The Impact of Mature National High-Tech Zone Development on Sustainable Smart City Development in China

Yun Qiu[1, #], Min Huang[2, #, *], Yuchen Cao[3, #]

[1]College of Business Administration China University of Petroleum 834000, Karamay, China

[2]School of Sports Economics and Management Central University of Finance and Economics

[3]College of Economics and Management Nanjing Agricultural University 210095, Nanjing, China

*Corresponding author: huangmin_0910@163.com

[#]equally contributed to this works

Abstract. In recent years, the rapid economic development of China's regions has led to a significant increase in urbanization, but this has been accompanied by significant resource consumption and pollutant emissions. So it is crucial to enhance sustainable development while achieving efficient urban development. Also National High-Tech Industrial Development Zones (NHTIDZs) have enhanced regional industrial agglomeration and technological innovation. This paper measured the Sustainable Smart Development level of cities and the development level of NHTIDZs. And using linear regression confirmed that high-tech zone development is closely related to urban development. Then used an Artificial Neural Network model to investigate the deeper correlation between the two. The results demonstrated that. (1) Although National High-tech Zone Index (NHTZI) had a significant effect on Sustainable smart cities index (SSCI), the effect was less than its grading index. (2) The ANN analysis shows that the Scale of the NHTIDZs has the greatest impact on the SSCI and also on the four SSCI classification indicators

Keywords: Artificial Neural Network; CRITIC method; Sustainable Smart City; National High-tech Zone.

1. Introduction

Currently, 56.2% of the world's population lives in urban area and the proportion of the global urban population is expected to increase to 68% by 2050 [1]. While urbanization has contributed to the world's economic development, it has also created challenges in terms of air pollution, congestion, waste management and healthcare. In order to achieve sustainable urban development, several countries have participated and set climate targets in recent years, such as the Paris Agreement [2]. China also formally proposed a carbon emissions target at the UN General Assembly general debate in September 2020. Recently, Internet Information Technology (ICT) is seen as a key factor in reducing greenhouse gas emissions and improving energy efficiency in cities with the benefits of lower costs, resource conservation, and increased efficiency. Therefore, the level of Sustainable Smart City development is a valid indicator to effectively quantify the all-round development of cities.

Due to the negative relationship between economic development and environmental governance, the formulation of legal policies and the improvement of the design of development plans are effective ways to control the ecology of the region and to balance the economy and the environment. In recent years, the Chinese government has made many efforts to promote economic growth while ensuring ecological benefits such as formally approving the establishment of National High-tech Industrial Development Zones (NHTIDZs) in 1991 to promote technological innovation through industrial clusters. A few scholars have focused on policy evaluation of national high-tech zones. Huang and Wang [3] have studied the policy impact of national development zones on firms' exports. Wang and Yang [4] analysed the impact of upgrading from provincial self-constructed high-tech zones to national high-tech zones on the efficiency of urban innovation. Wang and Feng [5] explored the impact of national high-tech zones on economic development and environmental pollution at national, regional and administrative levels. Wang and Yang [6] analysed the impact of national high-tech zone construction and its mechanisms on urban eco-innovation. They both use a DID model to assess policies before and after their occurrence, but do not explore the relationship between the actual level of development of national high-tech zones and urban development.

More recently, cities have been striving to achieve smart city goals rather than sustainable development goals [7]. About the definitions of smart cities, according to Caragliu et al. [8], the concept of 'smart city' can be understood as emphasising the importance and potential of ICT to help cities gain a competitive advantage. The Climate Group et al. [9] define a smart city as a city that strategically uses data, information and communication technologies to deliver efficient services to citizens, monitor policy outcomes, manage and optimise existing infrastructure, adopt cross-sectoral collaboration and enable new business models. In the different EU [10] perspective, the smart city concept supports the idea of environmental sustainability with the main objective of reducing greenhouse gas emissions in urban areas through the deployment of innovative technologies. Thus, the development of smart cities ultimately serves the high quality of urban development and is more sustainable. However, currently in the country smart cities have less content on climate change and environmental protection, and less use of smart tools in achieving sustainability goals. So, it is important to establish an effective sustainable smart city indicator system for urban development.

