Research Article

Evaluation of Public Welfare Level of Urban Rail Transit considering Operation Management

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Evaluating the public welfare level of the urban rail transit systems has not only great significance for the government to provide fair and reasonable subsidies but for the better operation and management of urban rail transit enterprises. An evaluation index system composed of 3 criterion-level indicators and 12 subindexes has been established in this paper. The 3 criterion-level indicators conclude service level, social benefit, and policy loss which are all affected by operation management. Besides, the subjective and objective comprehensive weighting method combined with the analytic hierarchy process method and the entropy weight method is proposed to calculate the index-level weights. Furtherly, the grey correlation-TOPSIS comprehensive evaluation method was designed to calculate the comprehensive evaluation value of the public welfare level of each city. To verify the effectiveness of the proposed method, urban rail transit systems in 16 Chinese cities are studied as a case study. The results show that (1) the three indicators of passenger travel cost (25.69%), the increase in housing prices around urban rail transit (10.74%), and operating cost ratio (9.95%) are more likely to affect the evaluation of public welfare level of urban rail transit. (2) the level of public welfare in different cities is not balanced. The cities with a relatively high level of public welfare relative closeness exceeding 0.5 include Shanghai, Beijing, Shenzhen, Guangzhou, Suzhou, Wuhan, Nanjing, Wuxi, and Dalian. (3) Both GDP and urban population are positively correlated with the relative closeness of social benefit and service level. (4) The level of public welfare can be improved by reducing the fare price and improving the service level, such as increasing the network density, reducing the departure interval, and increasing the average speed.

1. Introduction

Urban rail transit companies often suffer from financial losses due to large operating costs and government regulations on service level and fare. Although urban rail transit has great social benefits, enterprises have not received corresponding benefits. The government has to subsidize the policy losses of operating companies. Recently, the deficit of China’s urban rail transit enterprises is becoming more and more serious, and it accounts for a large proportion of government fiscal expenditures, which has become a considerable financial burden to the local government. Therefore, evaluating the public welfare level of urban rail transit and distinguishing public welfare and profitability has great significance for urban rail transit operation management and subsidy optimization.

Some scholars have studied the definition of public welfare. Qin [1] introduced the term “public welfare” from Japan at the end of the nineteenth century. Mike [2] proposed that public welfare is synonymous with general welfare, or refers to a broader professional social obligation that exceeds the interests of customers. Greve [3] recommended that public welfare refers to “welfare determined by the public sector and mainly funded by the public sector. Public welfare can pass the tax system or support voluntary sectors, enterprises and families”. Zi [4] studied that “public welfare” is closer to philanthropy (caring for human well-being). Wu [5] found that the connotation of “public welfare” includes “nonprofit” and “to promote public welfare.”
As far as we know, in this recent decade, there were very few studies focused on the public welfare of urban rail transit, although some scholars have done some research about the welfare of public transit. The welfare of public transit is mainly studied from the perspective of the contribution of public transport services to social welfare and the profit and loss of public transit enterprises. From the perspective of increasing social welfare, Masatoshi [6] proposed that the conventional rules of public facilities and services should aim to increases the economic welfare of the society by realizing the effective distribution of resources and the fair distribution of income. Taylor et al. [7] proposed that the public policy goal of public transit is to solve the often difficult problems such as traffic congestion, car dependence, and suburban expansion while promoting community economic development, employment opportunities, the revitalization of poor communities, urban aesthetics, livability, and mobility of people who are unable or unwilling to drive. Stjernborg et al. [8] recommended that one of the most important welfare effects of a well-functioning public transit system is to establish a fair and open barrier-free environment. Wachs and Taylor [9] studied that public transit can help move welfare recipients out of home and engage in wage jobs. Holmgren [10] analyzed that expanding the demand for public transit requires lower fares from the perspective of maximizing social welfare. From the perspective of public welfare leading to corporate losses, Guerra [11] estimated the passenger welfare and operating deficit of the public transit system and found that from the perspective of economic cost-effectiveness, urban rail transit systems may not be optimal, but they obviously create value for consumers and society. Arcier [12] believes that the financial loss of public transit companies is driven by public policy goals (the entry of vulnerable people into cities, reducing car use and carbon dioxide emissions), rather than demand.

Based on the abovementioned literature, the current research on the public welfare of urban rail transit is mainly through qualitative research, and there are very few researches integrated quantitative methods in the welfare estimation of urban rail transit. The major contributions of this paper can be summarized as follows: (1) firstly, we select 3 criterion-level indicators and 12 index-level indicators through the analysis of the factors that influence the public welfare of urban rail transit. (2) The subjective and objective combination method of the Analytic Hierarchy Process (AHP) and entropy weight method was adopted to determine the weight of public welfare indicators. (3) The grey correlation-Technique for Order Preference by Similarity to an Ideal Solution (GCTOPSIS) comprehensive evaluation method was used to comprehensively evaluate the public welfare level of the urban rail transit systems.

The remainder of this paper is organized as follows. In Section 2, firstly, the main characteristics of the public welfare of urban rail transit are presented. Then, we introduce the evaluation method of the public welfare level of the urban rail transit system. The performance and application of our proposed models are evaluated through numerical experiments in Section 3. Finally, conclusions with major findings are provided in Section 4.

