2.2. Survey Data Analysis

(1) Questionnaire survey

The questionnaire was distributed online, with its content integrated into an online survey format on the "Questionnaire Star" platform. A QR code was generated and shared across various social media platforms, and a total of 426 validly completed questionnaires were collected.

(2) Data statistics and analysis

The statistical data for the personal attribute section are shown in Figure 1.



(**a**) Age (**b**) Gender (**c**) Monthly income (**d**) Driving experience

Figure 1. Cross statistics of personal characteristics and willingness to share rides.

According to the statistical results of personal attribute data, younger individuals are more willing to choose ridesharing than older individuals, males are more willing to choose ridesharing than females, individuals with lower monthly incomes are more willing to choose ridesharing than those with higher monthly incomes, individuals without a driver's license are more willing to choose ridesharing than those with a driver's license, and individuals with longer driving experience are more willing to choose ridesharing than those with shorter driving experience.

The statistical data for the travel attributes section are shown in Figure 2.

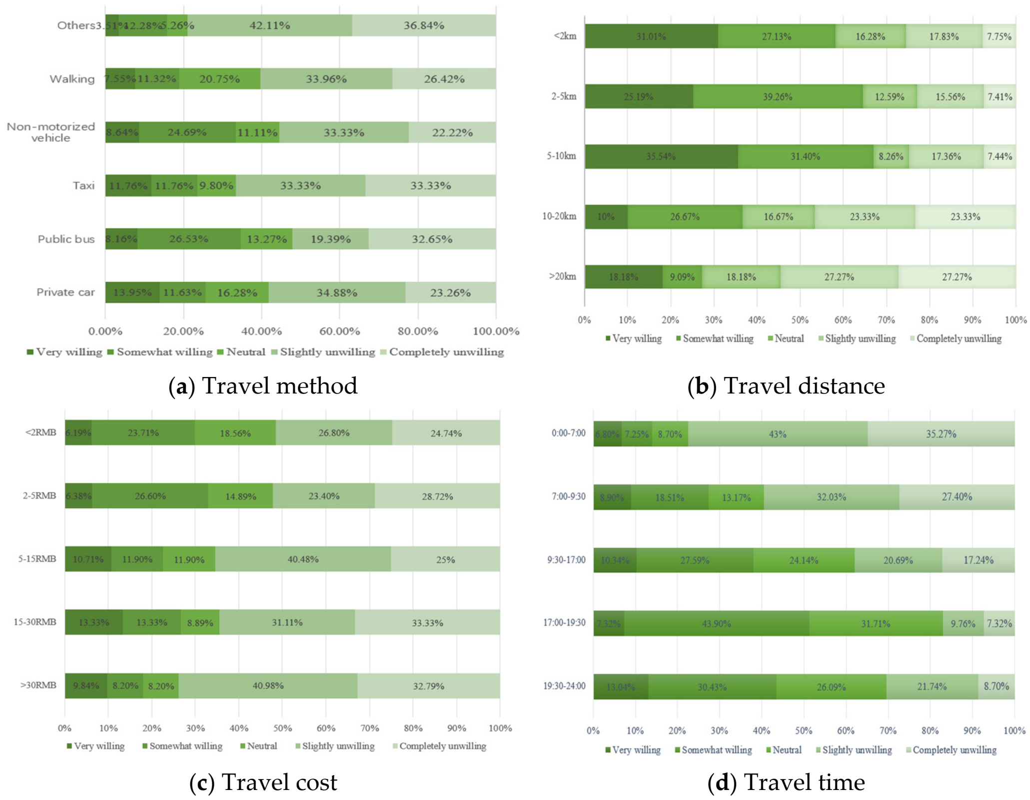


Figure 2. Cross statistics of travel attributes and willingness to share rides.

According to the statistical results of the travel attribute data, it can be seen that individuals who travel by taxi or private car have a stronger willingness to engage in carpooling, followed by those who use public transportation and non-motorized vehicles. Groups with shorter travel distances are more willing to choose carpooling than those with longer travel distances. Groups with lower travel costs are more willing to carpool than those with higher travel costs. Groups whose travel time does not fall within the morning rush hour are more willing to carpool than those whose travel time falls within the rush hour. Groups experiencing more congestion during their travel are more willing to carpool than those with less congestion. Groups with flexible travel times are more willing to carpool than those with less flexible travel times.

The statistical results for the cognitive attributes of carpooling on public lanes are shown in Figure 3.

According to the statistical results of the cognitive attributes of shared bus lanes, most travelers agree that carpooling using bus lanes can save time. Travelers have some concerns about the safety of carpooling but have a low level of understanding of the related road policies. Additionally, most travelers have a low tolerance for detour time, with less than 10 min being acceptable.

Through the analysis of the survey data, it can be concluded that travelers show a strong willingness to engage in carpooling and hope to improve travel efficiency through the shared bus lane strategy. During their journeys, travelers tend to choose travel options that are time-efficient, highly safe, and affordable. At the same time, most travelers place high importance on the timeliness, cost-effectiveness, and comfort of carpooling, with a relatively higher level of concern for safety.

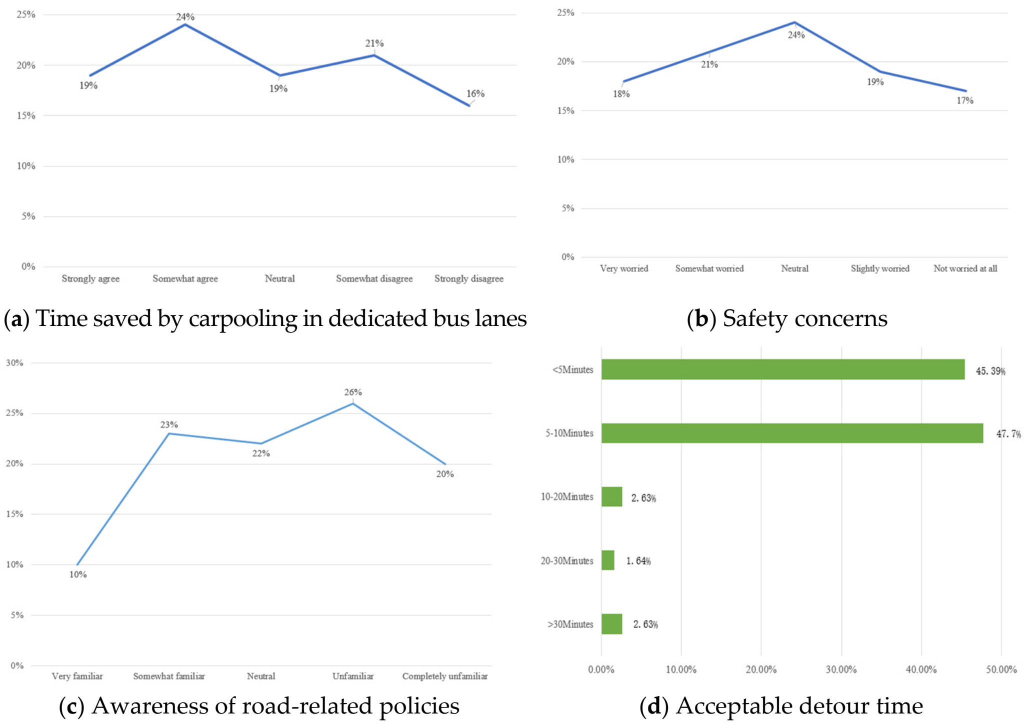


Figure 3. Statistical results of cognitive attributes of shared bus lanes.

3. Carpooling Decision-Making Model for Bus-Exclusive Lanes

3.1. Analysis of Travel Choice Behavior

In the shared travel scenario, travelers' carpooling choices are influenced by multiple factors. Cumulative prospect theory (CPT), as a psychological decision-making model, offers unique advantages and feasibility, making it suitable for explaining decision-making processes in uncertain and complex environments, such as the one applied in this study.