In order to measure the level of sustainable urban development as well as the level of smart development in a more comprehensive way, some studies have constructed and assessed the Sustainable Smart City (SSC) indicator system. Bhattacharyaa et al [11] provide a Smart Sustainable City Development Index to assess the sustainable urban development performance in developing countries. Carli et al [12] propose a multi-criteria decision-making technique to assess the sustainable development of metropolitan areas. Many international standards have been proposed based on local urban development realities, such as International Organisation for Standardisation (ISO) 37120: 2014 [13], ISO 37120: 2018 [14], ITU-T Y.4901/L.1601 [15], ITU-T Y.4902/L.1602 [16], ITU-T Y.4903/L.1603 [17]. and China New Smart City Evaluation Index (GB/T 33356-2016) [18] Through a consistent and standardised approach to sustainable progress measurement, relevant indicators for the Sustainable Smart City Index are defined in these standards.

Furthermore, China's economic growth has been accompanied by the formation and expansion of NHTIDZs in recent years, but the impact of this has yet to be assessed. This paper proposed to use an Artificial Neural Network (ANN) approach to investigate the impact of the mature national high-tech zone development index on cities’ sustainable smart development level, and create two index system to measure the development level of sustainable smart city and NHTIDZs. The results can be used to predict the role of mature national high-tech zones for future cities.

2. Innovative industry clusters on sustainable smart city indicator system construction

2.1 High-tech Industrial Development Zone Index (NHTZI) System

China's National High-tech Industrial Development Zones (NHTIDZs) are the backbone of China's high-tech industry and a key driver of innovation and economic growth in China. Being a national high-tech zone will lead to a significant increase in policy advantages for enterprises, enjoying more favourable national-level administrative, land resources, export and tax policies, which is a major strategic arrangement for China. As a result, national high-tech zone policy has become a major practical concern for both academics and policy makers. [18] In order to investigate the impact of the development of NHTIDZs on the comprehensive development index of sustainable urban intelligence in financial, economic, scale and technological terms, a national high-tech zone index (NHTZI) system was established as shown in Table 1 according to the former research.

Table 1 NHTZI indicator system

Evaluation system	Tier 1 indicators	Secondary indicators	Reference
National High-tech Industrial Development Zone Development Level	Economic indicators X_E	Total industrial output X_{E1}	[19]
		Operating income X_{E2}	[20]
		Profitability X_{E3}	[20]
	Size indicators X_S	Number of enterprises included in the statistics X_{S1}	[21]
		Employed population at the end of the year X_{S2}	[21]
	Science and Technology Indicators X_T	Proportion of personnel engaged in scientific and technological activities X_{T1}	[21]
		Internal expenditure on scientific and technological activities as a percentage of operating revenue X_{T2}	[19]

2.2 Sustainable Smart City Indicator (SSCI) System

Sustainable smart cities (SSC) are innovative cities that use ICTs to improve quality of life, the efficiency of city operations and services, and competitiveness, while ensuring that the economic, social, environmental and cultural needs of all generations are met. While cities where all municipal systems and services are connected do not yet exist, many cities have bought into the sustainable smart city path, relying on ICT to improve energy efficiency, improve waste management, improve housing and health security, optimise traffic flow and safety, detect air quality, and improve water and sanitation systems.

In order to assess the performance of SSCI, many smart city indices and frameworks have been proposed to support local governments in policy formulation at the city level. SSCI is a complex system consisting of multiple elements, and the construction of an evaluation indicator system for sustainable wisdom should not only reflect sustainable indicators objectively and effectively, but also show the main features and contents of a smart city. The selection of indicators should follow the principles of comprehensiveness, relevance, operability and people-orientation in the selection of indicators. Combined with existing evaluation indicator systems, this paper selects the following indicators to measure SSCI.

