Optimizing Urban Rail Transit Policies via Passenger Flow Impact Modeling

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Abstract

China's current rail transit planning and management policies are mainly based on specific city macro indicators to control the construction and development of rail transit, but in recent years, some cities have serious problems of rail transit passenger flow shortage.In order to explore the influence pattern and evolution of macro indicators on passenger flow, this study selects 2019 and 2023 as the comparison time period, and adopts the ridge regression model to construct the urban rail transit passenger flow impact model for the cities that have already operated rail transit.The results show that: the existing policies of Gross Domestic Product and general budget revenue from local finances have a continuous and significant impact on the total volume and intensity of urban rail transit passenger flow, and the influence of the urban resident population size index on the passenger flow characteristics is gradually decreasing; outside of the policy, the share of urban tertiary output and the density of resident population in urban area will have a significant impact on the characteristics of the passenger flow, and the trend of the impact is gradually increasing; the passenger flow of the Type I large city intensity has a strong correlation with tourist reception. As a result, this study proposes optimization suggestions for urban rail transit planning, construction and management policies to promote the healthy operation and development of urban rail transit.

Keywords: *urban rail transit; rail transit policy; urban macro-indicators; passenger flow impact models; ridge regression models*

1. Introduction

Against the background of the current rapid urbanization process, the urban rail transit system, as an important infrastructure for easing urban traffic congestion and promoting regional economic development, continues to expand its construction scale and speed.In order to ensure the scientific planning and healthy development of rail transit projects, a set of urban rail transit access indicator system has been established under China's administrative framework, which aims to provide a clear basis for the declaration and approval of urban rail transit projects by unifying certain objective indicators. Over the years, these access policy indicators have played a basic and effective regulatory role in guiding the orderly construction of urban rail transit and avoiding disorderly expansion, reflecting the forward-looking and practical nature of policy formulation.However, with the profound changes in the economic structure of cities and the acceleration of population mobility, although the control indicators in the existing access policy have been optimized and adjusted many times, especially in recent years when targeted improvements have been made in response to the new dynamics of urban development, they are still insufficient to ensure that the passenger flow volume and the intensity of passenger flow after the operation of the metro reach the expected goals. Specifically, the limitations of the existing indicator system in predicting and evaluating the development potential of passenger flow of the rail transit are becoming more and more obvious, and it is of limited help in guaranteeing the actual passenger flow after the rail transit is put into operation.Therefore, it is not only of theoretical value but also of urgent practical significance to analyze the effectiveness of the existing access policy indicators and to explore and identify macro indicators that can more effectively reflect the characteristics of urban rail transit passenger flow, in order to optimize the access policy of urban rail transit and to promote the sustainable development of the rail transit system. In this context, this study is devoted to constructing a policy optimization framework based on the annual passenger flow impact model, with a view to providing a scientific basis and strategic support for the healthy development of urban rail transit.

In recent years, with the massive construction of urban rail transit, the research on the characteristics of urban rail transit passenger flow and its influencing factors from different perspectives has gradually increased, however, a large number of studies are mainly limited to the level of passenger flow at stations in terms of object selection, aiming to provide suggestions for the planning of rail transit line network.For example, Jin Yu[1] used the passenger flow data of Shanghai rail transit stations to quantitatively analyze the significant factors affecting the time-varying pattern of passenger flow from the aspects of land use and transportation by using the cluster analysis algorithm and the establishment of multinomial logit regression model; Li Qingjia[2] and others quantitatively analyzed the impact of built environment factors within the attraction range of passenger flow on the characteristics of different types of stations through the establishment of an unordered multiclassified logistic regression model. Guo Ruili[3] and others used spatial measurement model to delineate the multilevel influence zone of rail stations based on multimodal connection, and explored the multilevel effect of the influence factors of passenger flow in Wuhan's rail stations in terms of built environment, external connectivity and multimodal transportation.Few studies have been conducted to assess the overall development potential of cities in the pre-planning and construction phase.Although Bian Zhaoyang[4] established an evaluation index system for rail transit development potential through factor analysis, giving three public factors, namely, the level of comprehensive development of the city, the per capita economic level, and the population distribution of the urban area, which to a certain extent can provide guidance for the planning and construction of rail transit in the future in China, Ouyang Zhijian and others[5] took the development of rail transit in Guangzhou as an example, and from the land use along the route, the level of the city's economy, and elaborated on the factors affecting the scale of passenger flow from six aspects, such as land use along the route, the level of urban economy, and the potential growth prospects of the central area of the city, etc. Li Ming[6], Yang Peimin **Chyba! Nenalezen zdroj odkazů.**, etc. s ummarized the development of China's urban rail transit planning, construction, and management policy and put forward the views of the

