Comprehensive Evaluation and Planning Optimization of Urban Development Levels in Xinjiang Based on POI Data

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Abstract. This study constructs a multidimensional mathematical model for evaluating and optimizing the development level of cities in Xinjiang based on multi-source data. For housing price prediction and existing housing stock estimation, a multi-factor linear prediction model is established. This model comprehensively considers four major factors-economic, service, location, and policy-with corresponding weight coefficients assigned: the economic factor carries a weight of 0.35, and the service factor a weight of 0.25. Model solutions predict housing price ranges for major Xinjiang cities between 5,668-7,308 RMB/m^2, with an average forecast of 5,379 RMB/m^2. The total existing housing stock is estimated at approximately 73.32 million units. For quantifying and classifying urban service levels, a multidimensional evaluation system encompassing four core domains—healthcare, education, transportation, and commerce-was constructed. Principal component analysis was applied to reduce the dimensionality of the service level matrix, revealing that the first principal component explained 99.93% of the variance, indicating high correlation among service domains. Subsequently, the K-means clustering algorithm categorized cities into four types: excellent service, good service, weak service, and developing service. For urban resilience assessment and investment demand planning, a four-dimensional resilience evaluation model was established, comprising infrastructure (weight 0.4), economy (weight 0.3), society (weight 0.2), and environment (weight 0.1). Based on the resilience index, an investment demand assessment model and a weakness identification algorithm were constructed. Model results indicate a total investment requirement of 259.8 billion yuan, with Urumqi achieving the highest comprehensive resilience index. Finally, for smart city development planning and benefit assessment, an evaluation model for current and target smart levels was established. Investment allocation ratios were determined across five key domains — smart transportation, smart government services, etc. — projecting over 50% improvement in urban development levels.

Keywords: POI data, multi-factor prediction model, urban resilience evaluation.

1. Introduction

Against the backdrop of accelerating global population aging, heightened economic uncertainty, and increasingly frequent extreme weather events, sustainable urban development and enhanced resilience have become critical issues in regional planning. Particularly for key western regions like Xinjiang, the urgent challenge lies in scientifically leveraging existing data resources to systematically evaluate urban development levels and formulate targeted development strategies [1-2]. This study aims to establish a comprehensive mathematical model system spanning economic forecasting, service level assessment, resilience enhancement, and smart city development to provide scientific guidance for high-quality urban development in Xinjiang. Previous research has predominantly focused on single-dimensional analysis, lacking a systematic solution that integrates housing prices, services, resilience, and smart city development within a unified framework. The innovation of this section lies in its pioneering integration of a multi-factor housing price prediction model, a service level quantification and classification model based on principal component analysis and K-means clustering, a four-dimensional urban resilience assessment model, and a smart city development planning model. This forms a closed-loop modeling system addressing four core urban development challenges. Furthermore, the model not only delivers quantitative evaluation results but also proposes a differentiated investment plan with a total investment requirement of 259.8 billion yuan based on resilience assessment outcomes. A gap identification algorithm clearly defines priority development directions for each city. The research approach unfolds around four core issues: First, establishing a multi-factor housing price prediction model and an existing housing stock estimation model; second, constructing an urban service level evaluation system and applying principal component analysis and K-means clustering for classification; Third, a four-dimensional urban resilience evaluation model is developed, incorporating investment demand assessment and gap identification algorithms. Finally, a smart city development assessment and investment allocation model is established to guide smart city advancement [3].

2. Establishment and Solution of the Model

2.1. Multi-factor Housing Price Forecasting and Existing Housing Valuation Model Development and Application

2.1.1 Establishment of the Housing Price Prediction Model

A multi-factor housing price prediction model is established, considering four categories of factors: economy, services, location, and policies [4-5]:

Where: - $\mathrm{P_0} = 4000$ is the base housing price (yuan/m²) - $\mathrm{E_i}$ is the economic factor, reflecting the impact of GDP level - $\mathrm{S_i}$ is the service factor, reflecting the POI service level - $\mathrm{L_i}$ is the location factor, reflecting the geographical advantage - $\mathrm{Po_i}$ is the policy factor, reflecting the intensity of policy support

Calculation of economic factor:$E_i = 8000 \cdot \frac{G_i - G_{min}}{G_{max} - G_{min}}$; Calculation of service factor:$S_i = 6000 \cdot \frac{S_i - S_{min}}{S_{max} - S_{min}}$; Calculation of location factor:$L_i = 5000 \cdot \frac{D_i - D_{min}}{D_{max} - D_{min}}$; Calculation of policy factor:$Po_i = 3000 \cdot \frac{N_i - N_{min}}{N_{max} - N_{min}}$.