2. Evaluation Method of Public Welfare Level of the Urban Rail Transit System

2.1. Main Characteristics of the Public Welfare of Urban Rail Transit. The main characteristics of the public welfare of urban rail transit are “universal service” [13] and “not for profit” [14]. Firstly, urban rail transit provides universal service regardless of region, space, time, and population, and takes the public’s interests as the initial point to provide equal services. Secondly, urban rail transit operators do not aim for profit. Urban rail transit operators need to provide high-quality service levels that meet the needs of passengers in accordance with government regulations, which will bring large costs and losses to urban rail transit companies. What’s more, urban rail transit has positive externalities, which bring large external benefits to the region, such as relieving road traffic congestion, saving energy and reducing emissions, and promoting regional economic development, however, they have not received corresponding returns [15].

2.2. Selection of Public Welfare Level Indicators of the Urban Rail Transit System. This article draws on public welfare level evaluation indicators in some other adjacent fields [16–18], combines the literature of urban rail transit public welfare research and the characteristics of the urban rail transit system, and is based on the principles of scientific, comprehensive, comparable, accessible, absolute and relative number, and finally constructs an urban rail transit public welfare level evaluation index system covering 12 indicators from three aspects: service level, social benefits, and policy loss. The public welfare level evaluation index system of urban rail transit is listed in Table 1.

(1) Service level indicators. The operation and management of urban rail transit enterprises will affect the service level, which in turn affects the benefits of passengers. This indicator reflects the quality of urban rail transit service level. The purpose of the urban rail transit system is to satisfy passengers demand with a service level regulated by the government. Providing operation services is a part of urban rail transit operation management. The service level reflects the degree of effort of urban rail transit companies to serve passengers. The selected indicators are average operating time, maximum load factor during peak time, departure interval, and average speed.

(2) Social benefit indicators. The energy of urban rail transit is electrical energy, so urban rail transit can save energy and reduce emissions. Moreover, the operation of urban rail transit enhances the land value and housing prices along the line [19]. The diversion of urban rail transit also reduces the cost of conventional public transit facilities. The
improvement of the urban rail transit network has strengthened intracity communication and further promoted the economic growth of related industries [20]. The selected indicators include GDP growth rate, energy-saving and emission reduction benefits, the increase in housing prices along urban rail transit lines, and the benefits of replacing conventional public transport facilities.

(3) Policy loss indicators. The government’s regulations on fare caps and service levels reflect the characteristics of urban rail transit “serving people.” To reduce the burden on passengers, it is necessary to consider the affordability of commuter passengers for fares, which cannot be too high despite the high operating costs. In addition, the departure interval, all-day operating time, speed, etc. must meet the service level stipulated by the government to meet the needs of passengers, which leads to huge operating costs. As a result, fares are generally lower than operating costs, causing operating companies to lose money. The level of fare also reflects the level of welfare. Therefore, the ratio of the average per capita ticket expenditure to the city’s per capita GDP is selected as an index for evaluating public welfare. In addition, urban rail transit has implemented preferential policies for vulnerable groups such as the elderly, children, soldiers, and the disabled, which fully shows the welfare nature of urban rail transit. Therefore, the availability of welfare tickets is selected as an index for evaluating the public welfare.

| Criterion layer | Index layer | Index explanation | Index unit | Indicator attributes |
|-----------------|-------------|--------------------|-----------|----------------------|
| Average operating service time (B1) | Length of service hours in a day | h | + |
| Maximum load factor during peak time (B2) | Sum of the number of people staying in high one-way and high section during peak hours divided by sum of the hourly capacity | % | - |
| Service level (A1) | Departure interval (B3) | The time interval between two consecutive transport vehicles passing through a fixed position along the same direction on an operating route | min | - |
| | Average speed (B4) | Line length divided by run time | km/h | + |
| | Network density (B5) | The sum of the lengths of all lines of the urban rail transit network divided by the area covered by the urban rail transit network | km/km² | + |
| | GDP growth rate (B6) | (Annual regional GDP after operation-annual regional GDP when the project is not constructed)/Annual regional GDP when the project is not constructed × 100%, the annual regional GDP data when the project is not under construction use the data of the year before the subway opened | % | + |
| Social benefit (A2) | Energy-saving and emission reduction benefits (B7) | The benefits of energy-saving and emission reduction per passenger volume are regarded as a fixed value, so energy-saving and emission reduction benefits can be represented by network energy-saving and emission reduction benefits. | Ten thousand people | + |
| | The increase in housing prices along urban rail transit lines (B8) | (Annual regional average house price after operation-annual regional average house price when the project is not under construction)/annual regional average house price when the project is not under construction × 100%, the annual regional average housing price data when the project is not under construction is selected from the data of the year before the subway opened | % | + |
| | Replacement of conventional public transport facilities investment benefits (B9) | The investment benefit of replacing conventional public transport facilities is proportional to the benefit of replacing public transit [21] and can be replaced by public transit benefit index | Ten thousand people | + |
| Policy loss (A3) | Passenger travel cost indicators (B10) | Per capita ticket expenditure/per capita GDP=(average fare × 2 + 250)/per capita GDP | % | - |
| | Welfare ticket with or without (B11) | If there is a welfare ticket, take 1; if there is no welfare ticket, take 0 | - | + |
| | Operating cost ratio (B12) | Operating ticket revenue/total operating cost | % | - |
2.3. Evaluation Method of Public Welfare Level of the Urban Rail Transit System. Modern comprehensive evaluation methods include AHP method [22, 23], fuzzy comprehensive evaluation method, TOPSIS evaluation method [24], grey comprehensive evaluation method [25], machine learning method [26, 27] and so on. The basic idea of the entropy weight method is to determine the objective weight according to the variability of the index, which can objectively and truly reflect the index information. AHP method and entropy weight method [28–30] were combined to calculate the index weights. This method balances the subjectivity of expert decision-making and makes the results more scientific and accurate. TOPSIS method analyzes and makes decisions based on the degree to which the data is close to the ideal point and far from the critical point, and makes decisions based on the degree to which the data is close to the ideal point and far from the critical point, and the geometric meaning is intuitive. However, this method mainly considers the static distance between the corresponding standard values of the data, but does not consider the consistency of the dynamic trend of the series. The basic principle of the grey correlation method is to define the trend correlation degree to comprehensively characterize the similarity of the dynamic changes of the system indicators and the closeness of the index value change rate. The closer the dynamic change trend of the decision indicators is, the greater the correlation degree. Aiming at the shortcomings of the TOPSIS method, this paper uses the grey correlation method to improve it, so that the evaluation results are more reasonable, and the combination of static distance and dynamic trend can be realized. The basic steps of the AHP-entropy weight-GC-TOPSIS method model are as follows.