adjustments, but most of the existing studies have reached a relatively ambiguous conclusion, and there is still no study that explicitly provides constructive advice for the selection of the indicators of the access policy of the rail transit.Therefore, it is necessary to clarify the urban macro-indicators that may have an impact on the overall passenger flow characteristics of rail transit based on the existing rail transit declaration policy, and to improve the accuracy and operability of the assessment model by limiting the specific conditions of each type of indicator to ensure that it can provide practical advice for the policy.Although the related analysis of passenger flow influencing factors of rail transit based on various models and evaluation analysis has been relatively mature, providing available algorithms for more accurate identification of passenger flow influencing factors and passenger flow prediction using data on urban land use, population, economy, and transportation.For instance, Gan Zuoxian et al.[8] developed models for analyzing passenger flow at urban rail transit stations based on Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), and semi-parametric GWR. Foreign scholars have established interaction models between passenger flow at stations and the built environment surrounding the stations using the Direct Demand Model (DRM)[9]. Alternatively, a multi-scale geographically weighted regression model can be employed to explore the facilitative mechanism of the built environment on the public transportation system[10]. However, despite their varying advantages in passenger flow prediction, the existing passenger flow impact models all fail to circumvent issues with model accuracy arising from strong autocorrelation among independent variables. Additionally, while passenger flow impact models for a single time period can to some extent highlight significant influencing indicators, they are unable to accurately predict the trend of influence of these indicators.

To address the limitations of existing research, this study proposes a passenger flow impact model based on the Ridge Regression Optimization algorithm, incorporating features of urban macro-indicators. The aim is to circumvent the issue of multicollinearity among independent variables and ensure that all relevant indicators in existing policies can be evaluated and analyzed. By selecting 2019 and 2023 as comparison periods and targeting cities with operational rail transit systems, this study first conducts Spearman's and Pearson's correlation analyses to screen out significantly related indicators. Subsequently, a Ridge Regression model is employed to construct a passenger flow impact model for urban rail transit. This model not only accurately identifies significant impact indicators but also visually analyzes the influence mechanism of urban macro-indicators on the total passenger flow and passenger flow intensity of rail transit from a dynamic evolution perspective. Furthermore, it predicts the trends of action for each indicator and offers optimization suggestions for subsequent planning, construction, and management policies related to urban rail transit.

2. Sample Selection and Index Construction

2.1 Sample Selection

In light of the specific context of China's current economic and social development, research on the application conditions for urban rail transit construction needs to fully integrate the current state of urban development and the dynamic evolution of transportation demand over time. Considering the significant interference of the COVID-19 pandemic on urban rail transit passenger flow data between 2020 and 2022, which rendered the data from this period unrepresentative, this study prudently selects the years 2019 and 2023 as representative years for comparative analysis. Taking Chinese cities with operational urban rail transit projects as case studies, the aim is to deeply analyze the various factors in the urban macro-indicator system that affect rail transit passenger flow and their characteristics of impact; at the same time, this study strives to summarize the changes in the role and differences in effectiveness of various influencing indicators over time, in hopes of providing a scientific basis for promoting the sustainable development of urban rail transit.

2.2 Indicator Construction

Since passenger flow is an important indicator of the effectiveness of rail transit in the transportation system, and passenger flow intensity directly affects the operation and financial status of rail transit. These two indicators can intuitively judge the healthy development level of urban rail transit and can also serve as an important basis for analyzing the effectiveness of policies. Therefore, the total passenger flow and passenger flow intensity of the city for the year are selected as the dependent variables.