Firstly, CPT emphasizes the asymmetry between losses and gains, which better aligns with people's subjective perception of potential risks in real decision-making situations. This characteristic enables the model to more accurately predict how individuals weigh potential losses (such as reduced social comfort or increased detour time) and potential gains (such as improved travel speed or reduced traffic congestion) in the carpooling scenario.

Secondly, CPT introduces the reference dependence effect, considering the impact of a decision-maker's reference point on the decision. In the study of the scenario where bus-only lanes are opened to carpooling vehicles, people's expectations and reference points are based on the scenario where bus-only lanes are not open to carpooling vehicles. This framework allows for a deeper understanding of how reference points shape people's attitudes toward carpooling decisions, providing a more realistic and comprehensive foundation for the model.

Additionally, CPT models the psychological phenomenon of loss aversion, where people are more sensitive to losses than to equivalent gains. In this study, CPT can help us better understand travelers' strong reactions to potential losses, allowing for more accurate predictions of their willingness to carpool. This psychological effect is particularly crucial in complex transportation decision-making scenarios.

Therefore, developing a model based on cumulative prospect theory provides a powerful tool for studying travelers' carpooling behavior in scenarios where bus-only lanes are opened to carpooling vehicles. The advantage of CPT lies in its consideration of people's subjective perceptions of uncertainty and risk, more realistically reflecting the psychological weighting process of decision-makers in actual environments, and offering a robust theoretical framework to more comprehensively understand and explain travelers' decision-making [28].

3.2. The Establishment of the Carpooling Decision-Making Model for Bus-Exclusive Lanes

(1) Travel cost

The travel cost for carpooling includes transportation cost, time cost, and combination cost during the carpooling process. The combination cost involves waiting time and spatial loss cost. Considering the varying sensitivity of travelers to each cost component, perception weight coefficients are introduced. The travel cost expression is shown in Equation (1).

$$Z = T\gamma + M\rho + S\omega \tag{1}$$

Z—Comprehensive travel cost;
T—Time cost;
γ—Time perception weight parameter;
M—Travel expenses;
ρ—Travel expense perception weight parameter;
S—Carpooling combination cost;
ω—Carpooling combination cost perception weight parameter.

To calculate the time cost, the value of time needs to be quantified. Since the value of time varies across regions, local average wages are used to standardize and quantify it, eliminating regional differences. The calculation of time cost is also related to travel time. In the modeling scenario, travelers' carpooling decisions influence road conditions, thereby affecting travel time. A road impedance model is used in this study to calculate travel time, considering the impact of travelers' decisions on traffic flow. The calculation expressions are shown in Equations (2)–(4).

$$T_j = t_j \times t_\beta = t_1 \times \left(1 + \varphi \times \left(\frac{C_j}{Q_j}\right)^{\varnothing}\right) \times (1 + \gamma_j) \times M_0 \tag{2}$$

$$t_j = t_1 \times \left(1 + \varphi \times \left(\frac{C_j}{Q_j}\right)^{\varnothing}\right) \times (1 + \gamma_j) \tag{3}$$

$$t_1 = \frac{L}{V_1} \tag{4}$$

T_j—Time cost of travel mode j;
t_j—Travel time of travel mode j;
M_0—Local average hourly wage;
t_1—Travel time of vehicles on the road segment under free-flow conditions;
C_j—Number of vehicles for travel mode j;
Q_j—Lane capacity for travel mode j;
$\varphi, \varnothing$—Model coefficients;
γ_j—Bus stop adjustment factor.

The travel time of carpool vehicles and buses is affected by bus stops. When calculating travel time, a bus stop adjustment factor should be included. For solo driving trips, $\gamma_j = 0$.

(2) Flow constraints

In this study, flow constraints refer to the condition where the total travel demand remains constant while travelers choose different travel modes. Since various travel modes accommodate different numbers of passengers, they result in different vehicle flows on the road. Therefore, under the condition of constant total travel demand, the flow constraint is expressed as shown in Equation (5).

$$Q = \sum C_j \times N_j \tag{5}$$

Q—Total number of travelers;
N_j—Number of passengers carried by travel mode j.

(3) Setting reference points

In travel decision-making, travelers use the travel cost of solo driving as a reference point to evaluate the safety, comfort, and convenience of other travel modes. The reference point expression is shown in Equation (6).

$$Z_{j0} = T_{j0} \times \gamma + M_{j0} \times \rho \tag{6}$$

Z_{j0}—Comprehensive expected cost corresponding to travel mode j;
T_{j0}—Expected time cost corresponding to travel mode j;
M_{j0}—Expected travel expense corresponding to travel mode j.

(4) Determining the value function

When making travel decisions, travelers need to comprehensively consider actual conditions and travel costs to evaluate various travel modes. Therefore, the concept of loss and gain value is introduced as an evaluation metric. The loss and gain value can more intuitively reflect the relative value of various travel modes for travelers, helping them make more reasonable travel choices. The calculation formula is shown in Equation (7).

$$H_j = Z_{j0} - Z_j \tag{7}$$

H_j—Gain or loss of travel mode j compared to the reference point;
Z_{j0}—Travel reference point set by the traveler;
Z_j—Actual comprehensive travel cost corresponding to travel mode j.

If the loss and gain value is positive, i.e., $H_j > 0$, the actual travel cost is less than the expected travel cost, indicating that this travel option is better than traveling by driving alone. Conversely, if the loss and gain value is negative, i.e., $H_j < 0$, the actual travel cost exceeds the expected travel cost, indicating that this travel option is more expensive and unfavorable for individual travel.

The value function expression is established as shown in Equation (8).

$$V(H_j) = \begin{cases} H_j^{\varepsilon} & H_j \geq 0 \\ -\theta(-H_j)^{\mu} & H_j \leq 0 \end{cases} \tag{8}$$

$V(H_j)$—Relative value of travel mode j;
$\varepsilon,\ \mu$—Risk sensitivity coefficient;
θ—Loss aversion coefficient.

(5) Determining the decision probability weighting function

Based on the traveler's perceived probability function, the decision probability weighting function is determined to make the model more realistic. Specifically, the probability weighting function is divided into two aspects: one for the decision probability weighting function when perceived as a gain, and the other for the decision probability weighting function when perceived as a loss. The mathematical expressions are shown in Equations (9) and (10).

$$f^{+}(P_j) = \frac{P_j^{\nu}}{\left[P_j^{\nu} + (1 - P_j)^{\nu}\right]^{\frac{1}{v}}} \tag{9}$$

$$f^{-}(P_j) = \frac{P_j^{\xi}}{\left[P_j^{\xi} + (1 - P_j)^{\xi}\right]^{\frac{1}{\xi}}} \tag{10}$$

P_j—Perceived probability of travelers choosing travel mode j;

$f^{+}(P_j)$—Decision probability weighting function when the traveler's perception is a gain;

$f^{-}(P_j)$—Decision probability weighting function when the traveler's perception is a loss;

v—Risk attitude coefficient when perceived as a gain;

ξ—Risk attitude coefficient when perceived as a loss.

The decision probability weighting function is further categorized based on the positive or negative value of the gain–loss, as shown in Equation (11).

$$f^{\pm}(P_j) = \begin{cases} f^{+}(P_{je}) & V_j \geq 0 \\ f^{-}\left(P_{jl}\right) & V_j < 0 \end{cases} \tag{11}$$

P_{je}—Decision probability weighting function when the gain–loss value is positive;

P_{jl}—Decision probability weighting function when the gain–loss value is negative.