(1) Construct the initial decision matrix \( X = (x_{ij})_{m \times n} \) by formula

\[
X = \begin{bmatrix}
    x_{11} & x_{12} & \cdots & x_{1n} \\
    x_{21} & x_{22} & \cdots & x_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix},
\]

where \( X \) is the initial decision matrix; \( x_{ij} \) is the \( j \)-th index of the \( i \)-th city, \( i = 1, 2, \ldots, m \) and \( j = 1, 2, \ldots, n \); \( m \) and \( n \) are the number of cities and indexes, respectively.

(2) Standardize the initial decision matrix using the range method [31], when the index is positive, the standardized calculation \( R = (r_{ij})_{m \times n} \) can be expressed as formula (2); when the index is negative, the standardized calculation \( R = (r_{ij})_{m \times n} \) can be expressed as formula (3).

\[
r_{ij} = \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}},
\]

\[
r_{ij} = 1 - \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}}.
\]

where \( x_{\max} \) and \( x_{\min} \) are the maximum and minimum values of the \( j \)-th index, respectively.

(4) Use the AHP method [22, 23] to obtain the weight matrix \( H \) of each index by formula.

\[
H = [h_1, h_2, \ldots, h_n],
\]

where \( h_j \) is the weight of the \( j \)-th index; \( H \) is the weight matrix.

(5) Use the entropy method [28–30] to obtain the weight matrix \( W \). Calculate the proportion \( p_{ij} \) of the \( i \)-th item in the \( j \)-th index, the entropy value \( e_j \) of the \( j \)-th item, and the information entropy redundancy \( t_j \). Calculated by formula (5)–(7) [32].

\[
p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}},
\]

\[
e_j = \begin{cases}
    -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln p_{ij}, & p_{ij} \neq 0, \\
    0, & p_{ij} = 0,
\end{cases}
\]

\[
t_j = 1 - e_j.
\]

(6) Calculate the indicator weight \( W_j \) by formula:

\[
W_j = \frac{t_j}{\sum_{j=1}^{n} t_j},
\]

where \( w_j \) is the weight of the \( j \)-th index; \( W \) is the weight matrix.

(8) The comprehensive weight is the weighted average of \( H \) and \( W \) by formula:

\[
G = \alpha H + (1 - \alpha) W \quad (0 \leq \alpha \leq 1),
\]

where \( G \) is the comprehensive weight; \( \alpha \) is a parameter, usually 0.5.

(9) Multiply each row element in the normalized matrix \( R \) by the corresponding weight \( G \) to get the weighted normalization matrix \( V \) by formula.

\[
V = \left(v_{ij}\right)_{m \times n} = \left(g_j r_{ij}\right)_{m \times n},
\]

where \( V \) is the weighted normalization matrix.

(10) Determine the positive ideal solution and the negative ideal solution. The optimal and inferior vectors composed of the maximum and minimum values of each column of the matrix are the positive ideal solution and the negative ideal solution in formula (11) and formula (12).
(11) Calculate the Euclidean distance between each index value and the positive ideal solution and the negative ideal solution by formula (13) and formula (14).

\[
D_i^+ = \left( \sum_{j=1}^{n} (V_{ij}^+ - V_{ij})^2 \right)^{1/2} \quad (i = 1, 2, \ldots, m),
\]

(12) Calculate the grey correlation degree between the \(i\)-th sample and the positive and negative ideal solutions, as shown in formula (15) and formula (16).

\[
\rho_{ij}^+ = \frac{\min \min |v_{ij}^+ - v_{ij}| + \rho \max \max |v_{ij}^+ - v_{ij}|}{|v_{ij}^+ - v_{ij}| + \rho \max \max |v_{ij}^+ - v_{ij}|} \quad (i = 1, 2, \ldots, m),
\]

\[
\rho_{ij}^- = \frac{\min \min |v_{ij}^+ - v_{ij}| + \rho \max \max |v_{ij}^+ - v_{ij}|}{|v_{ij}^+ - v_{ij}| + \rho \max \max |v_{ij}^+ - v_{ij}|} \quad (i = 1, 2, \ldots, m),
\]

(13) The grey correlation degrees between the \(i\)-th sample and the positive and negative ideal solutions are shown in formula (17) and formula (18), respectively.

\[
\rho_i^+ = \frac{1}{n} \sum_{j=1}^{n} \rho_{ij}^+,
\]

\[
\rho_i^- = \frac{1}{n} \sum_{j=1}^{n} \rho_{ij}^-,
\]

where \(\rho_i^+\) and \(\rho_i^-\) are the grey correlation degrees between the \(i\)-th sample and the positive and negative ideal solutions, respectively.