Comparing the urban rail transit construction management and approval-related policy documents issued by the country in the past, it can be seen that the current documents mainly make clear stipulations on the local fiscal revenue, population size, and GDP, and other macroeconomic indicators of cities applying for rail transit construction. The commonalities and differences in the conditions for applying for urban rail transit as stipulated by the three documents are shown in Table 1. The aforementioned urban rail transit construction management and approval policies issued successively by the country generally show a trend of continuously raising the approval threshold.

Tab. 1. Comparison of Differences in Urban Rail Transit Application Conditions

Document Name	Year	Population Scale/ ten thousand people	Local General Budget Revenue/ hundred million yuan	GDP/ hundred million yuan	Passenger Flow Indicators	Note
Document No. 81	2003	300（Urban Population）	100	1000	Unidirectional peak hour section passenger flow of more than 30,000 person-times	-
Document No. 49	2015	300（Urban Population）	100	1000	Unidirectional peak hour section passenger flow of more than 30,000 person-times, with a recent passenger flow intensity not lower than 0.7person-times/(day·km)	New: The government's capital contribution shall not be less than 40%, and the proportion of government funds in the current year's budget shall not exceed 5%.
Document No. 52	2018	300（Registered Permanent Population）	300	3000	Unidirectional peak hour section passenger flow of more than 30,000 person-times, with a recent passenger flow intensity not lower than 0.7person-times/(day·km)	Specify a planning period of 5-6 years, requiring that 70% of the investment from the previous round of planning be completed.

Despite this, some cities still experience poor passenger flow indicators. Therefore, this paper focuses on six urban macro-development characteristics, including urban land development, urban population, economic development, urban transportation development, and urban influence. It combines the indicators of urban rail transit application conditions in existing rail transit access policies to establish a set of 12 influencing indicators, including local general budget revenue, Gross Domestic Product, urban population size, urban built-up area, urban population density, per capita disposable income of urban residents, the proportion of the tertiary industry output in the urban area, whether there are restrictions on car purchase and restrictions on driving, urban car ownership, rail transit ticket prices, and urban administrative level (Table 2). The aim is to explore the significance and characteristics of their impact on the two dependent variables, total passenger flow and passenger flow intensity.

Tab. 2. Impact Indicator System

Latent Variable	Visible variable	Notation
Site	Urban built-up area	YD1
Demographic	Size of urban resident population	RK1
	Density of resident population in urban area	RK2
Economics	Gross Domestic Product	JJ1
	Disposable income per urban resident	JJ2
	General budget revenue from local finances	JJ3
	Share of urban tertiary output	JJ4
Policy	policy of limiting the purchase of small cars	ZC1
	Policy on limiting the use of small cars	ZC2
Transportation	vehicle ownership	JT1
	Railway fares	JT2
City Influence	Municipal administrative level	YX1

3. Data Sources and Research Methods

3.1 Data Sources

The data for annual passenger flow and passenger flow intensity in the dependent variables are mainly based on the urban rail transit statistical and analytical reports for 2019 and 2023 published on the official website of the China Urban Rail Transit Association. The data and specific situations for the 12 urban macro-development indicators in the independent variables are sourced from the statistical yearbooks on the official websites of various city statistical bureaus, official websites of transportation or traffic management departments of various cities, the Traffic Management Bureau of the Ministry of Public Security, and the official websites of various city governments, as detailed in Table 3.

Tab. 3. Data Sources

Name of data	Source of data
Total Urban Rail Transit Passenger Traffic Data, 2019, 2023	China Urban Railway Transportation Association Official Website
Total Urban Rail Transit Passenger Traffic Data, 2019, 2023	China Urban Railway Transportation Association Official Website
Total Urban Rail Transit Passenger Traffic Data, 2019, 2023	China Urban Railway Transportation Association Official Website
Data on the built-up area of the city, the size of the resident population in the city, and the density of the resident population in the city	Official website of each city's statistical office
Gross Domestic Product data, disposable income per capita of urban residents, general budget revenue of local finances, and the ratio of urban third-sector production value data	Official website of each city's statistical office
Data on small car purchase and driving restriction policies	Official website of each city's transportation or traffic management department
Vehicle ownership data	Traffic Management Bureau of the Ministry of Public Security
Data on rail transit fares by city and city administrative level	Official website of the people's government of each city

Variables in the urban macro-development indicators are classified into continuous variables and categorical variables, with different correlation processing methods adopted for different types of variables. Pearson correlation analysis is used for the dependent variable with continuous variables, while Spearman correlation analysis is used for the dependent variable with categorical variables.