Thus, the cumulative probability weighting functions are calculated, as shown in Equations (12)–(15).

$$g_{je}^{+} = f^{+}(P_{je} \cup P_{je+1} \cup \cdots \cup P_{jE}) - f^{+}(P_{je+1} \cup \cdots \cup P_{jE}) \tag{12}$$

$$g_{jl}^{-} = f^{-}(P_{jl} \cup P_{jl+1} \cup \cdots \cup P_{jL}) - f^{-}(P_{jL+1} \cup \cdots \cup P_{jL}) \tag{13}$$

$$g_{jE}^{+} = f^{+}(P_{jE}) \tag{14}$$

$$g_{jL}^{-} = f^{-}(P_{jL}) \tag{15}$$

g_{je}^{+}—Cumulative probability decision weighting function when the decision is perceived as a gain;

g_{jl}^{-}—Cumulative probability decision weighting function when the decision is perceived as a loss.

(6) Calculating the cumulative prospect value

Based on the reference point, value function, and decision weighting function determined above, the cumulative prospect value for each travel mode can be calculated. The expression is shown in Equation (16).

$$CPV_j = \sum_{e=0}^{E} g_{je}^{+} \times V(H_{je}) + \sum_{l=1}^{L} g_{jl}^{-} \times V\left(H_{jl}\right) \tag{16}$$

(7) Behavioral decision

In cumulative prospect theory, travelers make decisions based on a comparison between the overall travel cost and the expected travel cost. This involves comparing the cumulative prospect values of different travel modes. The decision is made according to the principle of maximizing the cumulative prospect value, as expressed in Equation (17).

$$CPV = max\left[CPV_j\right] \tag{17}$$

4. Bus Lane Operational Efficiency Evaluation Model

4.1. Determining Evaluation Indicators

The purpose of allowing carpooling private cars to use the bus-only lanes is to improve road traffic efficiency and enhance traffic flow, but it may affect the operation of buses. Therefore, when evaluating the traffic benefits of the bus-only lane-sharing strategy, research should be conducted from three perspectives—the efficiency of social vehicle traffic, the efficiency of bus traffic, and the overall road traffic efficiency—while exploring management methods that preserve the advantages of public transportation. Economic and social indicators can reflect the economic benefits for individual travelers and the overall transportation system. Carpooling and sharing strategies can reduce the economic burden on individuals, such as by lowering transportation costs or shortening travel time. These strategies will encourage the choice of more economical travel modes, enhancing the utilization of the bus system and improving overall transportation efficiency. The carpooling strategy also aims to reduce the use of private cars, thereby reducing exhaust emissions and air pollution. Ecological benefit indicators can help assess the environmental impact of the carpooling strategy, such as reduced exhaust emissions and lower levels of air pollution. This strategy encourages travelers to choose travel modes with higher resource utilization, promoting the effective use of resources. Based on the above analysis, this paper selects evaluation indicators for the operational efficiency of bus lanes by comprehensively considering the benefits in three aspects. The goal is to analyze the overall impact of the shared bus lane strategy on road efficiency from the perspectives of traffic efficiency, economic efficiency, and ecological efficiency. The preliminary selected evaluation indicators are shown in Table 2.

Table 2. Preliminary indicators for evaluating bus-lane-sharing strategies.

Indicator Type	Indicator Name	Indicator Symbol
Traffic efficiency indicators	Social vehicle speed	I_1
	Bus vehicle speed	I_2
	Passenger flow in general lane section	I_3
	Passenger flow in bus lane section	I_4
	Average vehicle occupancy	I_5
	Road saturation	I_6
Economic efficiency indicators	Average personal travel cost	U_1
Environmental efficiency indicators	Total CO_2 emissions	E_1
	Per capita travel CO_2 emissions	E_2

(1) Traffic efficiency evaluation indicators

The speed of private vehicles is represented by the average travel speed of private vehicles, reflecting the overall operational efficiency of the private vehicle traffic flow. The calculation formula is shown in Equation (18).

$$I_1 = \frac{\sum T_i^{soc}}{C^{soc}} \tag{18}$$

T_i^{soc}—Travel time of private vehicles, with the unit being h;

C^{soc}—Traffic volume of private vehicles, with the unit being pcu/h.

The speed of buses is represented by the average travel speed of buses, which is used to evaluate the operational efficiency and service level of bus transportation. The calculation formula is shown in Equation (19).

$$I_2 = \frac{\sum T_i^{bus}}{C^{bus}} \tag{19}$$

T_i^{bus}—Travel time of buses, with the unit being h;
C^{bus}—Traffic volume of buses, with the unit being pcu/h.

The number of people passing through a regular lane section refers to the total number of people passing through the regular lane, reflecting the service level of the regular lane. The calculation formula is shown in Equation (20).

$$I_3 = \sum C_i^{l0} \times N_i^{l0} \tag{20}$$

C_i^{l0}—Number of vehicles passing through the regular lane section;
N_i^{l0}—Number of passengers per vehicle passing through the regular lane section.

The number of people passing through a bus-only lane section refers to the total number of passengers passing through the bus-only lane, reflecting the passenger flow and utilization of the bus-only lane. The calculation formula is shown in Equation (21).

$$I_4 = \sum C_i^{lb} \times N_i^{lb} \tag{21}$$

C_i^{lb}—Number of vehicles passing through the bus-only lane section;
N_i^{lb}—Number of passengers per vehicle passing through the bus-only lane section.

The average passenger capacity of vehicles refers to the average number of passengers carried by a vehicle, reflecting the utilization rate of seating resources. The calculation formula is shown in Equation (22).

$$I_5 = \frac{\sum C_i^{l0} \times N_i^{l0} + \sum C_i^{lb} \times N_i^{lb}}{C^{l0} + C^{lb}} \tag{22}$$

C^{l0}—Traffic volume passing through the regular lane section, with the unit being pcu/h;
C^{lb}—Traffic volume passing through the bus-only lane section, with the unit being pcu/h.

Road saturation refers to the ratio of traffic volume to road capacity, which is an important indicator for evaluating the level of traffic congestion and road usage efficiency. The calculation formula is shown in Equation (23).

$$I_6 = \frac{C_L}{C_D} \tag{23}$$

C_L—Traffic volume on the road, with the unit being pcu/h;
C_D—Road capacity, with the unit being pcu/h.

(2) Economic Benefit Evaluation Indicators

The average personal travel cost refers to the average expense required for all travelers to complete one trip within a certain period. The calculation formula is shown in Equation (24).

$$U_1 = \frac{\sum Q_i \times H_i}{\sum Q_i} \tag{24}$$

Q_i—Number of travelers using travel mode i;
H_i—Travel cost of travel mode i, with the unit being CNY.

(3) Ecological Benefit Evaluation Indicators

The total carbon dioxide (CO_2) emissions refer to the total amount of CO_2 emitted by various types of vehicles on a specific road segment within a certain period. The calculation formula is shown in Equation (25).

$$E_1 = \sum C_i \times K_i \times \partial_i \quad (25)$$

C_i—Number of vehicles using travel mode i;
K_i—Fuel consumption of the vehicles, with the unit being L/100 km;
∂_i—CO_2 emissions per unit of fuel consumed, with the unit being g/L.

The per capita CO_2 emissions from travel refer to the average amount of CO_2 emitted by each traveler due to their travel activities within a certain period. The calculation formula is shown in Equation (26).

$$E_2 = \frac{E_1}{Q} \quad (26)$$

E_1—Total CO_2 emissions, with the unit being L;
Q—Total number of travelers.

