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Article

Biomechanical insights from molecular to systemic levels in comparison and transformation paths of urban renewal governance modes under the "new normal" via data mining technique

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Abstract: In the urban development "new normal" of China, urban renewal governance transformation resembles the complex orchestration within cellular molecular biomechanics. Just as cells and molecules interact in a hierarchical and coordinated manner, diverse stakeholders and policies in urban renewal must align. The current urban and rural planning has underplayed the essential governance models. Here, data mining is the microscope to dissect urban renewal, similar to how biologists study molecular biomechanics. Examining cases like Shenzhen's, Guangzhou's "three old" renovations, and Beijing's "key villages" renovations is like observing different cellular responses. Each stakeholder and policy factor in urban renewal can be seen as molecular elements. Their interactions, like molecular forces, determine the system's behavior. By integrating new institutionalism theory, we map a transformation path, much as understanding molecular pathways guides biological system changes. Our data mining model, like a biomechanical analysis tool, shows strong capabilities. It can handle and describe the multimodal information of urban renewal. The significant performance improvement over the baseline model parallels the enhanced understanding gained from advanced biomechanical studies. This approach offers a new perspective, using the principles of cellular molecular biomechanics to optimize urban renewal governance and drive sustainable urban development.

Keywords: biomechanical systems; urban development; updated governance model; "new normal"

1. Introduction

The management of urban renewal governance first appeared in the 1970s in the last world and is widely used worldwide [1,2]. The main challenges facing urban renewal in China include the optimization of urban spatial structure, urban ecological restoration, historical and cultural protection, urban landscape shaping, residential community construction, new urban infrastructure construction, renovation of old urban communities, and construction and reinforcement of urban flood control and drainage facilities [3,4]. These challenges reflect the complexity and multidimensionality of urban renewal, and require comprehensive consideration of factors at multiple levels such as economy, society, culture and environment. The transformation of the urban renewal governance model is necessary because it involves the transformation of urban development and construction methods, and is necessary to promote the adjustment and optimization of urban structure and meet the people's growing demand for a better life [5,6]. Urban renewal action is not the renewal of old urban areas or historical blocks in a narrow sense, but the transformation of urban development and construction methods, which contains very rich content [7,8].

Urban renewal is of great and far-reaching significance for improving people's livelihood, stimulating domestic demand, enhancing the charm and vitality of cities, and comprehensively enhancing the comprehensive competitiveness of cities at home and abroad. Urban renewal action is an eternal theme of urban sustainable development, with profound social and humanistic connotations. While reshaping the spatial material form and functional organization, it also renews the spiritual life, social network and values of modern people.

Under the "new normal", urban renewal will become one of the main directions of urban development. Large economically developed cities such as Beijing, Guangzhou, Shenzhen, and Shanghai have taken the lead in carrying out local practice of urban renewal due to the dual pressures of industrial transformation and land resource bottlenecks [9,10].

In the inner renewal process of these cities, how do the "government", "developers" and "residents" who play a leading role participate in the renewal decision-making process? How do they balance the benefits and costs of all parties? Interrelationship? What is the effect of urban renewal implementation under different modes? To answer some questions, this paper first sorts out the theoretical framework of urban renewal governance mode, and then analyzes the transformation of "key villages" in Beijing since 2008, the transformation of "three old's" in Guangzhou and Shenzhen.

The contributions of this paper mainly include the following three aspects: (1) Using data mining technology to effectively model the governance model of urban renewal governance. (2) Integrate multi-source information into data mining, put forward the basis of multi-source mapping, and realize an efficient data mutual learning mechanism. (3) Based on scientific experimental results, quantitatively and qualitatively give the transformation path of the city.

2. Related works

2.1. Urban renewal governance model and its transformation

Urban renewal should achieve the comprehensive goals of economic development, social equity, and environmental improvement, while considering the interests of all relevant groups. Existing research takes the practice of western urban renewal as a case, and according to the different composition of social subjects participating in governance, summarizes the governance mode of urban renewal since World War II as government-led, public-private cooperation, collaborative governance, and autonomous governance. type, etc. [11]. According to the differences in policy objectives, it is summarized as promoting economic growth, social reform, and social welfare, etc. In practice, urban renewal governance often involves several basic models at the same time, and is constantly adjusted according to different social needs, political forces and the specific environment of the renewal community [12]. Although the governance model of urban renewal in these regions is always adjusted and changed, in general, since the 1980s, with the advancement of globalization and the spread of neoliberal ideas, developed countries such as Europe and North America have gradually In the transition from Fordism to post-Fordist society, urban renewal has gradually shifted from the "monopoly governance" of the government and the "dual governance" of the government and developers to the "multiple governance" of the government, developers and society [13,14]. In the field of public management, [15,16] believed that local governments should actively transform traditional management methods to form a policy system that can effectively reach consensus in a more open and diverse environment with the participation of multiple decision-makers [17]. H1. In the field of urban and rural planning, Healy et al believe that the "institutional capacity" that can be reached among different participants should be cultivated. Urban and rural planning needs to transform the original theoretical system with technology as the single core, to maintain the overall interests of regional development. To achieve effective governance of urban space, actively participate in the competition among decision-making bodies to advocate "communication planning" and "collaborative planning". The institutional construction of urban renewal model transformation requires manpower from two aspects: "structure" and "participant": on the one hand, establish laws, regulations and norms that are conducive to participation and communication [18,19].