The weight coefficients are set as: $\alpha = 0.35,\ \beta = 0.25,\ \gamma = 0.20,\ \delta = 0.20$.

2.1.2 Housing Stock Estimation Model

A housing stock estimation model is established based on population size and housing demand:

Where: - $\mathrm{A_{avg}} = 35\ \mathrm{m}^2$ is the per capita housing area - $\mathrm{A_{house}} = 90\ \mathrm{m}^2$ is the average housing area per household

2.1.3 Model Solution Results

The housing price prediction results for each city are obtained through MATLAB calculation:

$$\text{Predicted Housing Price Formula} = 3000 \cdot \frac{\text{Relevant Indicators}}{\text{Normalization Factor}} \tag{1}$$

The average predicted housing price is $5379\ \mathrm{yuan/m^2}$, and the total housing stock is approximately 73.32 million units [6-8].

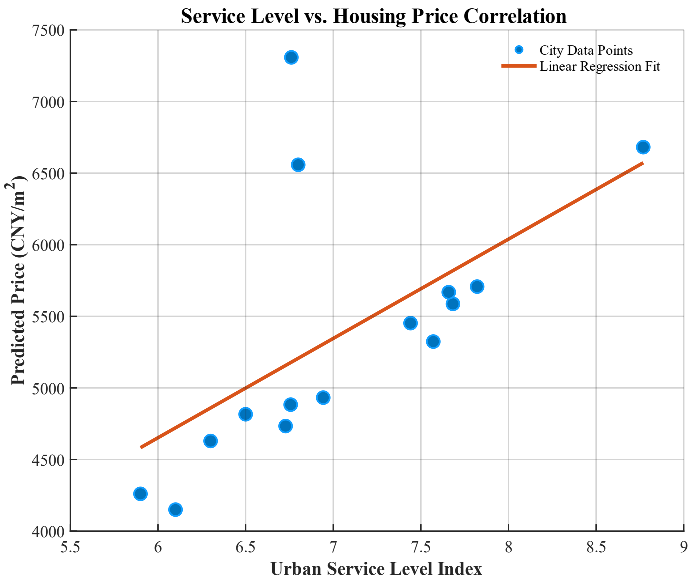

Figure 1: Relationship between Urban Service Level and Housing Price

The figure 1 shows the scatter plot of urban service level index and predicted housing price, with a trend line added. The horizontal axis represents the urban service level index (ranging from 5.5 to 9), and the vertical axis represents the predicted housing price (ranging from 4000 to 7500 yuan/m²).

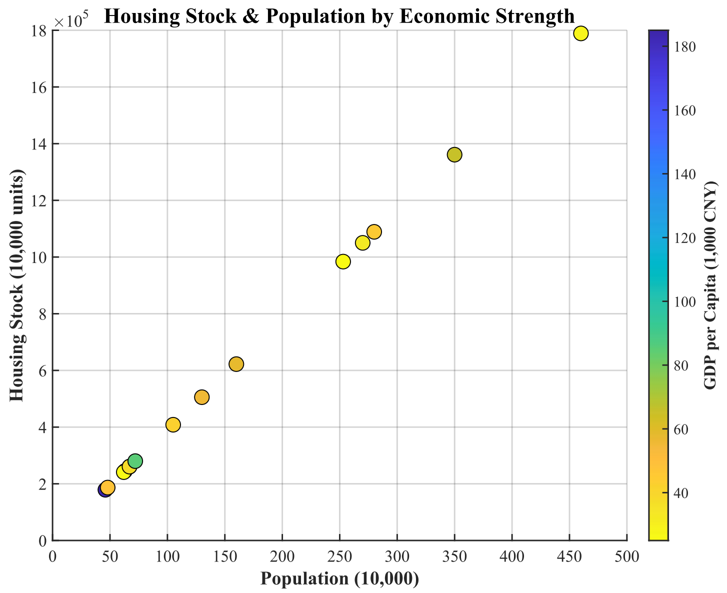

Figure 2: Relationship between Population and Housing Stock

The figure 2 shows the scatter plot of population (ranging from 0 to 500 ten thousand people) and housing stock (ranging from 0 to 180 ten thousand units), with the color depth representing the per capita GDP level.