Table 2 SSCI evaluation indicator system

Evaluation system	**Tier 1 indicators**	**Secondary indicators**	**Reference**
Sustainable Smart Cities Index	Population and Economy Y_{PE}	Total population at the end of the year Y_{P1}	[19]
		Natural growth rate Y_{P2}	[22]
		Gross regional product per capita Y_{M2}	[13]
		Gross regional product growth rate Y_{E2}	[13]
		Secondary sector value added as a proportion of GDP Y_{E3}	[13]
		Tertiary sector value added as a proportion of GDP Y_{E4}	[13]
	Ecosystem and Governance Y_M	Urban built-up land area Y_{M1}	[20]
		Area of greenery coverage in built-up areas Y_{M2}	[23]
		Greenery coverage in built-up areas Y_{M3}	[23]
		Number of public toilets Y_{M4}	[22]
		Industrial wastewater discharge Y_{M5}	[22]
		Industrial sulphur dioxide emissions Y_{M6}	[13]
		Industrial smoke, dust and fume emissions Y_{M7}	[13]
		Harmless disposal rate of domestic waste Y_{M8}	[22]
		Integrated utilization rate of general industrial solid waste Y_{M9}	[22]
		Centralized treatment rate of sewage treatment plants Y_{M10}	[22]
	Energy consumption Y_G	Annual electricity consumption Y_{G1}	[13]
		Industrial electricity consumption Y_{G2}	[13]
		Electricity for urban domestic consumption Y_{G3}	[13]
		Total gas supply Y_{G4}	[13]
		Total LPG gas supply Y_{G5}	[13]
	Digital Economy Y_D	Revenue from telecommunications business Y_{D1}	[18]
		Information transmission computer services and software industry Y_{D2}	[18]
		Number of Internet broadband access subscribers Y_{D3}	[15]
		Financial Inclusion Index Y_{D4}	[18]
		Year-end mobile phone subscribers Y_{D5}	[18]
		Number of international Internet users Y_{D6}	[15]

3. CRITIC method

The inter-criteria conflicting correlation method is an objective weighting method that takes into account the size of the variance of the indicators and the influence of the conflicting nature of the indicators on the weights. The method uses standard deviation to indicate the size of the difference in values taken between evaluation schemes; and indicator correlation to indicate the conflicting nature of the evaluation indicators, making it an effective method for studying the determination of objective weights for indicators. The specific steps of the method are as follows.

Step 1: Calculate the standard deviation.

$$\sigma_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}(x_{ij}-\overline{x}_j)^2} \tag{1}$$

Where: $\overline{x}_j$ is the mean of the indicators; X_j from the m program; σ_j is the standard deviation of X_j .

Step 2: Construct the correlation coefficient matrix.

$$r_{ij} = \frac{\sum_{i=1}^{n}(x_i-\overline{x}_i)(x_j-\overline{x}_j)}{\sqrt{\sum_{i=1}^{n}(x_i-\overline{x}_i)^2\sum_{j=1}^{n}(x_j-\overline{x}_j)^2}} \tag{2}$$

Where: $\overline{x}_i$ is the mean of all scenarios in the indicator X_i ; $\overline{x}_j$ is the mean of all scenarios in the indicator X_j ; r_{ij} is the correlation coefficient between the indicator X_i and the indicator X_j .

Step 3: Find the combined weight of each indicator W_{CRI}

$$\begin{cases} W_{CRI} = \dfrac{C_j}{\sum_{i=1}^{n} C_j} \\ C_j = \sigma_j \sum_{j=1}^{n}(1-r_{ij}) \end{cases} \tag{3}$$

4. Artificial Neural Networks

Artificial neural networks are numerical and mathematical models that simulate the neural structure of the human brain and possess strong parallel, distributed storage, processing, self-organisation, self-adaptation and self-learning capabilities, as well as being fault-tolerant, capable of simulation, recognition of binary images, fuzzy control and prediction, making them an effective tool for accurately dealing with non-linear systems. Neural networks are generally divided into an input layer, a hidden layer and an output layer. This paper gives the general topology of a three-layer neural network, each layer consisting of multiple artificial neuron elements, often referred to as neurons, as shown in Figure 1. The combination of signals from the neurons in the previous layer is received by the neurons in the next layer, and after a layer of transformation, the signals are transformed by an activation function. A weighted connection between the neurons sends the output of the neuron from the previous layer to the input of the neuron in the next layer. The main function of the neuron is to extract knowledge from the training data and store the learned knowledge as weights for the connections.