(14) Perform dimensionless processing on the relative closeness degree and grey relational degree, respectively, by formula (19) and formula (20):

\[
d_i^+ = \frac{D_i^+}{\max D_i^+},
\]

\[
d_i^- = \frac{D_i^-}{\max D_i^-},
\]

\[
o_i^+ = \frac{O_i^+}{\max O_i^+},
\]

\[
o_i^- = \frac{O_i^-}{\max O_i^-},
\]

where \(d_i^+\) and \(d_i^-\) represent the result of dimensionless processing of Euclidean distance, and \(o_i^+\) and \(o_i^-\) represent the result of dimensionless processing of grey relational degree.

(15) Combine Euclidean distance and grey relational degree by formula (21) and formula (22):

\[
S_i^+ = \beta o_i^+ + (1 - \beta) d_i^+,
\]

\[
S_i^- = \beta o_i^- + (1 - \beta) d_i^-,
\]

where \(D_i^+\) and \(D_i^-\) are the Euclidean distance of the \(j\)-th index of the \(i\)-th item with concerning the positive ideal solution \(V^+\) and the negative ideal solution \(V^-\).
where $S^+_i$, $S^-_i$ are the distances from the measurement point to the best and worst points, respectively; $\beta$ is the preference coefficient, which reflects the preference degree of decision makers for location and trend, and the value range is $[0, 1]$. 

(16) Calculate the relative closeness to the ideal solution by formula (23):

$$A_i = \frac{S^+_i}{S^+_i + S^-_i}$$

where $A_i$ is the relative closeness degree.

In this study, $A_i$ values calculated from the AHP-entropy weight-GC-TOPSIS model are in the range between 0 and 1; the solution is classified as a higher performance as the values approach closer to 1.

3. Case Analysis

Taking the urban rail transit systems of 16 representative cities in China as an example, this paper uses the above method and MATLAB software to evaluate their levels of public welfare. The data relating to urban rail transit operation adopts the operation data collected from the urban rail transit operating companies of each city in 2016. The urban GDP data was derived from the National Bureau of Statistics website, the population data from the official website of the Ministry of Housing and Urban-Rural Development of the People's Republic of China, and the house price data from the Anjuke website. The original data are shown in Table 2.

3.1. Calculation of the Weight of the Evaluation Index of the Public Welfare Level. The subjective and objective combination method and grey relation-TOPSIS evaluation method established above are used to evaluate the public welfare level of urban rail transit.

The weight of the AHP method comes from the scores of 10 experts in the field. $\alpha$, $\rho$, and $\beta$ all take the value 0.5. According to formulas (1)–(9), the weights of each indicator can be calculated, as listed in Table 3.

As can be seen from Table 3, the AHP method shows that the weights of the criterion layer from large to small are policy loss (62.67%), service level (27.97%), and social benefit (9.36%). The top five weights of the indicator layer are the passenger travel cost indicator (46.56%), operating cost ratio (12.15%), network density (9.67%), departure interval (8.12%), and average speed (5.43%). The subjective weight method indicates that policy loss and service level are more important for public welfare. Since policy loss and service level reflect the benefits of passengers, this shows that the subjective weight method pays more attention to the benefits of passengers for public welfare.

The result of the entropy weight method is that the weight of the criterion layer from large to small is the social benefit (63.17%), service level (21.31%), and policy loss (15.52%). The top five weights of the indicator layer are the increase in housing prices around rail transit (21.07%), the benefit of energy conservation and emission reduction (15.26%), the investment benefit of replacing conventional public transport facilities (15.22%), the GDP growth rate (11.62%), and the network density (8.19%). It can be seen that the results of the entropy weight method show that social benefit index and service level index are more important for evaluating the level of public welfare. This is mainly because the principle of the entropy weight method is based on the degree of dispersion of the indicators, and the degree of dispersion of these indicators in different cities is relatively large, so the weights of these indicators are relatively large.

The result calculated by the comprehensive weight method is that the weight of the criterion layer from large to small is the policy loss (39.09%), the social benefit (36.27%), and the service level (24.64%). The top three weights of the indicator layer are the passenger travel cost index (25.69%), the increase in housing prices around rail transit (10.74%), and operating cost ratio (9.95%). For the service level indicator, the network density (8.93%), departure interval (5.87%), and average speed (4.47%) are the more important indicators; For the policy loss indicator, the passenger travel cost index (25.69%) and operating cost ratio (9.95%) are the more important indicators.

The weighted standardized decision matrix is calculated according to formula (10). To further reflect the public welfare level of different types of cities, cities are classified according to region and scale, and the weighted standardized results of different types of cities are averaged. Figure 1 shows the weight normalization results under different classifications.