2.2. Data mining

In the field of smart city construction, Aydn and Durduran [20] explored the logical connection between information circulation, coordination and value-added from the perspective of information ecological chain, and constructed an urban governance information ecological chain model with these three elements as the core. The model aims to achieve the growth of information value through the efficient operation of the information ecological chain, thereby providing impetus for urban construction. The study also proposed a framework for the construction of the information ecological chain and deeply explored key elements such as platform construction, data governance and digital visualization. Since smart city construction involves a large amount of data, it is necessary to rely on big data technology for data integration, fusion and analysis to promote the informatization and intelligence of urban governance. Aliu et al. [21] analyzed the application scenarios of big data technology in the construction of county-level smart cities based on the relationship between smart cities and big data technology, and discussed the role of big data technology in promoting the construction of smart cities. Abbasianjahromi and Aghakarim [22] established a performance prediction model using decision tree technology, optimized it, and extracted key classification rules. The study analyzed in detail the impact of economic, resource, environmental and population factors on the modernization of government governance, and put forward corresponding suggestions. The accuracy of the BP neural network model was verified through data testing. The model provides theoretical support for government management and urbanization governance, and promotes the modernization process of government governance. Du et al.'s [23] research is based on news data from cities along the Beijing-Hangzhou Grand Canal, analyzes the current status of canal cultural heritage management, and explores the network structure characteristics of canal cultural heritage governance. The study found that the overall network structure density of cities along the canal is low and there is imbalance. A few key node cities such as Beijing, Xuzhou, Suzhou and Tianjin play a role of communication and bridge in the urban spatial structure. In addition, factors such as city size, economic development and cultural construction have an impact on the governance network structure of the canal cultural heritage. These findings provide new perspectives and strategies for the governance of canal cultural heritage. In the above methods, urban renewal management relies on information detection, and its main detection process is shown in **Figure 1**.

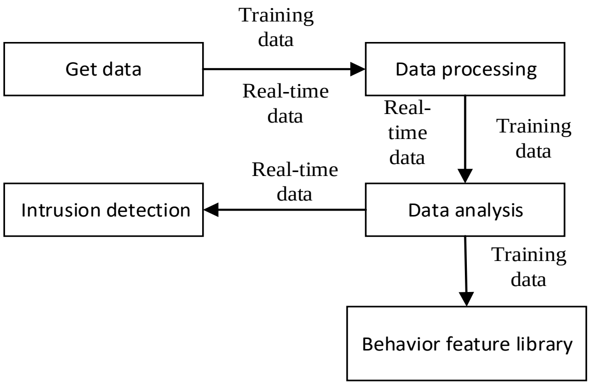


Figure 1. Information detection process.

3. Methods

The data flow and communication cycle of the information network system are relatively stable and have certain regularity. Most of the collected data is normal data, and only a very small amount of data is abnormal data. This feature provides a comparison for abnormal detection. In a good detection environment, if an accurate model can be constructed for the normal amount of data, the detection of abnormal behavior can be realized. The single-classification support vector machine (OCS-VM) algorithm is a special two-classification model based on support vector machines. It mainly achieves accurate classification by finding a hyperplane, and only needs one type of samples to achieve model training [24]. The hyperplane method is to use the kernel function to map the input data space into the Gaussian space and find the hyperplane in the mapped Gaussian space. The ideal hyperplane should separate the sample points and the origin to the greatest extent. Hyperplane diagram [25]. see **Figure 2**

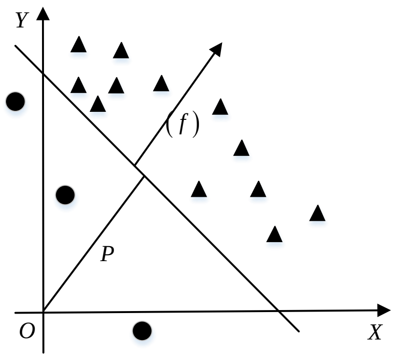


Figure 2. Hyperplane method.