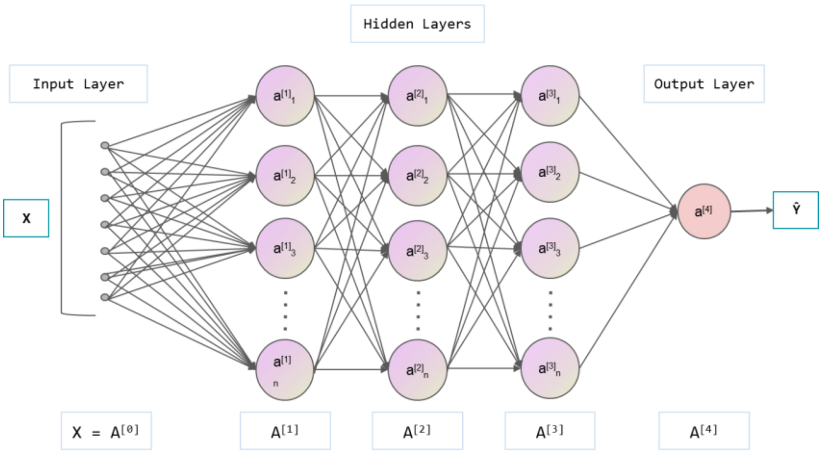


Figure 1 Neuron topology

5. Empirical analysis

5.1 Data collection and processing

A total of 27 cities were selected as samples from Zhongguancun in Beijing and the first batch of approved NHTIDZs that followed, containing the 27 earliest established NHTIDZs in China with mature development, including the four municipalities that represent the political and economic centre of China, and including several regional political and economic centre cities. The analysis of these 27 mature NHTIDZs policy cities better reflects the relevance of the high level of construction of China's NHTIDZs to the sustainable and intelligent development of cities.

All data were calculated and collated from the China Torch Program Statistics 2011~2019, China City Yearbook 2011~2019, China City Statistical Yearbook 2011~2019, City Construction Statistical Yearbook Statistical Yearbook of Provinces and Cities, Peking University Digital Inclusive Finance Index, Ministry of Science and Technology Torch High Technology Industry Development Centre website data, and then data normalization process.

5.2 Index measures

5.2.1 Measurement of the High-tech Industrial Development Zone Development Index

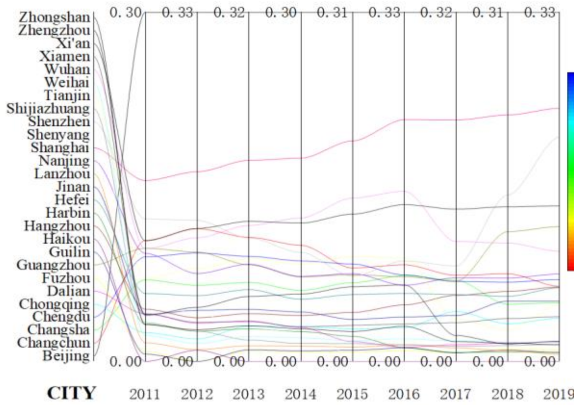
The weights of the seven indicators for the 27 mature NHTIDZs cities from 2011 to 2019 were determined according to the CRITIC method, where the sum of the weights of all indicators for the same year in the NHTIDZs was 1. The weight results of 2019 are given in Table 3, and the results of 2011-2018 are similar.