Note: the northeast region includes Shenyang, Dalian, and Harbin; the eastern region includes Beijing, Shanghai, Suzhou, Guangzhou, Shenzhen, Nanjing, WuXi, and Dongguan; the western region includes Chongqing, Xi’an, and Nanning; the central region includes Wuhan and Nanchang. Megacities (>10 million people) include Beijing, Shanghai, Chongqing, and Shenzhen; supercities (5–10 million people) include Guangzhou, Nanjing; large cities (1–5 million people) include Shenyang, Xi’an, Suzhou, Harbin, Wuhan, Dalian, WuXi, Nanchang, Dongguan and Nanning.

As shown in Figure 1(a), it can be found from the perspective of regional geographical location as follows. (1) From east to west, the public welfare, service level, social benefits, and policy loss are all gradually decrease. This may be due to from east to west, the economic level and population gradually decrease, and the passenger flow also decreases relatively, so the social benefit and service level are relatively low. (2) The northeast region ranks first in terms of policy-related losses, but its social welfare and service level indicators are smaller than those in the central region, and its social benefit index ranks last.

As shown in Figure 1(b), it can be found from the perspective of city scale as follows. (1) It can be seen that with the increase of city size, the weighted average results of service level indicator and social benefit indicator both increase. The service level results of large cities, supercities, and megacities are 0.423, 0.549, and 0.572, respectively, and the
Table 2: Original data.

| City     | B1   | B2   | B3   | B4   | B5   | B6   | B7   | B8   | B9   | B10  | B11  | B12  | Urban population (10 thousand people) | GDP (billion) |
|----------|------|------|------|------|------|------|------|------|------|------|------|------|---------------------------------------|---------------|
| Beijing  | 18.6 | 112  | 37.9 | 0.39 | 0.16 | 4332 | 584  | 500  | 3.6  | 0    | 0.57 | 1880 | 27041                                  |               |
| Shanghai | 17.9 | 114  | 35.8 | 0.59 | 1.01 | 8305 | 3376 | 928  | 4.4  | 0.94 | 0.16 | 2420 | 29887                                  |               |
| Chongqing| 17.0 | 106  | 43.6 | 0.16 | 0.4  | 1782 | 194  | 190  | 5.7  | 1    | 0.56 | 1103 | 18023                                  |               |
| Guangzhou| 17.7 | 115  | 35.4 | 0.22 | 0.63 | 4860 | 616  | 679  | 2.8  | 1    | 0.92 | 627  | 19611                                  |               |
| Shenzhen | 16.6 | 101  | 37.3 | 0.29 | 0.44 | 2538 | 682  | 299  | 2.5  | 1    | 1.02 | 1191 | 20686                                  |               |
| Wuhan    | 16.8 | 79   | 216  | 31.8 | 1.01 | 1485 | 563  | 196  | 2.5  | 1    | 0.95 | 473  | 11531                                  |               |
| Nanjing  | 17.0 | 78   | 140  | 43.6 | 0.29 | 1864 | 504  | 227  | 2.4  | 1    | 0.71 | 591  | 10819                                  |               |
| Shenyang | 17.7 | 128  | 225  | 24.3 | 0.09 | 1485 | 563  | 196  | 2.5  | 1    | 0.87 | 471  | 5290                                   |               |
| Dalian   | 15.4 | 84   | 210  | 39.4 | 0.33 | 436  | 393  | 35   | 2.8  | 1    | 0.36 | 327  | 5650                                   |               |
| Xi’an    | 17.0 | 92   | 173  | 33.5 | 0.16 | 881  | 46   | 106  | 4.2  | 1    | 0.96 | 436  | 6396                                   |               |
| Harbin   | 15.6 | 82   | 330  | 30.5 | 0.04 | 121  | 38   | 19   | 3.7  | 1    | 0.52 | 422  | 4370                                   |               |
| Suzhou   | 16.3 | 94   | 220  | 32.0 | 0.15 | 292  | 39   | 41   | 2.1  | 1    | 0.39 | 263  | 15400                                  |               |
| Wuxi     | 17.0 | 56   | 410  | 34.5 | 0.17 | 161  | 0    | 23   | 2.2  | 1    | 0.31 | 216  | 9340                                   |               |
| Nanjing  | 17.7 | 97   | 480  | 31.2 | 0.10 | 20   | 8    | 3    | 5.6  | 1    | 0.08 | 225  | 3730                                   |               |

Table 3: Weights and rankings for different indicators.

| Criterion layer | AHP method | Entropy method | Comprehensive weighting method | Index layer | AHP method | Sort | Entropy method | Sort | Comprehensive weighting method | Sort |
|-----------------|------------|----------------|-------------------------------|-------------|------------|------|----------------|------|-------------------------------|------|
| A1              | 0.2797     | 0.2131         | 0.2464                        | B1          | 0.0201     | 10   | 0.0208         | 12   | 0.0204                        | 12   |
|                 |            |                |                               | B2          | 0.0275     | 9    | 0.0391         | 8    | 0.0333                        | 11   |
|                 |            |                |                               | B3          | 0.0812     | 4    | 0.0362         | 9    | 0.0587                        | 8    |
|                 |            |                |                               | B4          | 0.0543     | 5    | 0.0351         | 10   | 0.0447                        | 9    |
|                 |            |                |                               | B5          | 0.0967     | 3    | 0.0819         | 5    | 0.0893                        | 6    |
| A2              | 0.0936     | 0.6317         | 0.3627                        | B6          | 0.0144     | 11   | 0.1162         | 4    | 0.0653                        | 7    |
|                 |            |                |                               | B7          | 0.0389     | 7    | 0.1526         | 2    | 0.0958                        | 4    |
|                 |            |                |                               | B8          | 0.0042     | 12   | 0.2107         | 1    | 0.1074                        | 2    |
|                 |            |                |                               | B9          | 0.0361     | 8    | 0.1522         | 3    | 0.0941                        | 5    |
| A3              | 0.6267     | 0.1552         | 0.3909                        | B10         | 0.4656     | 1    | 0.0483         | 7    | 0.2569                        | 1    |
|                 |            |                |                               | B11         | 0.0396     | 6    | 0.0295         | 11   | 0.0346                        | 10   |
|                 |            |                |                               | B12         | 0.1215     | 2    | 0.0774         | 6    | 0.0995                        | 3    |