4.2. Evaluation Indicator Selection

In this study, the selected evaluation indicators are relatively few, and the dataset is small, with no obvious patterns in data distribution. Based on these characteristics, the gray relational analysis method is chosen as the indicator selection method [29]. The gray relational analysis method establishes a mathematical model to calculate the gray relational coefficients, thereby improving the accuracy of the correlation between indicators. Additionally, it can capture the nonlinear relationships between indicators, better reflecting the potential connections and patterns among them. Finally, by combining the results of the gray relational coefficient calculations with real-world considerations, the evaluation indicators are effectively selected.

(1) Data standardization processing

Suppose the evaluation system consists of m evaluation objects and n evaluation indicators, forming the original data matrix $= (r_{ij})_{m\times n}$, $i = 1, 2, \cdots m$, $j = 1, 2, \cdots n$ which can be expressed as

$$R_{ij} = (r_{ij})_{mn} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \cdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{pmatrix} \quad (27)$$

In the equation: r_{ij}—the data of the j evaluation indicator for the i evaluation object.

For different types of indicators, the methods of standardization processing vary. The selected indicators include "maximization" indicators (the larger the indicator value, the better the evaluation result), "minimization" indicators (the smaller the indicator value, the better the evaluation result), and "interval" indicators (the closer the indicator value is to a certain interval, the better the evaluation result). Therefore, the range transformation method is used to process the data.

For "maximization" indicators, such as the speed of public transport vehicles, the standardization calculation is performed as shown in Equation (28).

$$r'_{ij} = \frac{r_{ij} - min(r_j)}{max(r_j) - min(r_j)} \tag{28}$$

For "minimization" indicators, such as the total carbon dioxide emissions, the standardization calculation is performed as shown in Equation (29).

$$r'_{ij} = \frac{max(r_j) - r_{ij}}{max(r_j) - min(r_j)} \tag{29}$$

For "interval" indicators, such as the number of passengers passing through a section of the bus lane, the standardization calculation is performed as shown in Equation (30).

$$r'_{ij} = \begin{cases} 1 - \frac{a_i - r_{ij}}{max(a_i - minr_{ij}, maxr_{ij} - b_i)} & r_{ij} < a_i \\ 1 & a_i \le r_{ij} \le b_i \\ 1 - \frac{r_{ij} - b_i}{max(a_i - minr_{ij}, maxr_{ij} - b_i)} & r_{ij} > b_i \end{cases} \tag{30}$$

The standardized evaluation matrix $R' = \left(r'_{ij}\right)_{m \times n}$ is obtained.

(2) Calculation of indicator correlation

The standardized data series are sequentially treated as reference series, while the standardized data series of all indicators are taken as comparison series. The absolute difference between the corresponding elements of the comparison series and the reference series is calculated one by one to obtain the difference series.

The reference series r_i^a:

$$r_i^a = \{r'_{ik} | k = 1, 2, \cdots, m\}, i = 1, 2, \cdots, n \tag{31}$$

The comparison series r_j^b:

$$r_j^b = \left\{r'_{jk} | k = 1, 2, \cdots, m\right\}, j = 1, 2, \cdots, n \tag{32}$$

The difference series Δ_{i-j}:

$$\Delta_{i-j} = \left|r_i^a - r_j^b\right|, i = 1, 2, \cdots, n, j = 1, 2, \cdots, n \tag{33}$$

The secondary maximum difference Δ_{max} and secondary minimum difference Δ_{min} can be obtained:

$$\Delta_{max} = \underset{i}{max}\,\underset{j}{max}\,\Delta_{i-j} \tag{34}$$

$$\Delta_{\min} = \underset{i}{min}\,\underset{j}{min}\,\Delta_{i-j} \tag{35}$$

The gray relational coefficient ξ_{i-j} is calculated:

$$\xi_{i-j} = \frac{\Delta_{min} + \delta\Delta_{\max}}{\Delta_{i-j} + \delta\Delta_{max}}, \delta \in (0, 1), i = 1, 2, \cdots, n, j = 1, 2, \cdots, n \tag{36}$$

In the equation, δ is the distinguishing coefficient. The distinguishing coefficient reflects the dynamic variation of the comparison series; the larger the value, the greater the fluctuation of the comparison series.

The relational degree is calculated as follows:

$$\gamma_{i-j} = \frac{1}{n} \times \sum_{j=1}^{n} \xi_{i-j}, i = 1, 2, \cdots, n, j = 1, 2, \cdots, n \tag{37}$$

In the equation, γ_{i-j} is the relational degree between indicator i and indicator j. From the above steps, the relational degree between each pair of indicators can be calculated, thereby establishing the relational degree matrix.

$$Y = \begin{pmatrix} \gamma_{1-1} & \gamma_{1-2} & \cdots & \gamma_{1-m} \\ \gamma_{2-1} & \gamma_{2-2} & \cdots & \gamma_{2-m} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{m-1} & \gamma_{m-2} & \cdots & \gamma_{m-m} \end{pmatrix} \tag{38}$$

Based on the relational degree matrix, the indicators are ranked, and highly correlated indicators are selected. The reasons for high correlations among indicators are analyzed in combination with practical considerations. Finally, the evaluation indicators are filtered to establish the performance evaluation indicator system for the shared strategy of dedicated bus lanes.

4.3. Establishing the Evaluation Model

(1) Calculating objective weights using the CRITIC method

The CRITIC method is an objective weighting method commonly used to determine the weights of evaluation indicators. It calculates weights by considering the correlation between evaluation indicators and the degree of data dispersion [30].

Calculate the standard deviation of the indicators. A larger standard deviation indicates greater differences between evaluation schemes, which implies higher contrast intensity.

$$\begin{cases} \overline{r'_j} = \frac{1}{m} \times \sum_{i=1}^{m} r_{ij} \\ \sigma_j = \sqrt{\frac{\sum_{i=1}^{m} \left(r'_{ij} - \overline{r'_j}\right)^2}{m-1}} \end{cases} \tag{39}$$

$\overline{r'_j}$—The mean value of the data for indicator j;

σ_j—The standard deviation of the indicator.

Calculate the correlation coefficient between indicators. A positive correlation coefficient indicates a positive relationship between indicators, a negative correlation coefficient indicates a negative relationship, and a correlation coefficient close to zero indicates a weak relationship between indicators.

$$v_j = \sum_{i=1}^{m} (1 - a_{ij}) \tag{40}$$

v_j—Indicator conflict;

a_{ij}—The correlation coefficient between indicator i and indicator j.

Thus, the amount of information is calculated to quantify the mutual relationship between indicators. The greater the amount of information, the higher the relative importance of the indicator to the decision-making problem. The calculation formula is shown in Equation (41).

$$C_j = \sigma_j \times v_j \tag{41}$$

The amount of information is then converted into specific weight values, i.e., the objective weights w_j^C.

$$w_j^C = \frac{C_j}{\sum_{j=i}^{n} C_j} \tag{42}$$

(2) G1 method for calculating subjective weights

The G1 method is a subjective weighting approach commonly used to handle the relative importance of multiple indicators in decision-making by evaluating the importance of each indicator to determine the weights. Based on the travelers' attention to the importance of each indicator, a subjective ranking is conducted. Let f_i represent the travelers' attention to indicator i, resulting in the indicator attention ranking $f_1' > f_2' > \cdots > f_{n-1}' > f_n'$. The correlation of attention to each indicator is analyzed, and the importance of adjacent indicators f_{i-1} and f_i is assigned values r_i in sequence. Based on this, weight calculation is performed, and the calculation formula is shown in Equation (43).

$$w_n^G = \left(1 + \sum_{j=2}^{n} \prod_{i=j}^{n} r_i\right)^{-1} \tag{43}$$

In the equation, w_n^G represents the subjective weight of the n indicator calculated using the G1 method.