Table 3 Indicator CRITIC Weights of NHTIDZs in 2019

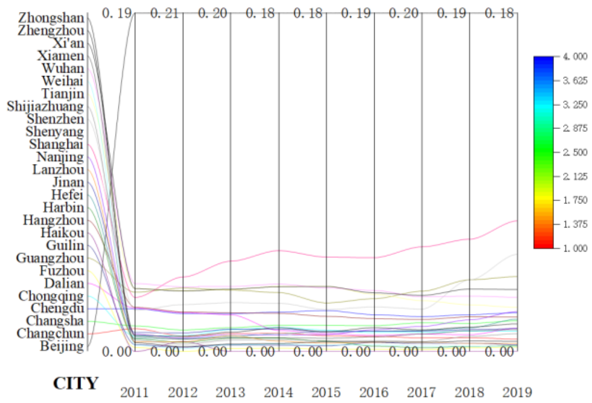
NHTZI	E1	E2	E3	S1	S2	T1	T2
Critic Weight	0.148	0.093	0.089	0.099	0.085	0.27	0.218

The weights of the indicators were used to distinguish the importance of the different indicators for the sustainability assessment. Then the NHTZI rating was calculated from the objective weights of the indicators, and the results are presented in Figure 2.

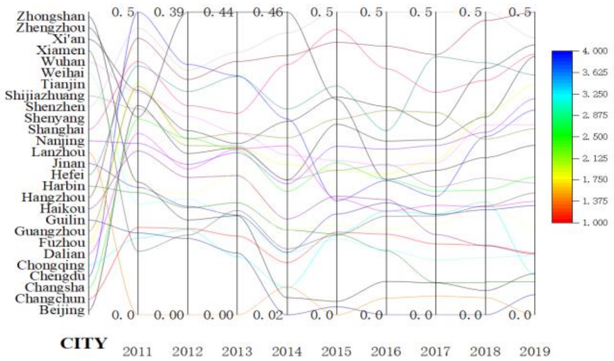
In terms of the evaluation of NHTZI, the results for the same city remained relatively stable across cities from 2011 to 2019, and the results for different cities were relatively different. Beijing's NHIZI levels from 2011 to 2019 were 82.2%, 74.6%, 76.6%, 69.8%, 79.7%, 79.3%, 78.9%, 81.2% and 92.2% respectively, all of which were the highest levels among cities shown in Figure (d). This advantage was still present in the Economic Indicator, Scale Indicator and Science and Technology Indicators, shown in Figure (a), (b), (c).



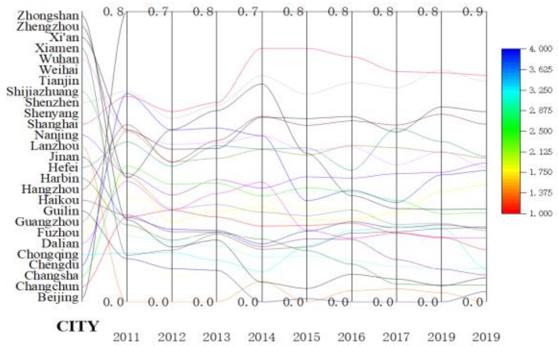
(a) Economic Indicator Measurements



(b) Scale Indicator Measurements



(c) Technology Indicator Measurements



(d) Total NHTZI Measurements

Figure 2 The Development Level of NHTIDZs

Figures (a), (b), (c) show the results of the NHTZI level 1 indicator measures for 2011-2019 respectively, and figure d indicates the results of the NHTZI measures. The vertical axis indicates the measurement results.

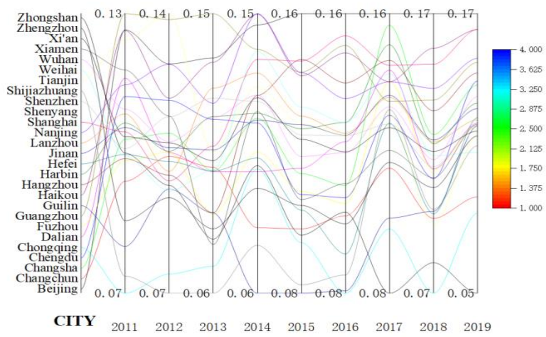
5.2.2 Measurement of Sustainable Smart Cities Index

Based on the CRITIC weighting method, the primary indicators weights of the SSC could be determined. The weight results of 2019 are given in Table 4, and the results of 2011-2018 are similar.