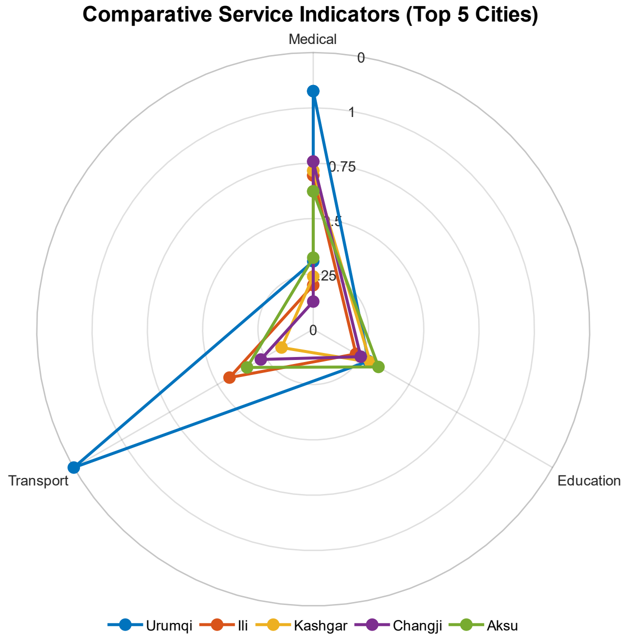

Figure 3: Comparison of Service Levels of the Top 5 Cities

The figure 3 compares the service levels of Urumqi City, Kashgar Prefecture, Ili Kazakh Autonomous Prefecture, Changji Hui Autonomous Prefecture, and Aksu Prefecture in five dimensions [9-10].