Continuous variables include built-up area, urban permanent resident population size, urban permanent resident population density, Gross Domestic Product, per capita disposable income of urban residents, local general budget revenue, the proportion of urban tertiary industry output, car ownership, and rail transit ticket prices. The calculation method for rail transit ticket prices is: selecting the number of kilometers that can be traveled with ticket prices from 2 to 10 yuan, to derive the average ticket price per kilometer; other data do not require complex preprocessing for analysis.

Categorical variables include policies on the restriction of car purchases, policies on the restriction of car usage, urban administrative levels, and the levels of the highest administrative officials in cities. For policies on the restriction of car purchases, they are categorized into two types, with an assignment method where 2 represents the existence of purchase restriction policies and 1 represents the absence of such policies. Similarly, for policies on the restriction of car usage, the assignment method uses 2 to represent the existence of usage restriction policies and 1 to represent the absence of such policies. Likewise, for urban administrative levels, an assignment method is used to categorize them into three types: 3 represents municipalities directly under the central government, 2 represents sub-provincial cities and provincial capitals, and 1 represents general prefecture-level cities, districts of municipalities directly under the central government, and national new districts, for analysis.

Firstly, multiple collinearity analysis is conducted on each indicator; secondly, based on the characteristics of the variables, the influencing indicators are classified and subjected to Spearman and Pearson correlation analyses with the health operation indicators of urban rail transit; finally, ridge regression (multivariate linear regression) analysis is performed to specifically determine which influencing indicators significantly affect the healthy development of urban rail transit and to analyze the dynamic trends of the degree of influence.

3.2 Research Methods

Multiple Linear Regression Model To quantify the impact of various urban macro-indicators on the characteristics of rail transit passenger flow, a multiple linear regression model is used for analysis. The conventional multiple linear regression model is:

$$y = x\beta + \varepsilon \tag{1}$$

In the formula: X is the matrix of independent variables, Y is the dependent variable; β is the vector of regression coefficients; ε is the error term. Typically, the least squares method is used for parameter estimation in this formula. The solution for the regression coefficients β is usually done using the matrix method, that is:

$$\hat{\beta} = (x'x)^{-1}x'y \tag{2}$$

However, when there is a strong autocorrelation among the independent variables, that is, when the correlation coefficients of the independent variables are close to 1 and X'X is approximately 0, using equation (2) to solve for model parameters will lead to unsolvable or overestimated variance problems, which means that the variance inflation factor (VIF) in the multicollinearity test for the independent variables is greater than 10, indicating the presence of multicollinearity. At this point, the conventional multiple linear regression model cannot reasonably derive the model algorithm. Therefore, to address the issue of multicollinearity among the independent variables, ridge regression optimization algorithm is introduced for modeling.

Ridge regression, also known as Tikhonov regularization, is essentially a biased estimation regression method used for analyzing data with multicollinearity. It abandons the unbiasedness of the ordinary least squares method by adding an L2 norm regularization term to the loss function. That is, a positive constant matrix kI is added to X'X in equation (2), stabilizing the problem and making it solvable.

$$\hat{\beta}\ (k) = (x'x + kI)^{-1}x'y \tag{3}$$

In the formula, k is the ridge parameter, k≥0; the the numerical value of K is usually selected in conjunction with the ridge trace plot, where I represents the identity matrix.When k=0,$\hat{\boldsymbol{\beta}}(k)=\hat{\boldsymbol{\beta}}$, representing that ridge estimation transitions to ordinary least squares method.As the value of k increases, the goodness of fit of the ridge regression equation will decrease.Therefore, when selecting the the numerical value of K, it should not be too large. In research, one should try to choose the smallest the numerical value of K at which the standardized regression coefficients tend to stabilize, in order to increase the model's precision.