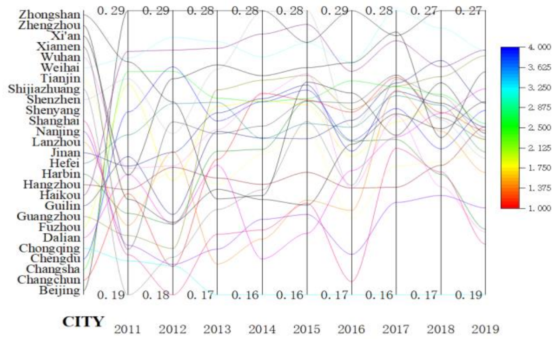
Table 3 Indicator CRITIC Weights of SSC in 2019

Indicator	**P1**	**P2**	**E1**	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**
weight	0.016	0.004	0.042	0.015	0.001	0.005	0.005	0.066	0.034	0.041
M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**	**M10**	**M11**
0.04	0.04	0.002	0.048	0.026	0.044	0.031	0.038	0.001	0.003	0.001
G1	**G2**	**G3**	**G4**	**G5**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
0.026	0.029	0.037	0.085	0.086	0.034	0.119	0.025	0.001	0.028	0.028

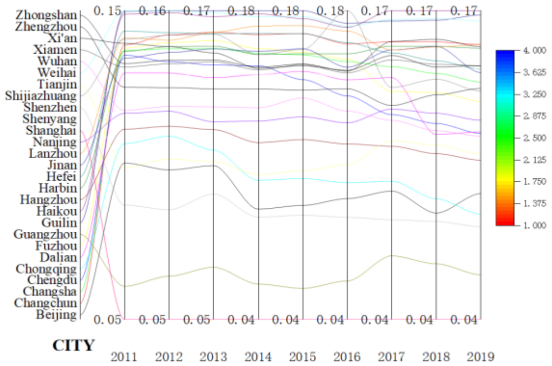
Based on the objective weights derived from the CRITIC method, the SSCI and its combined levels for the four dimensions were calculated and shown below. Beijing's SSCI levels were the highest among cities.



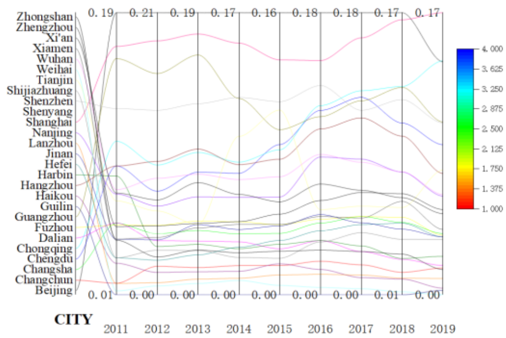
(a) Population and Economy Indicator Measurements



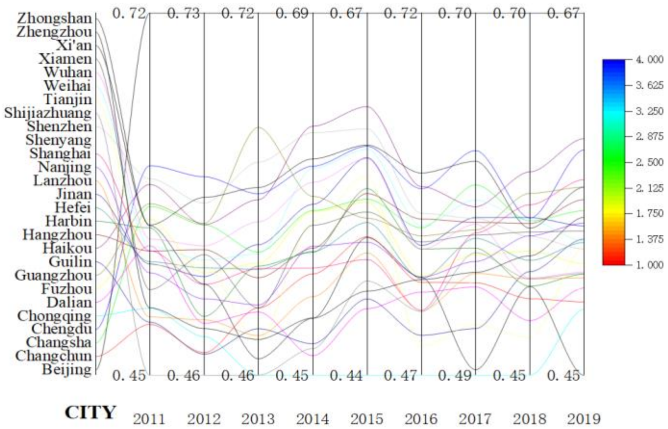
(b) Environment Management Indicator Measurements



(c) Energy consumer Indicator Measurements



(d) Digital Economy Indicator Measurements



(e) Total SSCI Measurements

Figure 3 The Development Level of SSCI

Figures (a), (b), (c), (D) show the results of the SSCI level 1 indicator measures for 2011-2019 respectively, and figure (e) indicates the results of the SSCI measures. The vertical axis indicates the measurement results.

5.3 Impact analysis

5.3.1 Linear Regression Analysis

In order to study the relationship between the level of development of high-tech zones and the level of sustainable urban intelligence, this paper used SSCI as the dependent variable and NHTZI and its Tier 1 indicators as the independent variable for regression analysis.