The weights of the remaining indicators are calculated sequentially, as shown in Equation (44).

$$w_{i-1}^G = r_{(i)} \times w_i^G, i = n, n-1, \cdots, 2 \tag{44}$$

(3) Combination of weights

In this paper, the deviation minimization method is used for the combination of weights. The deviation minimization method ensures that the combined weight results are more reasonable. The objective weights calculated using the CRITIC method and the subjective weights derived from the G1 method are linearly combined to obtain the final indicator weights, as shown in Equation (45).

$$w\prime = \lambda^C \times w^C + \lambda^G \times w^G \tag{45}$$

$w\prime$—The combined weight vector of the indicators;
w^C—The objective weight vector obtained using the CRITIC method;
w^G—The subjective weight vector calculated using the G1 method;
λ^C—The subjective weight combination coefficient;
λ^G—The objective weight combination coefficient.

Based on the idea of deviation minimization, the optimal combined weights are determined by minimizing the deviation between the combined weights, the objective weights, and the subjective weights. The goal is to find the optimal combined weights that achieve the smallest discrepancy, ensuring a more balanced and reasonable weighting scheme. That is, by minimizing the sum of the deviations between the combined indicator weights $w\prime$, the objective weights w^C, and the subjective weights w^G, the optimal linear combination coefficients λ^C and λ^G are sought. To achieve this goal, the objective function is established as shown in Equation (46), and the constraint conditions are specified as shown in Equation (47).

$$min\left(\left\|w\prime - w^C\right\|_2 + \left\|w\prime - w^G\right\|\right) \tag{46}$$

$$\lambda^C + \lambda^G = 1 \qquad \lambda^C, \lambda^G \geq 0 \tag{47}$$

According to the properties of matrix differentiation, the above formula can be transformed into a system of linear equations under the first-order derivative, as shown in Equation (48).

$$\begin{cases} \lambda^C \times w^C \times w^{CT} + \lambda^G \times w^C \times w^{GT} = w^C \times w^{CT} \\ \lambda^C \times w^G \times w^{CT} + \lambda^G \times w^G \times w^{GT} = w^G \times w^{GT} \end{cases} \tag{48}$$

By solving the above equation, the weight coefficients are obtained, and normalization is performed on them. The normalization process is expressed as shown in Equation (49).

$$\begin{cases} \lambda^{C\prime} = \frac{|\lambda^C|}{|\lambda^C|+|\lambda^G|} \\ \lambda^{G\prime} = \frac{|\lambda^G|}{|\lambda^C|+|\lambda^G|} \end{cases} \tag{49}$$

$\lambda^{C\prime}$—The optimal objective weight combination coefficient;

$\lambda^{G\prime}$—The optimal subjective weight combination coefficient.

Thus, the optimal combined weights are calculated, as shown in Equation (50).

$$w'' = \lambda^{C\prime} \times w^C + \lambda^{G\prime} \times w^G \tag{50}$$

w''—The optimal combined weights.

(4) Improved TOPSIS comprehensive evaluation model

Based on the combined weights obtained from the deviation minimization-based weighted combination method mentioned above, we construct a combination-weighted TOPSIS traffic operation efficiency evaluation model [31].

Multiply the standardized matrix R' by the optimal combined weight vector w'' to obtain the weighted standardized decision matrix X, as shown in Equation (51). In this matrix, each row represents an evaluation object (traffic operation condition), and each column represents an evaluation indicator.

$$X_{ij} = (x_{ij})_{mn} = \begin{pmatrix} w'_1 \times r_{11} & w'_2 \times r_{12} & \cdots & w'_n \times r_{1n} \\ w'_1 \times r_{21} & w'_2 \times r_{22} & \cdots & w'_n \times r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w'_1 \times r_{m1} & w'_2 \times r_{m2} & \cdots & w'_n \times r_{mm} \end{pmatrix} \tag{51}$$

x_{ij} represents the data of the j indicator for the i evaluation object, standardized based on the combined weights.

Based on the decision matrix, determine the positive ideal solution X^+ and the negative ideal solution X^+. The positive ideal solution represents the situation where the maximum value is achieved for each indicator, while the negative ideal solution represents the situation where the minimum value is achieved for each indicator. The calculation formulas are shown in Equations (52) and (53).

$$X^+ = \left(X_1^+, X_2^+, \cdots, X_n^+\right) = (max(x_{11}, x_{21}, \cdots, x_{m1}), \cdots, max(x_{1n}, x_{2n}, \cdots, x_{mn})) \tag{52}$$

$$X^- = \left(X_1^-, X_2^-, \cdots, X_n^-\right) = (min(x_{11}, x_{21}, \cdots, x_{m1}), \cdots, min(x_{1n}, x_{2n}, \cdots, x_{mn})) \tag{53}$$

Using the Euclidean distance method, calculate the Euclidean distance D_i^+ between the evaluated scheme and the positive ideal solution X^+. The calculation formula is shown in Equation (54).

$$D_i^+ = \sqrt{\sum_{j=1}^{m}\left(X_{ij}^+ - x_{ij}\right)^2} \tag{54}$$

Calculate the Euclidean distance D_i^- between the evaluated scheme and the negative ideal solution X^-. The formula is shown in Equation (55).

$$D_i^- = \sqrt{\sum_{j=1}^{m} \left(X_{ij}^- - x_{ij} \right)^2} \tag{55}$$

Based on the distance calculation results, calculate the closeness coefficient (proximity index) for each evaluation object. The closeness coefficient can represent the degree of proximity of the evaluation object to the positive ideal solution, as well as the degree of separation from the negative ideal solution. The calculation formula is shown in Equation (56).

$$B_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{56}$$

B_i—Closeness coefficient.

The closeness coefficient ranges between 0 and 1. A smaller closeness coefficient indicates poorer traffic operational efficiency, while a larger closeness coefficient indicates better traffic operational efficiency.

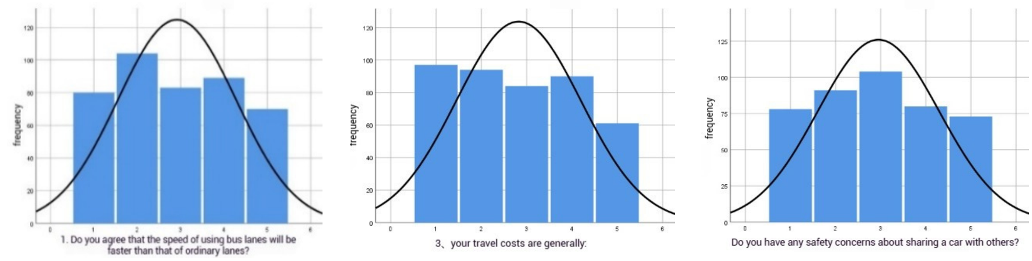
5. Case Analysis

Using a specific area in Nanchang, Jiangxi Province, as a case study, this research examines the impact of bus-lane-sharing policies and travelers' awareness of these policies on their travel decisions. Furthermore, it analyzes the traffic flow structure under different bus-lane-sharing policies. Through the analysis of calculation results, this study explores the influence of bus-lane-sharing policies on the operational efficiency of bus lanes.

5.1. Parameter Calibration

We further analyzed the questionnaire survey results to calibrate model parameters. We analyzed the factors influencing ridesharing willingness by categorizing the questions in the questionnaire. We investigated the impact of time-related factors, cost-related factors, and ridesharing combination factors on the willingness to share rides. We calibrated the weights of the three types of comprehensive travel costs based on the survey results. We calculated the correlation between different factors and the willingness to carpool to assess the degree of association between the three types of factors and carpooling willingness. We selected travel cost, agreement with the statement that using bus lanes is faster than regular lanes, and concerns about the safety of ridesharing as the three influencing factors from the questionnaire. We analyzed the correlation between these three types of data and the willingness to carpool.

We conducted a normality test on the survey data, The test results are shown in Figure 4.