4. Impact Indicator Analysis

4.1 Multicollinearity Test

In multiple regression analysis, high correlations among independent variables can lead to multicollinearity issues, affecting the predictive accuracy and the precision of significance tests of the model. The urban macro-indicators selected in this study inevitably exhibit high correlations, hence a multicollinearity test was first conducted, using the Variance Inflation Factor (VIF) as the measure. A VIF value less than 10 indicates that the test is passed.The test results show that there is a certain degree of collinearity in the urban built-up area, Gross Domestic Product, and local general budget revenue (VIF > 5)（Table 4）. Given that all indicators are based on policy documents and are significant, this paper introduces a ridge regression model to reduce the impact of multicollinearity, ensuring the stability and predictive power of the model.

Tab. 1. Results of Multicollinearity Test for Independent Variables

Year		YD1	RK1	RK2	JJ1	JJ2	JJ3	JJ4	JT1	JT2
2019	VIF	15.040	3.100	1.239	7.602	2.945	8.245	1.899	3.891	1.246
2023	VIF	7.847	4.691	2.342	12.584	3.142	6.842	1.663	2.152	1.391

4.2 Correlation Analysis

Correlation analysis was used to study the relationship between the total passenger flow and passenger flow intensity and the 13 influencing indicators in 2019 and 2023. The Spearman correlation coefficient (rs) and Pearson correlation coefficient (rs) can indicate the strength of the correlation. A significance level P < 0.05 in both types of correlation analyses represents a significant relationship between the independent and dependent variables, as seen in Table 5. The specific analysis shows that in both 2019 and 2023, the urban built-up area, urban permanent resident population size, Gross Domestic Product, per capita disposable income of urban residents, local general budget revenue, the proportion of urban tertiary industry output, and car ownership have significant correlations with the total passenger flow (P < 0.05). Except for the negative correlation between car ownership and total passenger flow, all other influencing indicators have a positive correlation with the total passenger flow (correlation coefficient values rs > 0). Whether the city has policies restricting car purchases and usage, the price of urban rail transit, and the administrative level of the city show no significant correlation with the total passenger flow (P > 0.05). Therefore, the above indicators are excluded from the subsequent regression model.

Tab. 5. Correlation Analysis of Total Passenger Flow and Impact Indicators

Year	Ratio	YD1	RK1	RK2	JJ1	JJ2	JJ3	JJ4	ZC1	ZC2	JT1	JT2	YX1
2019	rs	.922**	.840**	0.469	.886**	.576*	.946**	.752**	-0.164	.386	-.468*	-0.355	.506*
	P	0.000	0.000	0.124	0.000	0.016	0.000	0.000	0.489	0.197	0.024	0.096	0.014
2023	rs	.888**	.895**	.471**	.935**	.912**	.930**	.563**	-0.194	.366	-.572**	-0.315	0.414
	P	0.000	0.000	0.065	0.000	0.000	0.000	0.000	0.367	0.071	0.007	0.165	0.062

In the years 2019 and 2023, the correlation between urban built-up area, urban permanent resident population size, urban permanent

resident population density, Gross Domestic Product, local general budget revenue, the proportion of urban tertiary industry output, and car ownership with passenger flow intensity was significant (P <0.05), as seen in Table 6. Except for the negative correlation between car ownership and passenger flow intensity, the other significantly correlated indicators with passenger flow intensity all had a positive correlation (correlation coefficient values rs>0). Per capita disposable income of urban residents, car purchase restriction policy, car usage restriction policy, urban rail transit ticket prices, and urban administrative level showed no significant correlation with passenger flow intensity (P >0.05), hence the decision to exclude these indicators from the subsequent regression model.

Tab. 6. Correlation Analysis of Passenger Flow Intensity and Influencing Indicators

Year	Ratio	YD1	RK1	RK2	JJ1	JJ2	JJ3	JJ4	ZC1	ZC2	JT1	JT2	YX1
2019	rs	.753**	.873**	.842**	.542*	0.468	.581*	.726**	-0.347	0.365	-.560*	-0.358	0.258
	P	0.008	0.000	0.000	0.030	0.058	0.018	0.001	0.114	0.164	0.019	0.158	0.317
2023	rs	.772**	.740**	.714**	.622**	0.300	.626**	.524**	-0.247	.218	-.568**	-0.364	0.359
	P	0.000	0.000	0.000	0.000	0.174	0.000	0.001	0.216	0.312	0.005	0.088	0.092