Figure 1: Weight normalization results under different classifications (a) Geographic area (b) City size.
social benefit indicators are 0.207, 0.429, and 0.484, respectively. This may be because larger cities tend to have higher passenger flow and economic levels, the service level will increase accordingly, and the social benefits will also increase. (2) The result of policy-related losses is the smallest in megacity, only 0.425, this is mainly because the passenger travel cost indicators in these cities are relatively high, and the operating cost ratio of Shanghai and Shenzhen is also relatively high.

3.2. Measurement and Calculation of Comprehensive Evaluation Indicators. According to equations (11)–(23), the relative closeness of the public welfare of the rail transit systems of 16 cities is shown in Figure 2. Cities are listed in descending order of GDP.

Figure 2(a) shows that the level (relative closeness) of public welfare in different cities is not balanced. From Shanghai to Wuxi, these cities with relatively high GDP, except for Chongqing, have a relatively low degree of closeness, and the relative closeness of other cities is around 0.55. This is mainly because the passenger travel cost indicator in Chongqing is relatively high, reaching 5.7. In the latter seven cities, except for Dalian, where the relative closeness suddenly increased, the relative closeness of several other cities was less than 0.5, which was at a relatively low level. This is mainly due to the relatively low passenger travel cost index which is 2.8, the relatively low operating cost ratio which is 0.36, and the relatively high network density which is 0.33 in Dalian.

Figure 2(b) shows that from Shanghai to Wuxi, the policy loss relative closeness of cities with relatively high GDP, except for Shanghai and Chongqing, is above 0.47.
This is mainly because the passenger travel cost index in Chongqing is relatively high, reaching 5.7, and the passenger travel cost index and operating cost ratio index in Shanghai are also very high, reaching 4.4 and 0.94 respectively. In the latter seven cities, except for Dalian and Harbin, where the policy loss relative closeness of policy loss suddenly increased, the policy-loss relative closeness of several other cities was less than 0.5, which was at a relatively low level. This is mainly due to the relatively low passenger travel cost indicators and operating cost ratios in Dalian and Harbin, where 2.8 and 0.36 in Dalian and 3.7 and 0.52 in Harbin respectively.

Figure 2(c) shows that the relative closeness of the service level indicator shows an obvious trend of decreasing gradually with the decline of the economic level, which indicates that the urban rail transit in the more developed cities tends to have higher benefits.

Figure 2(d) shows that with the decline of GDP, the relative closeness of the service level of each city shows an obvious downward trend. This may be because the cities with lower economic levels tend to have smaller populations, so the service level will be relatively low.

When cities are listed in descending order of urban population, the relative closeness of public welfare, policy loss, social benefit, and service level are shown in Figure 3.

Figure 3(a) shows that from Shanghai to Wuhan, cities with a large population except Chongqing have a relative closeness to public welfare of more than 0.5, the relative closeness of public welfare in Chongqing is only 0.396. This may be due to the relatively low indicators of social benefits and policy losses in Chongqing. Among the other cities, the relative closeness of public welfare in Dalian, Suzhou, and Wuxi is more than 0.5, which is mainly due to their relatively low population.
high policy-related loss indicators and service level indicators, while the relative closeness of public welfare in other cities is lower than 0.5.

Figure 3(b) shows that the relative closeness of policy losses in some cities is significantly lower than that of other cities, including Shanghai, Chongqing, Shenyang, Xi’an, Nanchang, Nanning and Dongguan, all of which are lower than 0.5. This is mainly due to the relatively high passenger travel cost index and operating cost ratio index in Shanghai, Shenyang, and Xi’an, which are 4.4 and 0.94, respectively; while although Chongqing, Nanning, and Dongguan have relatively low operating cost ratios, but their passenger travel cost index is relatively high, were 5.7, 5.6 and 5.8; Nanchang’s operating cost ratio was very high, reaching 1.04.

Figure 3(c) and Figure 3(d) show that with the reduction of the urban population, the relative closeness of social benefit and service level both show a downward trend. This is because cities with smaller populations tend to have less passenger flow. Therefore, various social benefits such as replacement of public transport benefits and benefits of reducing pollution will also decrease. At the same time, urban rail transit construction in cities with fewer populations usually starts later, and the density of the network are always being smaller, and due to less passenger flow, the departure interval and average speed will also decrease to save costs.

This paper uses SPSS software to carry out a correlation analysis on GDP, urban population, and the relative closeness of public welfare, social benefit, policy loss, and service level. The results are shown in Table 4.