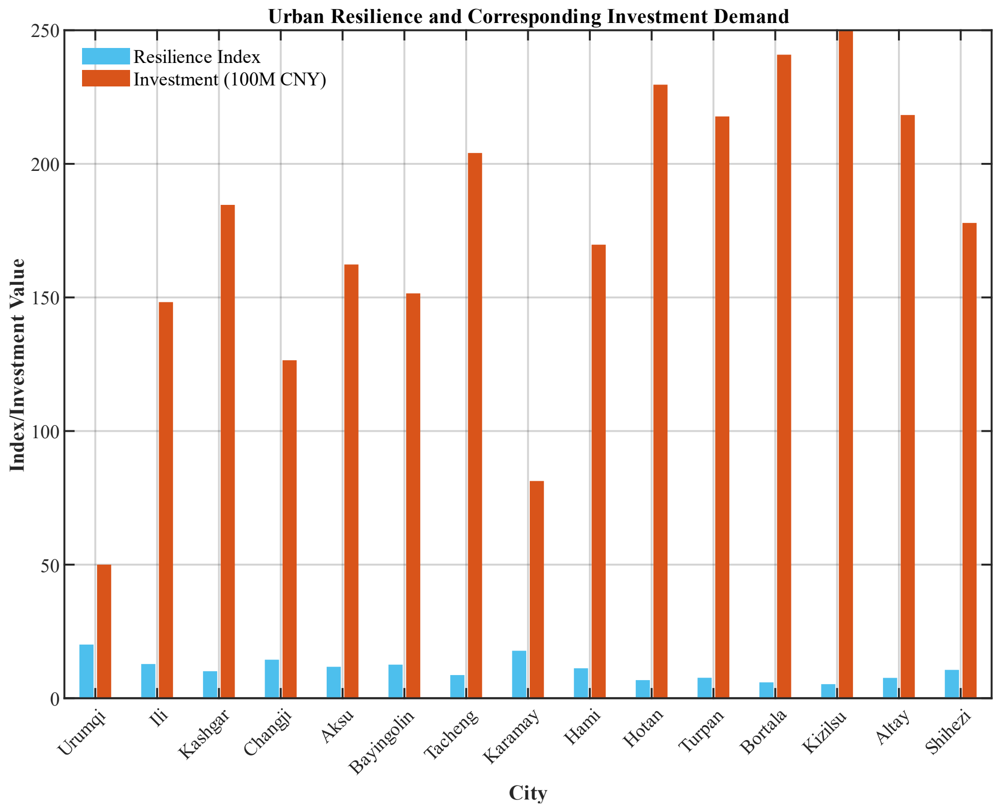

Figure 4: Urban Resilience and Investment Demand

The figure 4 shows the comprehensive resilience index (ranging from 0 to 250) and investment demand (ranging from 0 to 200 hundred million yuan) of each city, with the horizontal axis representing city numbers.

2.2. Quantitative Evaluation and Classification of Urban Service Levels Based on Principal Component Analysis and K-Means Clustering

2.2.1 Urban Service Level Evaluation Model

A multi-dimensional service level evaluation system is constructed, covering four core areas of urban basic services: medical services, education services, transportation services, and commercial services:

$$\text{Comprehensive Service Level Index} = \sum_{j=1}^{4} w_j \cdot C_{ij} \tag{2}$$

where w_j is the weight of each service category, and C_{ij} is the standardized score of cities i in the j-th type of service.

Medical service evaluation:

$$\text{Medical Service Score} = \alpha_1 \cdot \text{Relevant POI Indicators} + \varepsilon_1 \tag{3}$$

where $\alpha_1 = 0.3$, and ε_1 is the random disturbance term.

Education service evaluation:

$$\text{Education Service Score} = \alpha_2 \cdot \text{Relevant POI Indicators} \tag{4}$$

where $\alpha_2 = 0.4$.

Transportation service evaluation:

$$\text{Transportation Service Score} = \alpha_3 \cdot \text{POI Density} \tag{5}$$

where $\alpha_3 = 50$.

Commercial service evaluation:

$$\text{Commercial Service Score} = \alpha_4 \cdot \text{Relevant POI Indicators} \tag{6}$$

where $\alpha_4 = 0.5$.

2.2.2 Principal Component Analysis

Principal component analysis is performed on the service level matrix:

$$X = \text{Load Matrix} \cdot \text{Principal Component Score Matrix} + \text{Residual Matrix} \tag{7}$$

where X is the standardized service level matrix, and the load matrix is the principal component load matrix.

The variance explained by the first principal component reaches 99.93%, indicating a high correlation among various service fields.

2.2.3 Urban Cluster Analysis

The K-means algorithm is used to classify cities into 4 categories:

Cluster objective function:

$$J = \sum_{k=1}^{4} \sum_{x_i \in \text{Cluster } k} \|x_i - \mu_k\|^2 \tag{8}$$

This objective function achieves the optimal classification of urban service levels by minimizing the sum of squared Euclidean distances from each sample point to the center of its affiliated cluster. During the algorithm iteration process, the cluster center μ_i is recalculated based on the current samples in the cluster until the objective function converges.

Cluster results:

Excellent service type: Bayingolin Mongolian Autonomous Prefecture, Tacheng Prefecture, etc.

Good service type: Urumqi City, Karamay City

Weak service type: Ili Kazakh Autonomous Prefecture, Kashgar Prefecture, etc.

Developing type: Other cities

Distribution of Urban Service Level Classification in Xinjiang

Analysis of Urban Service Level Classification

Excellent service type: Various service indicators perform outstandingly and can serve as regional benchmarks. Excellent cities are mainly distributed in the economically developed northern Xinjiang region.