After conducting the correlation analysis, this study found that there is a significant correlation between the total passenger flow and seven indicators: urban built-up area, urban permanent resident population size, local general budget revenue, Gross Domestic Product, the proportion of urban tertiary industry output, per capita disposable income of urban residents, and car ownership. Similarly, there is a significant correlation between passenger flow intensity and seven indicators: urban built-up area, urban permanent resident population size, urban permanent resident population density, local general budget revenue, Gross Domestic Product, the proportion of urban tertiary industry output, and car ownership. By comparing the the numerical value of P and Rs, it can be observed that the significance of these influencing factors varies between 2019 and 2023. To further explore the specific impact and trends of these influencing factors on total passenger flow and passenger flow intensity, this study introduces a ridge regression model for further analysis after screening the aforementioned influencing indicators.

4.3 Ridge Regression Analysis

4.3.1 Selection of the numerical value of K

Using the influencing indicators selected after the correlation analysis as independent variables, and taking the total passenger flow and passenger flow intensity of urban rail transit in various cities for the years 2019 and 2023 as dependent variables, ridge regression analysis models were constructed. The resulting ridge trace plots are shown in Fig. 1. In the ridge trace plot for total passenger flow, when K is 0.10, the standardized regression coefficients of the independent variables tend to stabilize, indicating this as the optimal the numerical value of K for 2019. Similarly, the optimal the numerical value of K for 2023 is also found to be 0.10. Likewise, in the ridge trace plot for passenger flow intensity, the optimal the numerical value of Ks for both 2019 and 2023 can also be taken as 0.10 (Fig. 2).