The solution of the hyperplane is Equation (1),

$$\text{s.t.}\ \phi(x_i)\omega \geqslant \rho - \xi_i, \xi_i \geqslant 0 \tag{1}$$

Let the input training sample be $X_1, \ldots, X_1 \in X$, where $X \to H$ represents the input space to be mapped to the Gaussian space, ϖ represents the normal vector of the hyperplane, ρ represents the offset of the hyperplane, ξ represents the relaxation coefficient, which reflects the degree to which the sample conforms to the constraints. $V$is the trade-off coefficient, the value range is (0, 1), which is used to adjust the proportion of the support vector.

The offset of the hyperplane, representing the relaxation coefficient, reflects the degree to which the sample conforms to the constraints. $V$is the trade-off coefficient, the value range is (0, 1), which is used to adjust the proportion of the support vector.

In addition, the Lagrange operator is added to realize the solution of the hyperplane. The La-grange operator, see Equation (2),

$$L(\omega, \xi, \rho, \alpha, \beta) = \frac{1}{2}\|\omega\|^2 + \frac{1}{d}\sum_{i=1}^{l} \xi_i - \rho - \sum_{i}^{l} a_i\,(\omega x_i - \rho + \xi_i) - \sum_{i}^{l} \beta_i\,\xi_i \tag{2}$$

The selected Gaussian kernel function is Equation (3):

$$K(x_i, x_j) = \langle \phi(x_i), \phi(x_j) \rangle = exp\left(-g\left\|x_i - x_j\right\|^2\right) \tag{3}$$

The final decision function obtained by calculation is Equation (4):

$$f(x) = sgn\left(\sum_{i}^{n} \alpha_i\,K(x_i, x) - \rho\right) \tag{4}$$

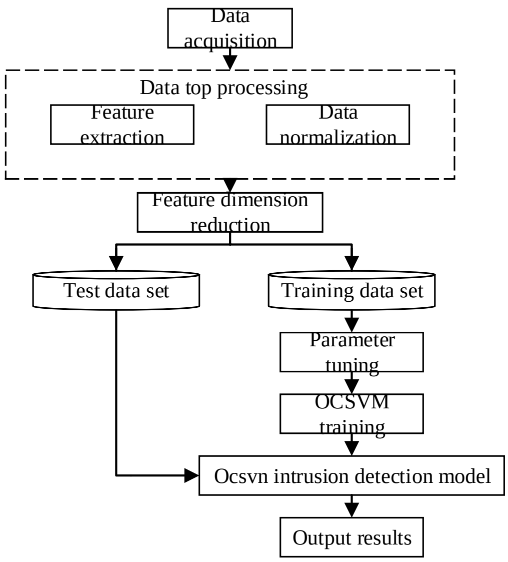


Figure 3. Detection model training process.

The collected data is input to the above detection model as a sample, and the training process is shown in **Figure 3**. Among them, the data preprocessing link is mainly to perform feature extraction and normalization on the original data, so that the data format meets the requirements of the algorithm data format. The second is to reduce the dimensionality of the data, extract features with statistical significance, reduce data redundancy, and thus improve the training speed. Then it is to optimize and adjust the model parameters, especially the two most important parameters, V and ρ, which have a great impact on the accuracy of the model. Finally, the trained model is validated against the test dataset.

3.1. Data sources

The data collection of this study adopted a variety of methods to ensure the diversity and comprehensiveness of the data. This paper obtained real-time monitoring data of urban traffic flow and air pollutant concentrations through cooperation with urban traffic management departments and environmental protection agencies. These data were collected by automated monitoring equipment over a continuous period of time, ensuring the time series and dynamic changes of the data. To ensure the representativeness of the data, we selected data from different seasons within a year to cover various environmental conditions and traffic patterns. Specifically, the data collection span is from January to December 2023, covering the changes of four seasons, including extreme weather events. Such a time span helps us understand the impact of different seasons on the urban renewal governance model. This article takes as an example to ensure sufficient data points for reliable statistical analysis. In the traffic flow data, data is collected once every hour, 24 data points per day, and a total of 8760 data points throughout the year. For air pollutant concentrations, we also adopted a similar collection frequency. In addition, urban POI (point of interest) data were collected at specific time points through a geographic information system (GIS) to support our environmental impact analysis. Through this meticulous data collection approach, we were able to construct a comprehensive dataset that includes not only traffic and environmental data, but also socioeconomic factors such as population density and land use type. The combination of these data provides us with a multi-dimensional perspective to evaluate the effectiveness of urban renewal governance models. In this way, our dataset provides a solid foundation for research and enhances the credibility and practicality of our findings.