2.3. Establishment of a Multi-dimensional Urban Resilience Evaluation System and Formulation of Differentiated Investment Planning Schemes

2.3.1 Urban Resilience Evaluation Model

A four-dimensional urban resilience evaluation model is established:

$$\text{Comprehensive Resilience Index} = w_1 R_{i1} + w_2 R_{i2} + w_3 R_{i3} + w_4 R_{i4} \quad (9)$$

where: - R_{i1} is infrastructure resilience, with weight $w_1 = 0.4$ - R_{i2} is economic resilience, with weight $w_2 = 0.3$ - R_{i3} is social resilience, with weight $w_3 = 0.2$ - R_{i4} is environmental resilience, with weight $w_4 = 0.1$

Calculation of infrastructure resilience:$R_{i1} = 0.4 \cdot R_i$; Calculation of economic resilience:$R_{i2} = 30 \cdot \frac{G_i - G_{min}}{G_{max} - G_{min}} + \varepsilon_{i2}$; Calculation of social resilience: $R_{i3} = 25 \cdot \frac{S_i - S_{min}}{S_{max} - S_{min}} + \varepsilon_{i3}$; Calculation of environmental resilience:$R_{i4} = 20 + \varepsilon_{i4}$.

2.3.2 Investment Demand Assessment Model

Investment demand is calculated based on the resilience evaluation results:

$$\text{Investment Demand} = I_0 + \lambda \cdot (\text{Maximum Resilience Index} - \text{City's Resilience Index}) \quad (10)$$

where: - $I_0 = 50$ hundred million yuan is the base investment amount - $I_{max} = 200$ hundred million yuan is the maximum investment limit - λ is the investment intensity coefficient

2.3.3 Shortcoming Identification Algorithm

The threshold method is used to identify the development shortcomings of each city:

$$B_{ij} = \begin{cases} 1 & \text{if } R_{ij} < \bar{R}_j \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

where B_{ij} indicates whether city i has a shortcoming in the j-th dimension, and $\bar{R}_j$ is the average level of the j-th dimension.

2.3.4 Solution Results

Cities with the top 5 comprehensive resilience indexes: 1. Urumqi City: 69.68 points 2. Ili Kazakh Autonomous Prefecture: 42.51 points 3. Kashgar Prefecture: 41.94 points 4. Changji Hui Autonomous Prefecture: 39.72 points 5. Aksu Prefecture: 38.80 points

The total investment demand is 259.8 billion yuan, among which Urumqi City has the largest demand of 33.26 billion yuan.