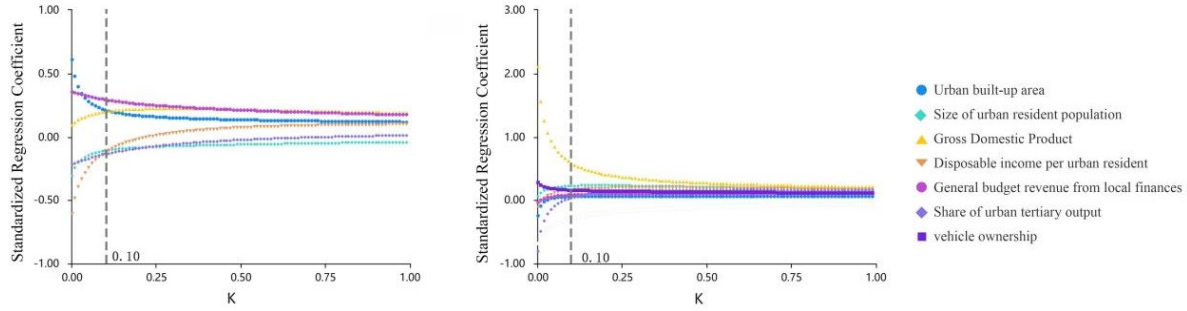

Fig. 1. 2019 & 2023 Ridge trace plot for total passenger flow

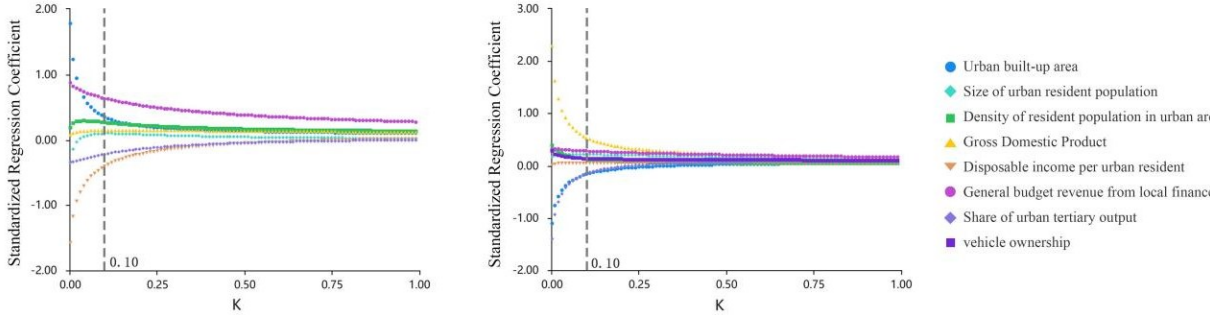

Fig. 2. 2019 & 2023 Ridge trace plot for passenger flow intensity

4.3.2 Results Analysis

Regression analysis on the influencing indicators of urban rail transit passenger flow volume shows that: the R2 for the 2019 model is 0.943, indicating that the indicators can explain 94.30% of the variation in total passenger flow; the R2 for the 2023 model is 0.911, indicating that the indicators can explain 91.10% of the variation in total passenger flow. This suggests that the impact model for total passenger flow has a good fit and the results are persuasive. The regression results show that among the influencing indicators, the urban

permanent resident population size, Gross Domestic Product, local general budget revenue, and the proportion of urban tertiary industry output have a significant positive impact on the total passenger flow of urban rail transit, with $P < 0.05$. Comparing the the numerical value of Ps between the two years reveals that the significance of the impact of Gross Domestic Product, local general budget revenue, and the proportion of urban tertiary industry output on the total passenger flow of urban rail transit shows a clear increasing trend; the significance of the impact of urban permanent resident population size on the total passenger flow of urban rail transit shows a clear decreasing trend（Tab. 7).

Tab. 7. Results of Ridge Regression Analysis between Influencing Indicators and Total Passenger Flow

Year	Ratio	YD1	RK1	JJ1	JJ2	JJ3	JJ4	JT1
2019	P	0.184	0.026*	0.035**	0.136	0.009**	0.015*	0.075
	R2				0.943			
	F				F (7,10)=11.619,p =0.002			
2023	P	0.272	0.049*	0.002**	0.067	0.008**	0.017**	0.082
	R2				0.911			
	F				F (7,10)=5.093,p =0.030			

Regression analysis on the influencing indicators of urban rail transit passenger flow intensity reveals that: the R2 for the 2019 model is 0.732, indicating that the indicators can explain 73.20% of the variation in total passenger flow; the R2 for the 2023 model is 0.928, indicating that the indicators can explain 92.80% of the variation in total passenger flow. This suggests that the impact model for passenger flow intensity has a good fit and the results are persuasive. The regression results show that among the influencing indicators, the urban permanent resident population size, urban permanent resident population density, Gross Domestic Product, local general budget revenue, and the proportion of urban tertiary industry output, five indicators significantly positively affect urban rail transit passenger flow intensity, with $P < 0.05$. Comparing the the numerical value of Ps between the two years, it is evident that the significance of the impact of urban permanent resident population density, Gross Domestic Product, local general budget revenue, and the proportion of urban tertiary industry output on urban rail transit passenger flow intensity shows a clear increasing trend; the impact of urban permanent resident population size on urban rail transit passenger flow intensity changes from significant to non-significant, with $P > 0.05$（Tab. 8).

Tab. 8. Results of Ridge Regression Analysis on Influencing Indicators and Per Capita Passenger Flow Intensity

Year	Ratio	YD1	RK1	RK2	JJ1	JJ2	JJ3	JJ4	JT1
2019	P	0.212	0.017*	0.034*	0.027*	0.574	0.045*	0.042*	0.735
	R2				0.732				
	F				F (7,10)=5.071,p =0.008				
2023	P	0.341	0.129	0.009**	0.001**	0.849	0.024*	0.002**	0.133
	R2				0.928				
	F				F (7,10)=16.032,p =0.000				

The above results indicate that the two indicators specified in the current urban rail transit planning and management policies, Gross Domestic Product and local general budget revenue, have a significant impact on both the total passenger flow and passenger flow intensity of urban rail transit, and the degree of influence is increasing, which is expected to continue to play a role in the future. However, the impact of urban permanent resident population size on the total passenger flow of urban rail transit shows a clear downward trend, and its impact on passenger flow intensity becomes gradually insignificant, suggesting that it will play a smaller role in the future. In addition to these, the proportion of urban tertiary industry output, which is not mentioned in the existing policies, has a significant impact on both the total passenger flow and passenger flow intensity of urban rail transit. The urban permanent resident population density has a significant impact on the passenger flow intensity of urban rail transit, and the degree of influence of these two indicators is showing an increasing trend, and it is preliminarily predicted that they will continue to play a role in the future.