3.2. Data preprocessing

Data preprocessing is a critical step that involves transforming raw data into a format that is suitable for analysis. The following steps and equations are applied to ensure the data is in the best condition for modeling:

Normalization: To scale the features to a common range, we use the min-max normalization equation:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{5}$$

where x is the original value, $\min(x)$ is the minimum value of the feature, and $\max(x)$ is the maximum value of the feature. The result x' is a normalized value between 0 and 1.

Feature Scaling: For certain machine learning algorithms, it is important to scale the features so that they have a mean of 0 and a standard deviation of 1. This is done using the following equation:

$$z = \frac{x - u}{\sigma} \tag{6}$$

where x is the original value, u is the mean of the feature, and σ is the standard deviation. The result z is a standardized value.

Missing Value Imputation: For handling missing values, we use the mean imputation method, which replaces missing values with the mean of the feature:

$$x_{imputed} = \mu_x \tag{7}$$

where $x_{imputed}$ is the imputed value for the missing data point, and μ_x is the mean of the feature x.

Data Transformation: To improve the performance of the support vector machine (SVM) algorithm, we apply a kernel function to transform the data into a higher-dimensional space. The Gaussian kernel function is used:

$$K(x, y) = \exp\left(-\frac{\left||x - y|\right|^2}{2\sigma^2}\right) \tag{8}$$

where x and y are the input data points, $\left||x - y|\right|$ is the Euclidean distance between them, and σ is a free parameter that defines the width of the Gaussian curve.

Dimensionality Reduction: To reduce the dimensionality of the data while retaining the most important features, we use Principal Component Analysis (PCA). The transformation of the original data *X* into the new feature space *Z* is given by:

$$Z = XW \tag{9}$$

where *W* is the matrix of principal components, and *Z* is the new feature space with reduced dimensions.

3.3. Construction of environment tensor model

Firstly, a continuous heavy air pollution event was selected and divided into five stages according to the generation and dissipation of pollution, and the basic temporal and spatial characteristics of air pollutant concentration, meteorology and road speed were analyzed during the process. Secondly, based on the maximum information entropy theory, an environment-traffic-meteorological maximum information model is constructed to quantitatively analyze the combined effect of traffic restriction measures and meteorological conditions on the concentration of air pollutants. Finally, based on the calculation of association rules, the association rules of atmospheric composite pollution under different meteorological conditions are given. The specific technical route is shown in **Figure 4**.

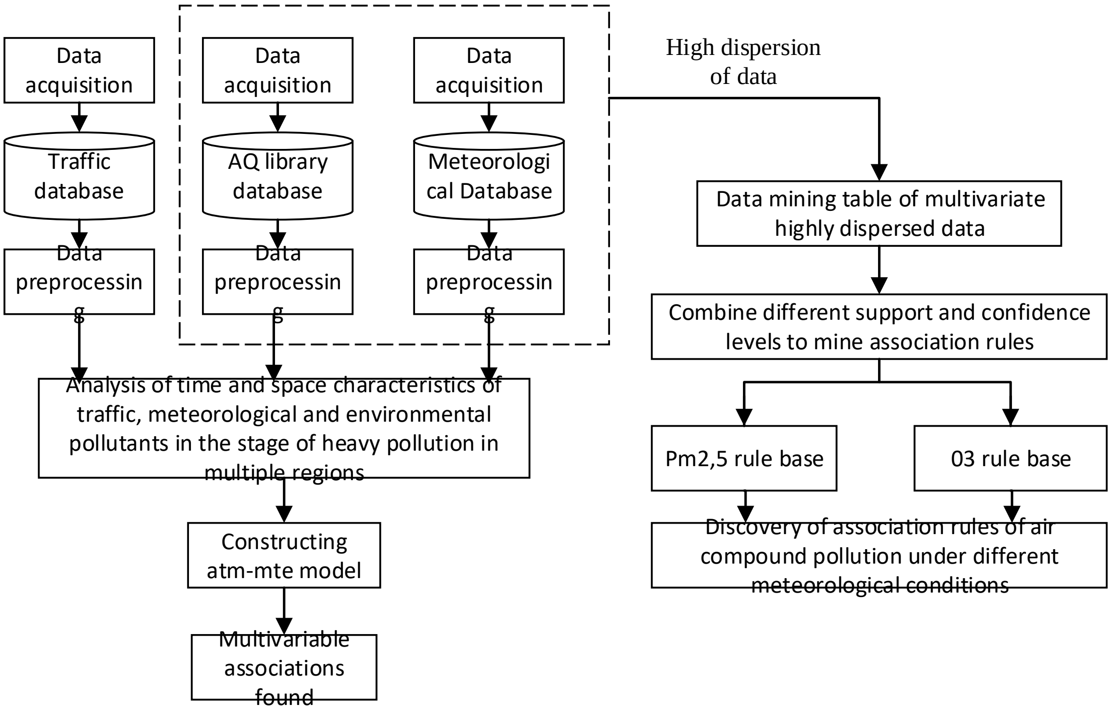


Figure 4. Technical route of air pollution correlation analysis research.