(**a**) Frequency statistics of time factors (**b**) Frequency statistics of cost factors (**c**) Frequency statistics of combined factors

Figure 4. Frequency distribution chart of survey data for three types of factors.

The valid survey sample size was greater than 50, and the normality test was based on the results of the Kolmogorov–Smirnov test. The test results are shown in Table 3.

Table 3. Normality test for survey data of three types of factors.

Statistical Factors	Statistics	Degrees of Freedom	Significance Value
Time factors	0.173	426	0.00
Cost factors	0.181	426	0.00
Combined factors	0.156	426	0.00

The significance values calculated are shown in the table above. The significance values for all types of factors are less than 0.05, indicating that the data for all three factors do not follow a normal distribution. Correlation analysis was conducted between the three types of data and the carpooling willingness survey results. Since the data do not follow a normal distribution, the Spearman correlation coefficient was used.

The significance values of the three factors are shown in Table 4, The sig. values for the three factors are all less than 0.05, indicating that all three factors have a significant correlation with carpooling willingness. The correlation coefficients are shown in the table above. The normalized correlation coefficients were used to assign weights to the components of the comprehensive cost. The calibrated results of the perceived travel cost weight coefficients are presented in Table 5.

Table 4. Correlation coefficient statistical table.

Statistical Factors	Spearman Correlation Coefficient	Significance Value
Time factors	−0.201	0.00
Cost factors	0.102	0.036
Combined factors	−0.111	0.023

Table 5. Calibration results of perceived travel cost coefficient weights.

Parameter Symbol	γ (Time Perception Weight Parameter)	ρ (Travel Expense Perception Weight Parameter)	ω (Carpooling Combination Cost Perception Weight Parameter)
Parameter value	0.485	0.246	0.268

To calculate time costs, travel time needs to be quantified. To make the model more realistic, a weighted average of the average wages of employees in urban non-private units and private units in Jiangxi Province is used. The calculation is as follows: $\frac{6098}{(8\times30)} = 0.42$ CNY/min, where 6098 CNY represents the average monthly wage in Jiangxi Province [31].

The sensitivity of the value function parameters to different travel modes has varying impacts. Based on existing research and model definitions, the calibration results are shown in Table 6.

Table 6. Calibration results of ridesharing decision model parameters.

Parameter Symbol	ε (Risk Sensitivity Coefficient)	μ (Risk Sensitivity Coefficient)	θ (Loss Aversion Coefficient)	ν (Risk Attitude Coefficient When Perceived as a Gain)	ξ (Risk Attitude Coefficient When Perceived as a Loss)
Parameter value	0.23	0.36	0.41	0.61	0.90

In this study, travel costs are calculated based on the improved road impedance function model. The road parameters are set as follows: total travel demand: $Q = 800$ *people*;

travel distance: $L = 10$ KM; general traffic lane capacity: $C = 1375\frac{\text{vehicles}}{\text{hour}}$; dedicated bus lane capacity: $C = 275$ vehicles/hour; fuel cost: $\frac{0.65\text{CNY}}{\text{km}}$; carpooling combination cost: 8 CNY/km; passing through 10 bus stops; peak hour bus flow: 30 buses.

The carpooling behavior studied in this paper does not involve route selection. That is, carpooling vehicles use only the dedicated bus lane, while non-carpooling vehicles use only the general traffic lane. When the capacity of carpooling vehicles is $C_n people/vehicle$, the flow constraint shown in Equation (57) exists.

$$\begin{cases} Q = Q_1 + Q_2 \\ C_1 = \frac{Q_1}{C_n} \\ C_2 = Q_2 \end{cases} \tag{57}$$

Q_1—The number of travelers choosing carpooling;

Q_2—The number of travelers choosing to drive alone;

C_1—The carpool vehicle flow;

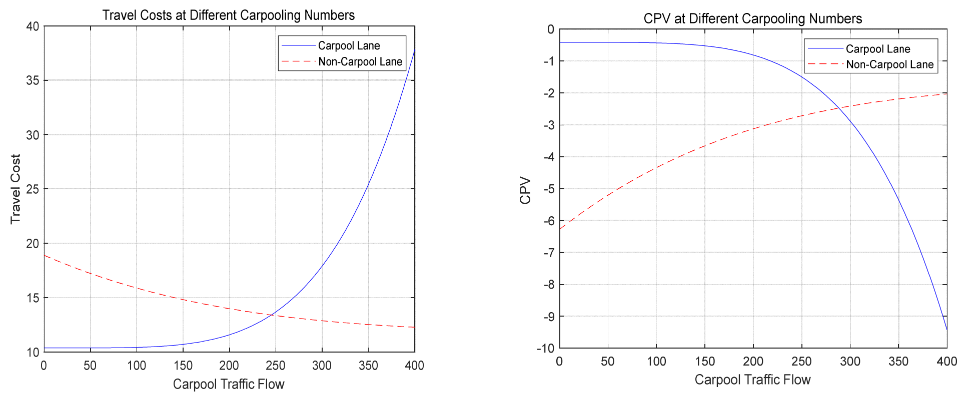
C_n—The required passenger capacity per carpool vehicle, as per the dedicated bus-lane-sharing strategy;

C_2—The flow of solo driving vehicles.

Substitute the above parameters into the carpooling decision-making model for calculation.

5.2. Analysis of Factors Influencing Carpooling Travel

Figure 5a shows the variation in travel costs for two types of travel modes under the cumulative prospect theory framework. Initially, with low traffic flow on the dedicated bus lane, carpooling has a clear advantage in terms of overall travel costs. However, as the number of carpooling vehicles increases, the bus lane becomes congested, causing the travel costs for carpoolers to gradually rise, eventually surpassing the costs of non-carpooling. As the number of carpoolers increases, the flow of vehicles on general lanes decreases, improving road congestion and leading to a gradual decrease in travel costs for non-carpoolers, which eventually fall below the carpooling travel costs.

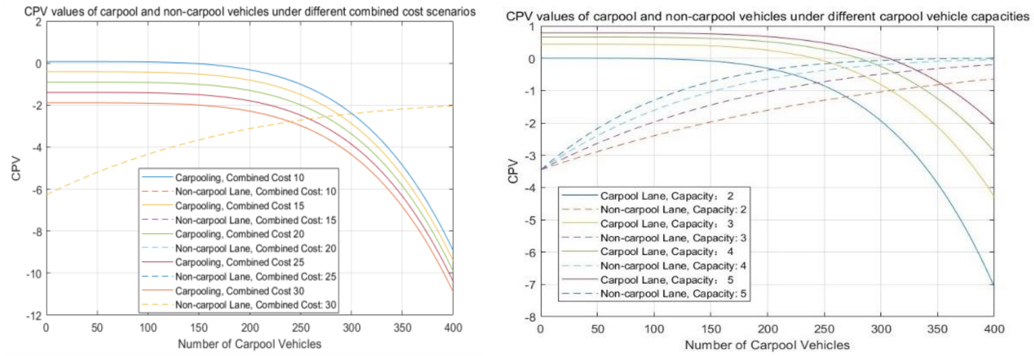


(**a**) Travel cost (**b**) CPV (Customer perceived value)

Figure 5. The impact of the number of shared rides on travel cost (**a**) and CPV (customer-perceived value) (**b**).

Figure 5b illustrates the variation trends in the cumulative prospect values of two travel modes under the cumulative prospect theory framework. When carpooling has a significant cost advantage, its cumulative prospect value is higher than that of non-carpooling, prompting travelers to prefer carpooling. However, as the number of carpoolers increases, the cost of carpooling rises, leading to a gradual decline in its cumulative prospect value. Once it falls below the cumulative prospect value of non-carpooling, travelers tend to opt for non-carpooling instead.