Given the decreased importance of the permanent resident population indicator, this study categorizes the sample cities of 2023 into three categories: megacities, super-large cities, and Type I large cities, based on urban population scale. Through quantitative analysis, this study explores the correlation between passenger flow intensity and Gross Domestic Product, general public budget revenue, the proportion of urban tertiary industry output, and urban permanent resident population density in these three types of cities, as shown in Tab 9.

Tab. 9. Correlation Analysis between Three Types of Cities and Influencing Indicators

Urban Type	Ratio	RK2	JJ1	JJ3	JJ4	Tourist Reception Volume
Mega-city	rs	.916**	.906**	.894**	.358*	-
	P	0.000	0.000	0.000	0.023	-
Metropolis	rs	.582**	.963**	.602**	.326*	-
	P	0.004	0.000	0.003	0.038	-
Type I Large City	rs	0.385*	0.413*	0.319*	.829**	.741**
	P	0.035	0.027	0.042	0.000	0.000

The study comparing these three city sizes found that the passenger flow intensity in megacities and super-large cities shows a strongly significant positive correlation with Gross Domestic Product, general public budget revenue, and urban permanent resident population density ($P < 0.1$, $rs > 0.5$), while the passenger flow intensity in Type I large cities is more strongly influenced by the proportion of urban tertiary industry output ($P < 0.1$, $rs > 0.5$). This indicates that in these cities, increases in population density, economic activity, and fiscal revenue are often accompanied by higher transportation demand. When comparing the passenger flow intensity characteristics of Type I large cities with those of megacities and super-large cities, it was found that although the urban permanent resident population size of Type I large cities is relatively smaller, their passenger flow intensity is unusually significant. Considering that urban rail transit passenger flow

mainly consists of urban permanent residents and tourists, a further analysis was conducted on the correlation between the passenger flow intensity of Type I large cities and the annual tourist reception volume, and the results showed a strong positive correlation ($P < 0.1$, $rs > 0.5$), indicating that for Type I large cities, the annual tourist reception volume is also an important urban macro-development indicator that will significantly impact the urban rail transit passenger flow intensity.

5. Policy Recommendations

In the formulation and optimization of urban rail transit planning and management policies, the following measures are recommended to enhance the scientific basis and practical effectiveness of the policies.

Given the significant impact of the tertiary industry's proportion on both total passenger flow and passenger flow intensity, it is suggested that this indicator be considered as one of the key indicators in urban rail transit planning and management policies. This indicator reflects the modernization level of the urban economic structure and has significant predictive value for passenger flow dynamics. Urban population density is a critical factor affecting the intensity of rail transit passenger flow. It is recommended to include urban permanent resident population density in policy indicators to more accurately assess and plan the carrying capacity of urban transportation facilities. Considering the decreasing trend of the impact of urban permanent resident population size on passenger flow, it is suggested that relevant departments enhance their focus on this indicator and re-evaluate and optimize it within the policy. For Type I large cities, it is recommended to specifically consider the indicator of tourist reception volume in the policy. Given the significant impact of the tourism industry on urban traffic flow, including tourist reception volume in policy indicators can help better manage the traffic pressure during peak tourism seasons in such cities. Finally, it is recommended to establish a dynamic monitoring mechanism to regularly assess the effectiveness of policy implementation and adjust policy indicators based on the evaluation results to better adapt to changes in urban development and transportation demand.

6. Conclusion

Future urban rail transit planning and management policies should place greater emphasis on the impact of economic structure indicators, industrial structure indicators, and population density on transportation demand. As the influence of urban permanent resident population size on passenger flow characteristics diminishes, policy formulation needs to adapt to population dynamics and optimize the indicator system. At the same time, considering the significant impact of the tourism industry on the traffic flow of certain cities, it is recommended that policies pay special attention to the tourist reception volume of Type I large cities. By optimizing the relevant indicators in the policy, the long-term stable operation and sustainable development of the urban rail transit system can be promoted.

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