3.4. Classification of pollution patterns based on environmental tensor decomposition

The method for classifying environmental PM2.5 pollution patterns based on CP decomposition proposed in this paper is shown in **Figure 5**. The location-historical daytime 3-order environmental tensor model is decomposed into the sum of R rank-one environmental pollution pattern tensors. Among them, each rank-one environmental pollution pattern tensor maintains the dimension of the original tensor before decomposition, and still has three dimensions of location-historical daytime, but each rank tensor can be written as a three-dimensional vector of location-historical daytime The outer product of, that is, it can represent the change pattern in three dimensions at the same time. Secondly, the decomposed rank tensor is reconstructed into a new tensor, and the reconstruction error of each dimension is calculated as the criterion for the decomposition and evaluation of the environmental tensor CP. Specific steps are as follows:

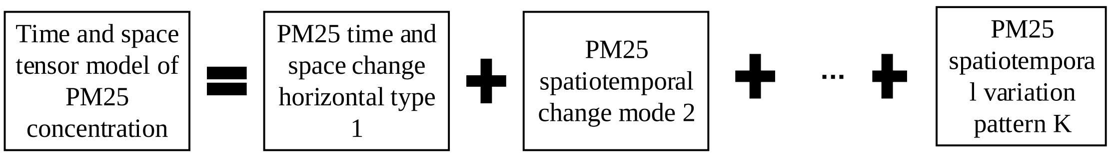


Figure 5. PM2 concentration. tensor CP mode.

3.5. Urban POI data model

To fully consider the impact of different types of points of interest in the city on ambient air pollution, an area with a radius of 4 km centered on the automatic ambient air monitoring station is set as the monitoring station's information service scope. In this way, the type and quantity of POIs within the information service range of each monitoring station are counted, and denoted as FD Frequency Density, where if refers to the quantity of the itch POI within a certain radius, and the statistical method is as shown in Equations (3)–(14). Due to the need to consider the environmental impact of different types of POIs, it is necessary to calculate the membership weight iNWS of a single POI point to any environmental site, where i indicates the itch POI point and j indicates the jet functional area. The style diagram is shown in **Figure 6**.

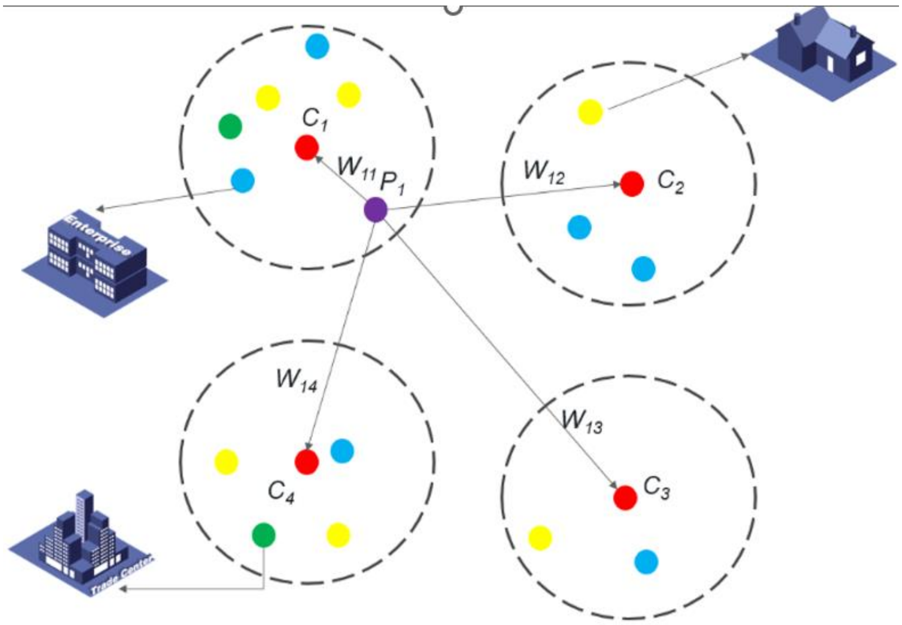


Figure 6. The relationship between POI and functional area membership.