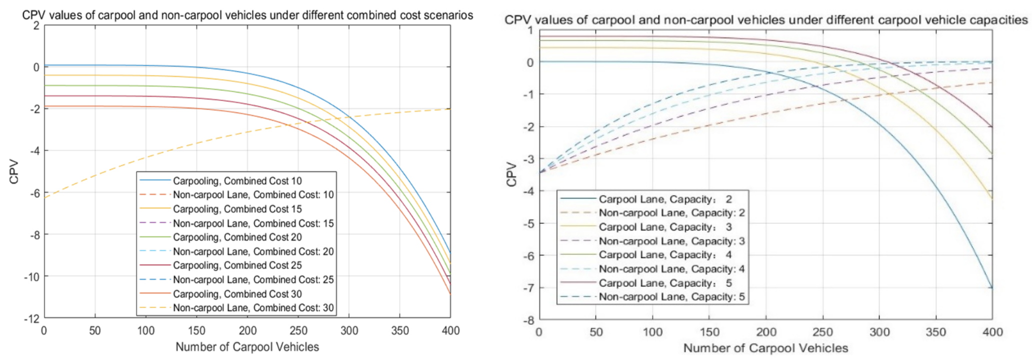
Figure 6a,b show the variation trends of cumulative prospect values for the two travel modes under different gain risk attitude coefficients and loss risk attitude coefficients, respectively, within the framework of cumulative prospect theory. Under varying gain and loss risk attitude coefficients, as the number of carpooling vehicles increases, the cumulative prospect value of the carpooling lane decreases significantly, while the cumulative prospect value of the non-carpooling lane grows slowly. Comprehensive analysis indicates that both the gain risk attitude coefficient and the loss risk attitude coefficient have a greater impact on the carpooling lane.



(**a**) Different combined costs (**b**) Different ridesharing vehicle capacities

Figure 6. CPV (customer-perceived value) of different travel modes under different return–risk attitude coefficients (**a**) and different loss–risk attitude coefficients (**b**).

Figure 7a illustrates the variation trends in cumulative prospect values for two travel modes under different carpooling combination costs within the cumulative prospect theory framework. As the carpooling combination cost gradually decreases, the cumulative prospect value of carpooling increases correspondingly. The point where the cumulative prospect values of carpooling and non-carpooling are equal shifts progressively to the right, indicating that more travelers tend to choose carpooling.



(**a**) Different combined costs (**b**) Different ridesharing vehicle capacities

Figure 7. CPV (customer-perceived value) of different travel modes under different combination costs (**a**) and under different shared car capacities (**b**).

Figure 7b illustrates the variation trends in cumulative prospect values for two travel modes under different carpooling vehicle capacities within the cumulative prospect theory framework. The larger the carpooling vehicle capacity, the lower the travel costs shared by carpoolers, resulting in higher initial cumulative prospect values. However, as the traffic flow on the dedicated bus lane gradually increases, the cumulative prospect value of carpooling decreases, eventually falling below that of non-carpooling. Consequently, travelers tend to shift their preference toward non-carpooling.

5.3. Comprehensive Benefit Evaluation

Based on the above analysis, when other factors remain constant, the cumulative prospect value is maximized when the carpool vehicle capacity is larger, indicating that carpool vehicle capacity is the factor that has the greatest impact on the traffic flow structure. Therefore, the traffic operation benefits of the bus-lane-sharing strategy are evaluated under different carpooling vehicle capacities.

The traffic volumes of each travel mode under different combination costs are shown in Table 7.

Table 7. Traffic flow structure under different ridesharing vehicle capacities.

	No Dedicated Bus-Lane-Sharing Policy	Ridesharing Vehicle Capacity 2	Ridesharing Vehicle Capacity 3	Ridesharing Vehicle Capacity 4	Ridesharing Vehicle Capacity 5
Ridesharing vehicle	0	311	297	285	269
Private vehicle	2560	2022	1705	1372	1005
Public transit	30	30	30	30	30

The average indicators are calculated using the indicator analysis formulas, with the passenger car equivalent conversion factor for buses set at 2.5 and the average number of passengers at 20. The statistical data for each indicator are shown in Table 8, and the results of the standardization process are presented in Table 9.

Table 8. Statistical table of indicator data.

	No Dedicated Bus-Lane-Sharing Policy	Ridesharing Vehicle Capacity 2	Ridesharing Vehicle Capacity 3	Ridesharing Vehicle Capacity 4	Ridesharing Vehicle Capacity 5
I_1	29.83	42.57	43.07	43.49	43.72
I_2	58.13	52.71	51.75	51.75	49.98
I_3	2560	1753	1705	1669	1627
I_4	600	1407	1455	1491	1533
I_5	1.22	1.54	1.56	1.58	1.61
I_6	0.62	0.49	0.48	0.48	0.47
U_1	27.45	14.50	14.02	13.68	13.29
E_1	23,971.76	14,132.09	13,822.68	13,590.20	13,373.57
E_2	7.59	4.47	4.37	4.30	4.23

Table 9. Statistical table of normalized data.

	No Dedicated Bus-Lane-Sharing Policy	Ridesharing Vehicle Capacity 2	Ridesharing Vehicle Capacity 3	Ridesharing Vehicle Capacity 4	Ridesharing Vehicle Capacity 5
I_1	0.15	0.21	0.21	0.21	0.22
I_2	0.22	0.20	0.20	0.20	0.19
I_3	0.27	0.19	0.18	0.18	0.17
I_4	0.09	0.22	0.22	0.23	0.24
I_5	0.16	0.20	0.21	0.21	0.21
I_6	0.24	0.19	0.19	0.19	0.19
U_1	0.33	0.17	0.17	0.16	0.16
E_1	0.30	0.18	0.18	0.17	0.17
E_2	0.30	0.18	0.18	0.17	0.17

A radar chart is plotted based on the standardized data to analyze the trend variations of the indicator data.

As shown in Figure 8, after implementing the bus-lane-sharing strategy, road saturation decreases, alleviating traffic congestion, and the travel speed of private vehicles is effectively improved. However, the speed of buses declines, with the impact increasing as carpooling vehicle capacity grows. The traffic volume on general lanes decreases significantly, while the traffic volume on bus lanes increases substantially. Under the bus-lane-sharing strategy, individual average travel costs, total CO_2 emissions, and per capita travel CO_2 emissions are significantly reduced.

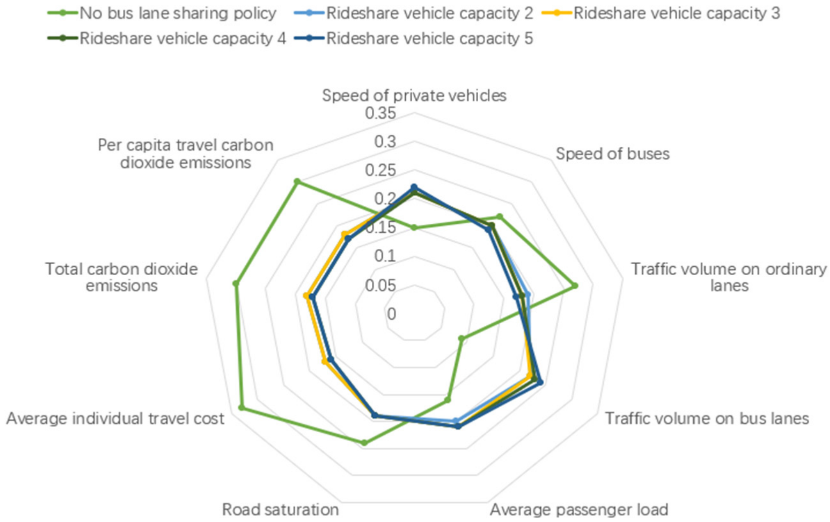


Figure 8. Radar chart of standardized data of each indicator under different carpooling capacities.