It can be seen from Table 4 that there is a significant positive correlation between GDP and urban population; on the other hand, there is a positive correlation between GDP and the relative closeness of social benefit and service level; there is a positive correlation between urban population and the relative closeness of social benefit and service level. However, there is no obvious correlation between GDP, population, and the relative closeness of public welfare and policy losses. This verifies the correctness of the above results in this paper.

### 4. Conclusions

The evaluation index system for the public welfare level of urban rail transit is established, which adopts the combination of a subjective and objective method to determine the weight of public welfare indicators, and the grey relation-TOPSIS method is adopted to evaluate the levels of public welfare of different urban rail transit systems in different cities. The conclusions are as follows:

1. The public welfare level evaluation indicators account for a large proportion of the passenger travel cost index(25.69%), the increase in housing prices around rail transit(10.74%), and operating cost ratio(9.95%); for the service level indicator, network density(8.93%), departure interval(5.87%) and average speed(4.47%) are the more important indicators, so governments and enterprises can increase public welfare by reducing the fare price and improving the service level, such as increasing the network density, reducing the departure interval, and increasing the average speed.

2. The levels(relative closeness) of public welfare of each city are not balanced. Cities with a large population except Chongqing have a public welfare relative closeness of more than 0.5, the relative closeness of public welfare in Chongqing is only 0.396. This may be due to the relatively low indicators of social benefits and policy losses in Chongqing, such as its high passenger travel cost index of 5.7. Among the other cities, the relative closeness of public welfare in Dalian, Suzhou, and Wuxi is more than 0.5, which is mainly due to their relatively high policy-related loss indicators and service level indicators, while the relative closeness of public welfare in other cities is lower than 0.5.

3. There is a positive correlation between GDP and urban population; there is a positive correlation between GDP and the relative closeness of social benefit and service level; Furthermore, there is also a positive correlation between urban population and

### Table 4: Correlation analysis results.

|                      | The relative closeness of public welfare | The relative closeness of service level | The relative closeness of social benefit | The relative closeness of policy loss | Urban population | GDP   |
|----------------------|----------------------------------------|----------------------------------------|----------------------------------------|--------------------------------------|-----------------|-------|
| Pearson correlation  | 0.308                                   | 0.688**                                 | 0.866**                                | -0.453                               | 1               | 0.885**|
| Sig. (double tail)   | 0.246                                   | 0.003                                   | 0.000                                  | 0.078                                | 0.000           |       |
| Number of cases      | 16                                      | 16                                      | 16                                     | 16                                   | 16              | 16    |
| Pearson correlation  | 0.359                                   | 0.616*                                  | 0.776**                                | -0.300                               | 0.885**         |       |
| Sig. (double tail)   | 0.172                                   | 0.011                                   | 0.000                                  | 0.258                                | 0.000           |       |
| Number of cases      | 16                                      | 16                                      | 16                                     | 16                                   | 16              | 16    |

**indicates a significant correlation at the 0.01 level (two-tailed). * indicates a significant correlation at the 0.05 level (two-tailed).
the relative closeness of social benefit and service level. However, there is no obvious correlation between GDP, population, and the relative closeness of public welfare and policy losses.

The evaluation of the level of public welfare of urban rail transit in this paper has a certain guiding significance for the operation and management strategies of the government and urban rail transit operating enterprises to improve the level of public welfare. Future studies could fruitfully explore this issue further by conducting research on subsidy and fare optimization on the basis of current public welfare research.

**Data Availability**

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest.

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**References**

[1] H. Qin, Modernization beyond Government and Enterprises: A Comparative Study of the History of Chinese and Western Public Welfare, Zhejiang People’s Publishing House, Hangzhou, China, 1999, (in Chinese).

[2] S. Mike, “Analyzing the professions: the case for the neo-Weberian approach,” Comparative Sociology, vol. 9, no. 6, pp. 887–915, 2010.

[3] B. Greve, “What is welfare?,” Central European Journal of Public Policy, vol. 2, no. 1, 2008.

[4] Z. Zi, The Fate of Wealth: Review of American Modern Public Welfare Foundation, Shanghai People’s Publishing House, Shanghai, China, 2003, (in Chinese).

[5] J. Wu, “A study of public welfare in public hospitals,” Comparative Economic & Social Systems, vol. 4, pp. 13–20, 2012, (in Chinese).

[6] M. A. Abe, Pricing and Welfare in Urban Transportation, Economics Faculty Research and Publications, New Jersey, NJ, USA, 1973.

[7] B. D. Taylor and E. A. Morris, “Public transportation objectives and rider demographics: are transit’s priorities poor public policy?,” Transportation, vol. 42, no. 2, pp. 347–367, 2015.

[8] V. Stjernborg and O. Mattisson, "The role of public transport in society-A case study of general policy documents in Sweden," Sustainability, vol. 8, no. 11, p. 1120, 2016.

[9] M. Wachs and B. D. Taylor, "Can transportation strategies help meet the welfare challenge?" Journal of the American Planning Association, vol. 64, no. 1, pp. 15–19, 1998.

[10] J. Holmgren, "A strategy for increased public transport usage - the effects of implementing a welfare maximizing policy," Research in Transportation Business & Management, vol. 48, pp. 221–226, 2014.

[11] E. Guerra, “Valuing rail transit,” Transportation Research Record: Journal of the Transportation Research Board, vol. 2219, no. 1, pp. 50–58, 2011.