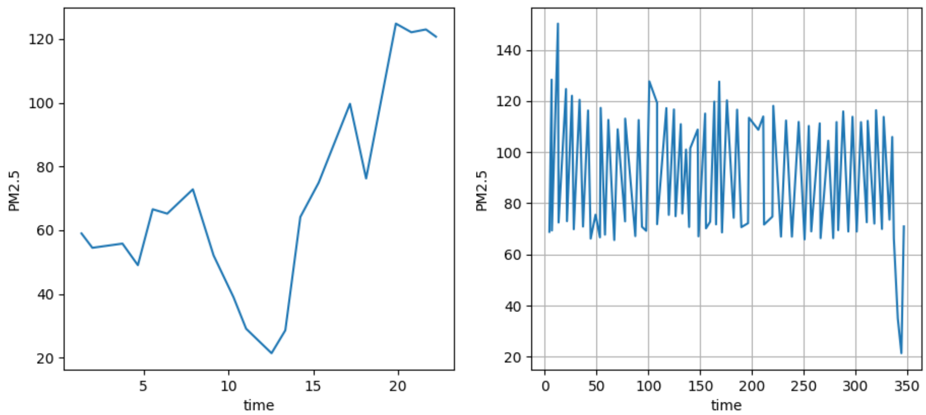
3.6. Environmental tensor CP decomposition results and function identification

Based on the decomposition of tensor CP, five types of environmental pollution patterns are divided, as shown in **Table 1**. Each type of PM2.5 pollution change pattern is described from the three dimensions of time-historical days-location. Combined with the trend of pollution changes and the types and quantities of surrounding POIs, the five types of PM2.5 change patterns are tentatively named as traffic area pollution patterns, living and residential areas pollution patterns, business district pollution patterns, industrial area pollution patterns, and ecological area pollution patterns. The geographic distribution of urban areas corresponding to various pollution patterns is depicted in different colors. Among them, red represents pollution patterns in industrial areas, purple represents pollution patterns in traffic areas, light brown represents pollution patterns in residential areas, dark blue represents pollution patterns in commercial areas, and green represents pollution patterns in ecological areas. From the regional attributes of the ecological zone pollution model, urban background points and open parks with many plants belong to this type, such as botanical gardens.

Table 1. Summary of results of environmental tensor decomposition and division of pollution modes.

Category	Temporary name	Point name
Pollution mode 1	Traffic area pollution mode	YDM, NSH, NZG, DSH, QM, LLH
Pollution mode 2	Pollution mode of living quarters	CP, MTG, MY, SY, TZ
Pollution mode 3	Pollution mode of business district	XZM, DS
Pollution mode 4	Pollution mode of industrial area	DX, YZ, YE, LX
Pollution mode 5	Ecological zone pollution model	WL, GY, AT, WSG, HDX, YG, GC, YQ, DL, BDL, MYSK, DG, YLD, ZWY, TT, FH, PG, HR

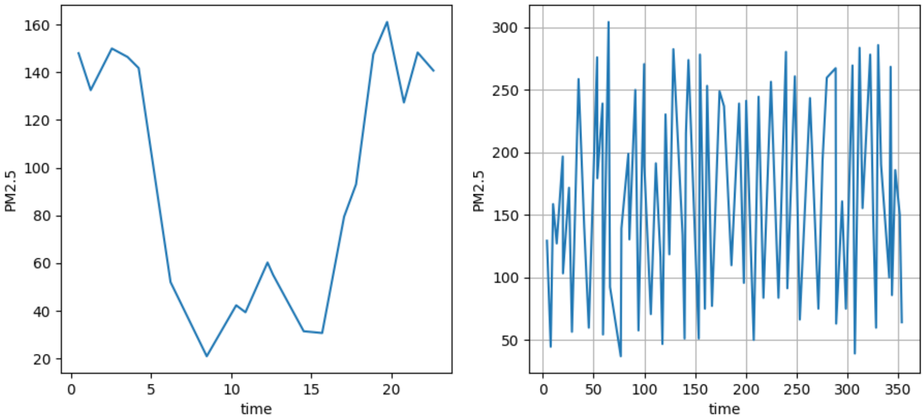
Figure 7a shows the hourly distribution of pollution patterns in the traffic area. There are two obvious peaks at 7:00 and 17:00 in one day, corresponding to the morning and evening peaks of traffic respectively; at night, because large diesel vehicles are allowed to enter the Fifth Ring Road, the concentration of particulate matter such as black carbon increases, which also causes One of the important reasons why PM2.5 concentrations are higher at night than during the day. **Figure 7b** shows a strong cyclical characteristic, which is closely related to the weekday-weekend traffic pattern; a short-term sudden trough appears at the end of the pattern, which corresponds to the Chinese New Year period in Beijing, where many vehicles are on urban roads. The reduction of traffic-related pollutants reduces the contribution of traffic-related pollutants to regional environmental quality to a certain extent. Such sites mainly include YDM, NSH, NZG, DSH, QM and LLH.