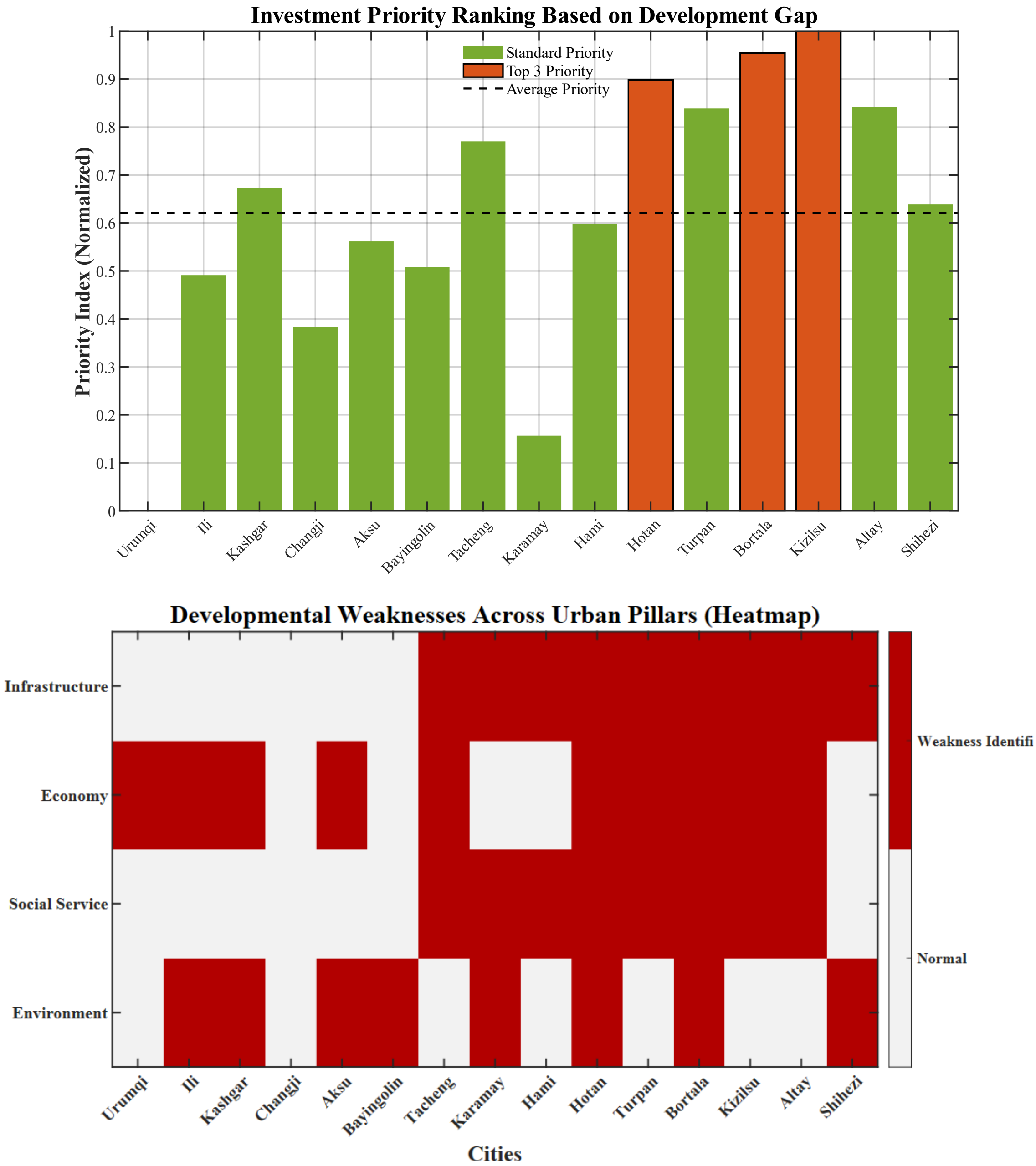

Figure 5: Investment Priority Ranking of Each City

The above figure 5 displays the investment priority index, with Kizilsu Kirghiz Autonomous Prefecture and other regions having the highest investment priority; the shortcoming matrix in the following figure shows the weak links of each city in the four development dimensions, with red areas indicating existing shortcomings.

2.4. Smart City Development Planning Model and Benefit Assessment for High-quality Development

2.4.1 Smart City Development Planning Model

A smart city development planning model is established, including smartness level evaluation and improvement models:

Current smartness level:

$$\text{Current Smartness Level} = a \cdot \text{Service Level Index} + b \cdot \text{Resilience Index} + c \cdot \text{Normalized GDP} \quad (12)$$

Target smartness level:

$$\text{Target Smartness Level} = \text{Current Smartness Level} \times (1 + \text{Expected Improvement Rate}) \quad (13)$$

2.4.2 Smart Investment Allocation Model

The investment allocation for smart city construction adopts a five-field structure:
Investment allocation ratio:
Smart transportation: 30%
Smart government affairs: 25%
Smart medical care: 20%
Smart education: 15%
Smart environmental protection: 10%

2.4.3 Benefit Evaluation Model

Evaluation of the benefits of smart city construction:

$$\text{Expected Improvement Amplitude} = \frac{\text{Target Smartness Level} - \text{Current Smartness Level}}{\text{Current Smartness Level}} \times 100\% \quad (14)$$

The expected average improvement amplitude exceeds 50%.