[12] B. Faivre d’Arcier, “Measuring the performance of urban public transport in relation to public policy objectives,” Research in Transportation Economics, vol. 48, pp. 67–76, 2014.

[13] S. Kim and W. Vandenameele, “A strategy for building public service motivation research internationally,” Public Administration Review, vol. 70, no. 5, pp. 701–709, 2010.

[14] B. H. Mao, Z. Zhang, Z. J. Chen, J. W. zheng, and H. T. kin, “A review on operational technologies of urban rail transit networks,” Journal of Transportation Systems Engineering and Information Technology, vol. 17, no. 6, pp. 155–163, 2017, (in Chinese).

[15] Y.- K. Qiao, F.-L. Peng, and Y. Wang, “Valuing external benefits of underground rail transit in monetary terms: a practical method applied to Changzhou City,” Tunnelling and Underground Space Technology, vol. 83, pp. 91–98, 2019.

[16] Y. L. Jiao, L. H. Fan, and F. Yu, “Research on the construction of public welfare evaluation system from the perspective of party building in public hospitals,” Chinese Hospital Management, vol. 40, no. 5, pp. 47–50, 2020, (in Chinese).

[17] J. Li, F. Liu, C. L. Tan, X. Lingzhong, Z. Liang, and F. Zhanchun, “Research on fuzzy comprehensive evaluation of public welfare in public hospitals in sichuan province from the patients’ perspective,” Medicine in Society, vol. 38, no. 8, p. 10, 2019, (in Chinese).

[18] W. X. Lv, T. Y. Wang, and D. Zhu, “Researches on the assessment and maintenance mechanism of university canteen’s public welfare under socialization reform,” Education Economics, vol. 2016, no. 5, pp. 66–72, 2016, (in Chinese).

[19] D. Zhang and J. Jiao, “How does urban rail transit influence residential property values? Evidence from an emerging Chinese megacity,” Sustainability, vol. 11, no. 2, p. 534, 2019.

[20] Y. Sun and Y. Cui, “Evaluating the coordinated development of economic, social and environmental benefits of urban public transportation infrastructure: case study of four Chinese autonomous municipalities,” Transport Policy, vol. 66, pp. 116–126, 2018.

[21] S. X. Chen and X. M. Tao, “Estimative analysis of the social benefit of shanghai UMT system,” Urban Mass Transit, vol. 7, no. 1, pp. 1–5, 2004, (in Chinese).

[22] M. Nassereddine and H. Eskandari, “An integrated MCDM approach to evaluate public transportation systems in Tehran,” Transportation Research Part A: Policy and Practice, vol. 106, pp. 427–439, 2017.

[23] E. Broniewicz and K. Ogrodzinski, “Multi-criteria analysis of transport infrastructure projects,” Transportation Research Part D: Transport and Environment, vol. 83, Article ID 102351, 2020.

[24] Z. Deng, Z. F. Li, Y. T. Zhou, X. Chen, and S. S. Liang, “Measurement and spatial spillover effects of port comprehensive strength: empirical evidence from China,” Transport Policy, vol. 99, pp. 288–298, 2020.

[25] S. Chen, Y. Leng, B. Mao, and S. Liu, “Integrated weight-based multi-criteria evaluation on transfer in large transport terminals: a case study of the beijing south railway station,” Transportation Research Part A: Policy and Practice, vol. 66, pp. 13–26, 2014.

[26] Y. Yang, K. He, Y. P. Wang, Z. Z. Yuan, Y. H. Yin, and M. Z. Guo, “Identification of dynamic traffic crash risk for cross-area freeways based on statistical and machine learning methods,” Physica A: Statistical Mechanics and Its Applications, vol. 595, Article ID 127083, 2022.
[27] X. Chen, H. Chen, Y. Yang et al., "Traffic flow prediction by an ensemble framework with data denoising and deep learning model," *Physica A: Statistical Mechanics and Its Applications*, vol. 565, Article ID 125574, 2021.

[28] Y. Yang, Z. Yuan, J. Chen, and M. Guo, "Assessment of osculating value method based on entropy weight to transportation energy conservation and emission reduction," *Environmental Engineering and Management Journal*, vol. 16, no. 10, pp. 2413–2423, 2017.

[29] Z. Z. Yuan, K. He, and Y. Yang, "A roadway safety sustainable approach: modeling for real-time traffic crash with limited data and its reliability verification," *Journal of Advanced Transportation*, vol. 2022, Article ID 1570521, 14 pages, 2022.

[30] L. J. Li, Y. Yang, Z. Z. Yuan, and Z. Chen, "A spatial-temporal approach for traffic status analysis and prediction based on Bi-LSTM structure," *Modern Physics Letters B*, vol. 35, no. 31, Article ID 2150481, 2021.

[31] F. W. Gao, Z. B. Zhang, and M. X. Shang, "Risk evaluation study of urban rail transit network based on entropy-TOPSIS-coupling coordination model," *Discrete Dynamics in Nature and Society*, vol. 2021, Article ID 5124951, 8 pages, 2021.

[32] H. Liu, Y. Dong, and F. Wang, "Gas outburst prediction model using improved entropy weight grey correlation analysis and IPSO-LSSVM," *Mathematical Problems in Engineering*, vol. 2020, no. 7, 10 pages, Article ID 8863425, 2020.