(a) **(b)**

Figure 7. Pollution patterns in traffic areas. **(a)** moments; **(b)** historical days.

Figure 8 shows that the pollution pattern in the industrial zone is quite different from that in the traffic zone, and the average concentration is higher than that in the traffic zone. **Figure 8a** shows that this type of pollution pattern has significantly higher concentrations at night than during the day. According to the surrounding POI information, this phenomenon is due to the existence of large industrial emission sources around the monitoring site, and the utilization rate of polluting facilities at night is lower than that during the day, that is, there is a "stealing phenomenon". This phenomenon also appeared in a regional ambient air quality study in Italy. For the pollution pattern on the historical days in **Figure 8b**, no obvious regularity can be seen, which is related to the normal operation of enterprises all year round. This type of points includes DX, YZ, YF and LX.



(a) **(b)**

Figure 8. Pollution patterns in industrial areas. **(a)** moments; **(b)** historical days.

4. Experiments

4.1. Model parameter selection

(1) Determination of input step size in the experiment, a total of 12 steps, 24 steps and 48 steps are selected as input, and the final input step is 24.

(2) Determination of the number of iterations the number of iterations is initially set to 2000 rounds, the algorithm automatically records the best prediction accuracy and iteration rounds, and automatically updates, and finally records the best training results.

(3) Set the error index training stage and verification stage, set the error score calculation method as Equation (10), the initial basic score is 2, with the update of the training result, the best score is automatically stored and updated, the lower the score represents the prediction The higher the accuracy.

$$\text{SMAPE}=\frac{100\%}{n}\sum_{i=1}^{n}\frac{(y_i-y_i^*)}{(y_i+y_i^*)/2} \tag{10}$$

Among them, y_i is the predicted concentration, y_i^* is the actual concentration, and the setting of SMAPE offsets the influence of the predicted score caused by the fluctuation of the actual concentration. In the prediction stage, set the prediction error to be calculated as Equation (11), which is the average error of the model prediction. In addition to the mean error, this chapter presents the error value for each of the 24 steps of forecasting to compare the accuracy of the reaction-sequence-to-sequence model for short- and long-term forecasts.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i+1}^{n}(y_i - y_i^*)} \tag{11}$$

4.2. Urban traffic passenger flow

Since the urban traffic passenger flow is divided into morning and evening peak periods and peaceful peak periods, the departure time interval of trains also changes with the change of passenger flow, and the data communication flow during different passenger flow periods also changes dynamically. To simulate the detection of data flow in different departure time intervals, three groups of data samples with different departure time intervals are simulated, and flood attack data are added to the samples. The data samples are shown in **Table 2**.

Table 2. Experimental samples.

Data number:	Departure interval/min	Number of normal data	Number of normal data
1	2	20.024	1464
2	3	18.723	1742
3	4	14.399	1369

The three sets of data are synthesized together to form a data input set, and one part of the synthesized data is used for training, and the other part is used as a test set, and the model is trained and verified according to the abnormal detection model process. The three groups of data are input into the detection model obtained by training, and the test simulation results are shown in **Table 3**. It can be seen from the simulation results that the detection model can show strong detection ability under different data traffic conditions, and there is no missed detection of attack data. The average false alarm rate for normal data is only 1.01%, and the average detection time is It is 4.61ms, which meets the requirements of network information security detection indicators and verifies the reliability and efficiency of the model.

Table 3. Statistics of simulation test results.

Data number:	Percentage of missed inspection	Percentage of false inspection/%	Detection time/MS
1	0	0.98	5.46
2	0	1.04	3.83
3	0	1.03	4.58
mean value	0	1.02	4.62

4.3. Air pollutant concentration prediction results

Table 4 shows the hour-by-hour forecast error of the series-to-series forecast model considering wind direction + time at forecast 24 h. For the first 6 h of the short-term prediction, the prediction accuracy is better; for the longer-term prediction of 12–24 h, although the prediction accuracy decreases when the prediction is shorter, compared with the literature LSTM prediction results, the prediction ability of the sequence-to-sequence model is still dominant. The comparison between the predicted value and the actual value is shown in **Figure 9**.

Table 4. Sequence model prediction results hour by hour (RMSE) in the next 24 h.