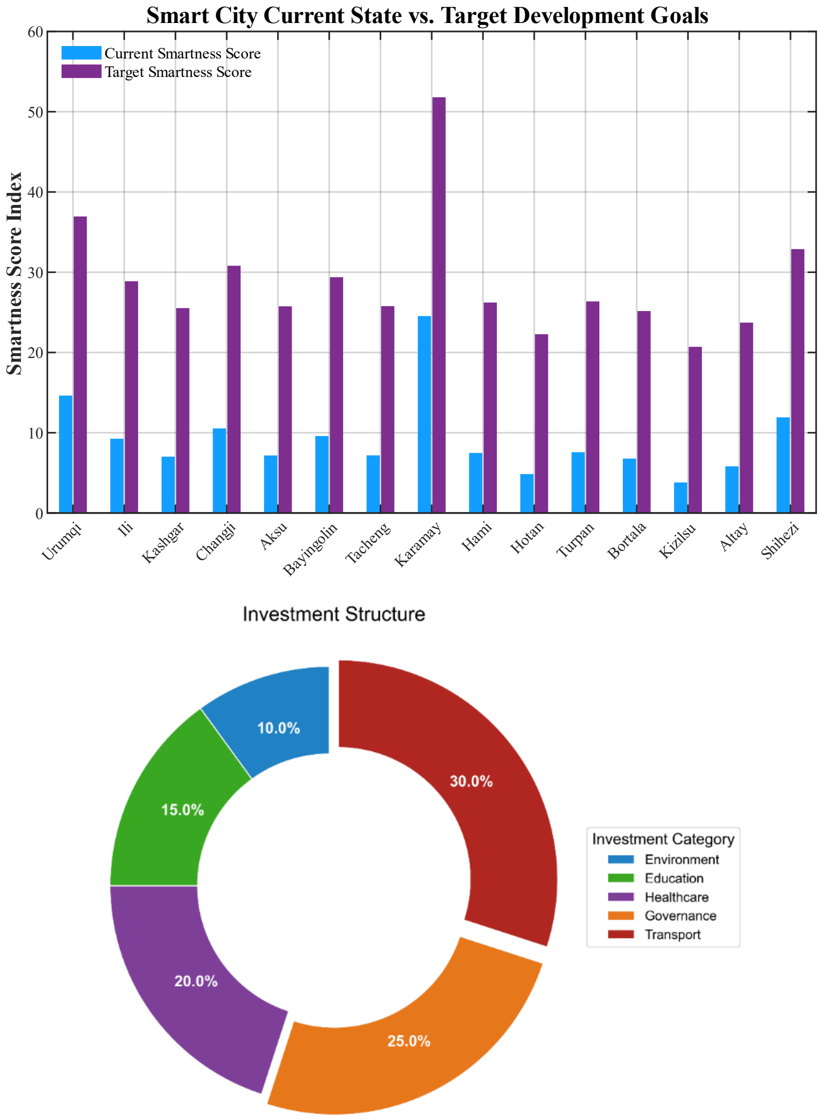

Figure 6: Smart City Development Planning

As shown in figure 6, the above sub-figure compares the current smartness level and target level of each city; the below sub-figure shows the investment structure allocation of smart cities, with smart transportation accounting for 30%, smart government affairs 25%, smart medical care 20%, smart education 15%, and smart environmental protection 10%)

3. Conclusions

The model development and solution section successfully construct a comprehensive urban development evaluation system covering economic, service, resilience, and smart city dimensions, providing quantitative analysis of key indicators for major cities in Xinjiang. For housing price forecasting, the multi-factor model provided scientifically grounded prediction ranges and existing housing stock estimates, offering data support for real estate market regulation. In urban service level analysis, principal component analysis extracted key service characteristics, while K-means clustering enabled precise classification of urban development types into service-excellent, service-good, and service-weak categories. For resilience assessment, a four-dimensional model quantifies each city's capacity to respond to extreme events, identifying Urumqi as the top-ranked city in comprehensive resilience. An investment demand assessment model calculates total investment requirements of 259.8 billion yuan, while a threshold method identifies shortcomings in infrastructure, economy, society, and environment dimensions across cities. Finally, the smart city development planning model provides clear investment allocation ratios and projects that smart city construction could yield over 50% improvement in urban development levels.

Limitations of this section's models include: the introduction of random disturbance terms in the service level evaluation's sub-indicator model may compromise assessment certainty; weighting coefficients for each dimension in the resilience evaluation model (e.g., infrastructure resilience weighted at 0.4) are preset values lacking sufficient empirical calibration across diverse urban contexts; Additionally, the shortfall identification algorithm employs a simple average threshold method, which may fail to accurately reflect relative differences among all cities, limiting its universality.

Future research should focus on dynamic model improvements and parameter optimization. First, sensitivity analysis or advanced optimization methods should be applied to the weight coefficients in the housing price prediction and resilience evaluation models to enhance the scientific rigor of parameter settings. Second, time-series data should be incorporated into service level assessments and resilience evaluations, establishing dynamic updating mechanisms to better capture real-time changes and long-term trends in urban development. Finally, benefit assessments for smart city investment allocation should adopt more complex economic indicators to ensure the investment allocation structure maximizes its driving effect on high-quality urban development.

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