According to the table 3 and 4, the F-test results for both models show a significance p-value of 0.000***, which presents significance at the level and rejects the original hypothesis, therefore the model is valid.

As shown in Table 5, it can be considered that the regression effect is significant at the 1% level, which means that there is a significant and positive influence of the level of development of high-tech zones on the level of sustainable wisdom of the city, and the regression coefficient between them is derived from the regression analysis.

Table 5 Results of linear regression analysis

Variables	Regression coefficient	standard error	T	P	R^2	F
const	0.5	0.005	98.604	0.000***	**within=0.02 between=0.446 overall=0.313**	**F=109.859 p=0.000*** **
NHTZI	0.147	0.014	10.481	0.000***		

As shown in Table 6, apart from Economy indicator, both Scale and Technology indicators have a significant impact on the SSCI, with Scale indicator having the greatest impact.

Table 6 Results of linear regression analysis

Variables	Regression coefficient	standard error	T	P	R^2	F
const	0.514	0.005	105.449	0.000***	**within=0 between=0.587 overall=0.465**	**F=69.279 p=0.000*** **
Economy	-0.093	0.084	-1.105	0.270		
Scale	1.009	0.151	6.696	0.000***		
Technology	0.07	0.023	3.048	0.003***		

Note: *, **, * represent 1%, 5%, 10% level of significance respectively**

Therefore, the regression equation for the NHTZI and SSCI is:

$$SSCI = 0.5 + 0.147 \times NHTZI \tag{4}$$

$$SSCI = 0.514 + 1.009 \times Scale + 0.07 \times Tech \tag{5}$$

5.3.2 Artificial Neural Network

Based on the above analysis, the ANN model was selected for further analysis in this paper, and the importance analysis of NHTZI and its secondary indicators on the prediction of SSCI and its secondary indicators was obtained as shown in Figure 4 and Figure 5(a)-(d). In this case, 70% of the data are randomly selected as the training set and 30% as the test set. The analysis uses data from 28 mature cities of high-tech zones from 2011 to 2019, so there are 252 samples in total. The number of samples in training set and test set is 176 and 76 respectively. Then the sensitivity of the input layer to the output layer is analysed by minimising the training error, and the relationship between the explanatory and dependent variables is investigated by calculating the synaptic weights at this point. The ANN errors for this training were small, with the average error in the training set at 5.3% and the average error in the test set at 7.2%, indicating that the model has a strong confidence level.

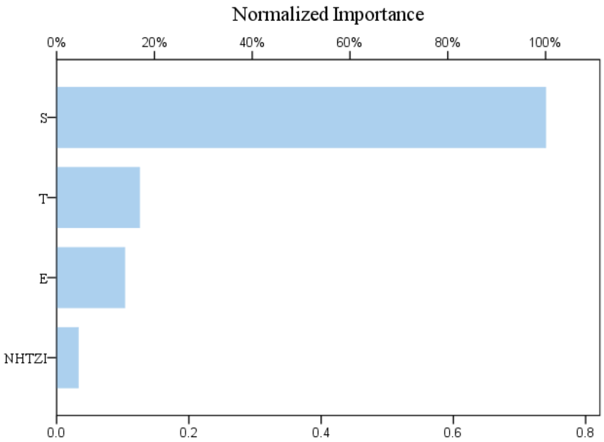
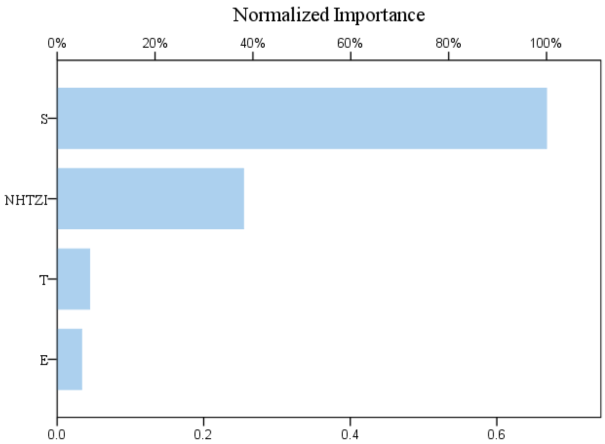
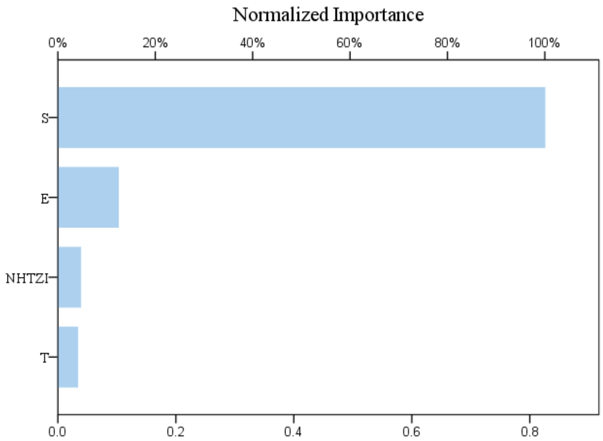