We calculated the gray relational degree of each indicator to obtain the gray relational degree between the indicators.

$A_1 \sim A_9$ represent the following: social vehicle speed, bus vehicle speed, traffic flow of general lane sections, traffic flow of bus lane sections, average passenger capacity, road saturation, individual average travel cost, total CO_2 emissions, and per capita CO_2 emissions during travel.

As shown in Table 10, the total CO_2 emissions and per capita CO_2 emissions during travel have the highest relational degree and are highly correlated. Since both indicators describe the carbon emission efficiency of traffic operations, there is redundancy between them, and only the total CO_2 emissions are retained. The relational degree between social vehicle speed and average passenger capacity is the second highest. Social vehicle speed can be used to evaluate traffic smoothness and assess the effectiveness of shared bus lane policies, while average passenger capacity can measure the utilization efficiency of public transportation and the popularity of ridesharing behavior. In this study, both have unique and important significance and are therefore retained.

Table 10. Gray correlation degrees between indicators.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9
A_1	1	0.8025	0.6779	0.8073	0.9400	0.7409	0.5922	0.6420	0.6420
A_2		1	0.7452	0.6224	0.8036	0.8729	0.6086	0.6853	0.6853
A_3			1	0.5962	0.7085	0.8736	0.8073	0.9100	0.9100
A_4				1	0.8816	0.7584	0.6449	0.6851	0.6851
A_5					1	0.7677	0.6023	0.6573	0.6573
A_6						1	0.6924	0.7798	0.7798
A_7							1	0.9733	0.9733
A_8								1	1.0000
A_9									1

After removing redundant data, the CRITIC method is used to calculate the objective weights, and the results are shown in Table 11.

Table 11. Objective weights calculated by the CRITIC method.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
Weight value	0.1207	0.1080	0.1233	0.1235	0.1308	0.1336	0.1312	0.1289

The G1 method is used to calculate the subjective weights by first analyzing the survey results and ranking the travelers' attention to each indicator. The attention levels are denoted as $f_{A1} > f_{A2} > f_{A3} > f_{A4} > f_{A5} > f_{A6} > f_{A7} > f_{A8}$ where $f_{A1} \sim f_{A8}$ represent travelers' concerns about social vehicle speed, bus vehicle speed, traffic flow of general lane sections, traffic flow of bus lane sections, average passenger capacity, road saturation, individual average travel cost, and total CO_2 emissions, respectively. The calculation results are shown in Table 12.

Table 12. Subjective weights calculated by the G1 method.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
Weight value	0.1207	0.2528	0.0980	0.1088	0.1317	0.0784	0.1580	0.0940

According to the principle of deviation minimization, the subjective and objective weights for each indicator are combined and assigned to obtain the composite weights of each indicator. The calculation results are shown in Table 13.

Table 13. Combined weight values.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
Weight value	0.08295	0.23721	0.10072	0.11038	0.1316	0.084344	0.15511	0.09776

Based on the composite weights of the comprehensive evaluation indicators for the operation efficiency of bus lanes, the TOPSIS comprehensive evaluation method is used to assess the overall efficiency of different schemes. The closeness coefficient of each scheme is calculated and ranked accordingly.

According to the principle of maximum closeness, as shown in Table 14, the operation efficiency of implementing the shared bus lane strategy is superior to the scenario without the sharing strategy. Moreover, different ridesharing vehicle capacities have varying impacts on travelers' travel decisions and the operation efficiency of the bus lanes. In this case, the operation efficiency of bus lanes is optimal when the ridesharing vehicle capacity is 5, while it is the worst when the capacity is 3. The analysis reveals that when the ridesharing vehicle capacity is small, the combination cost for ridesharing travel is low, and the difficulty of forming ridesharing groups is minimal. As a result, more travelers opt for ridesharing, leading to congestion in the bus lanes and adversely affecting bus operations, thereby causing an insignificant improvement in overall efficiency. Conversely, when the ridesharing vehicle capacity is large, the combination cost is high, and the difficulty of forming ridesharing groups increases. Consequently, fewer travelers choose ridesharing, which has little impact on the efficiency of bus lane operations. At the same time, it reduces traffic flow in the general lanes, resulting in a more noticeable improvement in overall road operation efficiency.

Table 14. Closeness degrees and rankings of different schemes.

	No Dedicated Bus-Lane-Sharing Policy	Ridesharing Vehicle Capacity 2	Ridesharing Vehicle Capacity 3	Ridesharing Vehicle Capacity 4	Ridesharing Vehicle Capacity 5
Closeness degree	0.3720	0.3745	0.3744	0.3746	0.3749
Ranking	5	3	4	2	1

According to the principle of maximum closeness, as shown in Table 14, the operation efficiency of implementing the shared bus lane strategy is superior to the scenario without the sharing strategy. Moreover, different ride-sharing vehicle capacities have varying impacts on travelers' travel decisions and the operation efficiency of the bus lanes. In this case, the operation efficiency of bus lanes is optimal when the ride-sharing vehicle capacity is 5, while it is the worst when the capacity is 3. The analysis reveals that when the ride-sharing vehicle capacity is small, the combination cost for ride-sharing travel is low, and the difficulty of forming ride-sharing groups is minimal. As a result, more travelers opt for ride-sharing, leading to congestion in the bus lanes and adversely affecting bus operations, thereby causing an insignificant improvement in overall efficiency. Conversely, when the ride-sharing vehicle capacity is large, the combination cost is high, and the difficulty of forming ride-sharing groups increases. Consequently, fewer travelers choose ride-sharing, which has little impact on the efficiency of bus lane operations. At the same time, it reduces traffic flow in the general lanes, resulting in a more noticeable improvement in overall road operation efficiency.

6. Conclusions

This paper aims to explore optimization methods for bus lanes, focusing on improving the utilization efficiency of bus lane resources while ensuring the priority of public transit. The ultimate goal is to maximize the utilization of urban transportation resources and alleviate urban traffic congestion. The following is a summary of the research work, conclusions, and limitations of this study.

This paper conducts a survey on the willingness to participate in ridesharing and analyzes the factors influencing ridesharing decisions. Under the scenario of opening bus lanes to ridesharing private cars, a ridesharing decision-making model based on cumulative prospect theory is established to analyze the impact of the bus-lane-sharing strategy on travelers' ridesharing decisions and the structure of traffic flow. In addition, a comprehensive evaluation model based on the TOPSIS method with combined weighting is established to assess the operational efficiency of bus lanes according to the degree of closeness. This model incorporates a combination of subjective and objective weights, improving the sensitivity and subjectivity of the TOPSIS method's weighting process. The research results show that the closeness degree without the bus-lane-sharing strategy is 0.3720, while the minimum closeness degree under the implementation of the shared bus lane policy is 0.3744, and the maximum closeness degree is 0.3749. Therefore, the overall road operational efficiency is better when the shared bus lane policy is implemented compared to the scenario without the sharing policy. When the number of ridesharing vehicles is relatively small and their capacity is large, the impact on the operational efficiency of bus lanes is minimal, and the overall road operational efficiency is improved.

During the questionnaire survey conducted in this study, the ridesharing willingness survey was somewhat limited due to the influence of online dissemination and the surveyed groups, resulting in incomplete coverage. In the analysis of ridesharing decisions for bus lanes, the scenario was set as a unidirectional closed road section. However, actual traffic operates in a network structure, necessitating further expansion of the scenario analysis to better reflect real-world conditions. Future research will focus on improving the ridesharing decision-making model for bus lanes, enhancing and innovating the algorithms to further improve the model's accuracy and applicability in practical contexts.

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Data Availability Statement: The survey data used to support the findings of this study are available from the corresponding author upon request.

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