Prediction step	Sequential model considering wind direction + time	Sequential model without considering wind direction + time
0	9.13	10.33
1	9.54	11.90
2	13.26	14.38
3	15.24	15.90
4	16.72	17.46
5	16.23	16.84
6	17.16	17.19
7	18.13	18.03
8	17.55	18.57
9	18.30	19.19
10	20.18	20.52
11	22.54	22.99
12	22.03	22.76
13	22.87	23.07
14	20.79	23.16
15	20.55	23.56
16	22.56	24.11
17	25.18	23.98
18	24.81	24.77
19	26.80	27.99
20	27.86	28.61
21	30.38	30.54
22	30.87	32.47
23	31.25	34.17

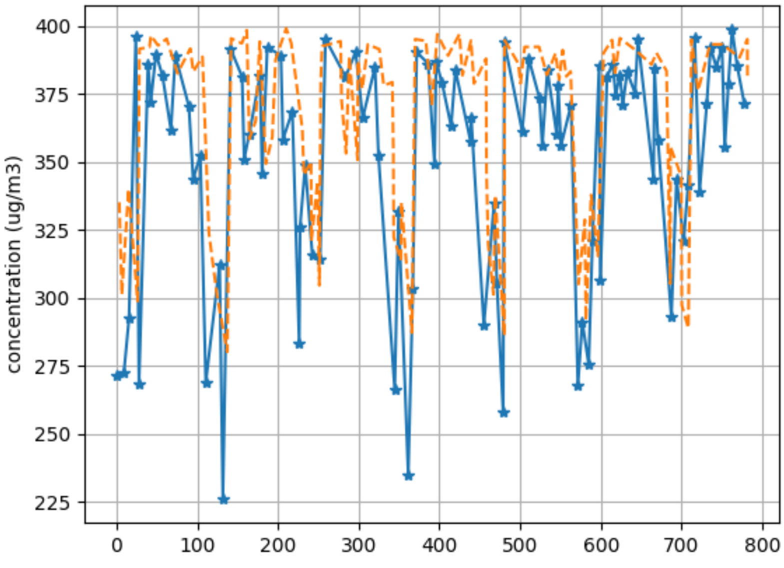


Figure 9. Comparison of predicted value and actual value.

Compared with other deep learning time series models, the series-to-sequence method considering wind direction shows better predictive ability in air quality index forecasting, as shown in **Table 5**.

Table 5. Comparison of forecast results of different time series.

Model category	**SMAPE**
Sequential model considering wind direction + time	0.538
Sequential model without considering wind direction + time	0.492
SLTM	0.503
RNN	0.514
CNN	0.814
ARIMA	0.672

5. Conclusion

This study has approached the complex issue of urban renewal governance under the “new normal” by employing data mining techniques to analyze and compare different governance models. Our findings indicate that the transformation of urban renewal governance is essential for achieving sustainable urban development. Through the case studies of Shenzhen, Guangzhou’s “three old” renovations, and Beijing’s “key villages” renovations, we have demonstrated that the integration of data mining with new institutionalism theory can provide a robust framework for understanding and predicting the effectiveness of various governance models.

Our proposed data mining model has shown strong modeling capabilities, effectively utilizing and characterizing multimodal information. The performance improvement over the baseline model is significant, highlighting the potential of our approach in urban renewal governance.

While our study provides valuable insights, it is not without limitations. First, the data used in this study is specific to certain cities, which may limit the generalizability of our findings to other urban contexts. Second, the data mining model, although robust, is subject to the quality and comprehensiveness of the data it is trained on. Additionally, the dynamic nature of urban environments means that models may need regular updates to remain accurate.

For future research, we suggest several directions to build upon our work. First, expanding the dataset to include more cities and diverse urban environments could enhance the model’s applicability and robustness. Second, exploring additional data sources, such as real-time social media data or satellite imagery, could provide a more comprehensive view of urban renewal processes. Third, investigating the long-term impacts of different governance models on social, economic, and environmental outcomes is crucial for understanding their sustainability.

Furthermore, future studies could also focus on developing more sophisticated models that can adapt to the dynamic changes in urban environments. This includes incorporating machine learning techniques that can learn from new data and continuously improve their predictions.

In conclusion, our study offers a novel perspective on urban renewal governance by leveraging data mining techniques. Despite its limitations, it paves the way for future research that can further explore the complexities of urban renewal and contribute to the development of more effective governance models.

Author contributions: Conceptualization, SH, JL, XZ, LP and YC; methodology, SH, JL, XZ, LP and YC; investigation, SH, JL, XZ, LP and YC; formal analysis, SH, JL, XZ, LP and YC; data curation, SH, JL, XZ, LP and YC; writing—original draft, SH, JL, XZ, LP and YC; writing—review and editing, SH, JL, XZ, LP and YC. All authors have read and agreed to the published version of the manuscript.

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Availability of data and materials: The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

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