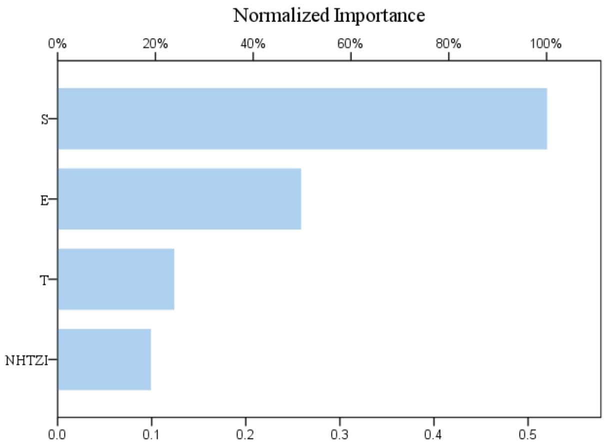
Figure 4 Importance of NHTZI and its Tier 1 indicators for SSCI prediction



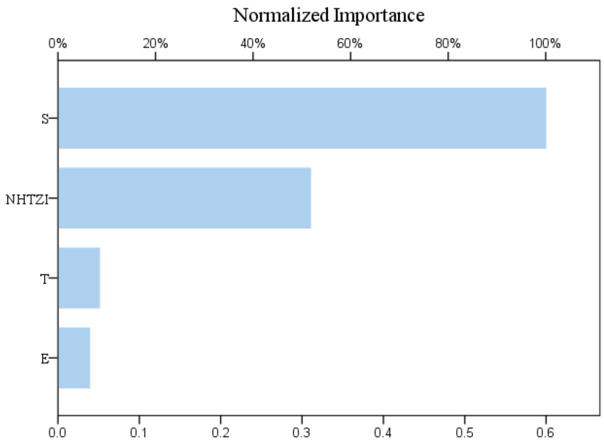
(a) Importance of NHTZI and its Tier 1 indicators for PE forecasting



(b) Importance of the NHTZI and its Tier 1 indicators for M forecasting



(c) Importance of the NHTZI and its Tier 1 indicators for G projections



(d) Importance of the NHTZI and its Tier 1 indicators for D projections

Figure 5 Importance of NHTZI for predicting SSCI secondary indicators

Scale (S), Technology (T) and Economy (E) are the Tier 1 indicators of NHTZI, Population and Economy (PE). SSCI Tier 1 indicators include M, Energy consumption (G) and Digital Economy (D).

As can be seen in Figure 4, S indicator has the greatest impact on sustainable smart city development with an importance of 80.5%. Weaker influences are T and E indicators with an importance of 9.4% and 6.7% respectively. The least influential is the composite indicator NHTZI, which is only 3.3% important.

In Figure 5, S has the most significant importance for SSCI Tier 1 indicators including PE, M, G and D, at 44.4%, 82.5%, 48.3% and 59.8% respectively, with the greatest importance for M forecasts, which has exceeded 80%, indicating that scale has a NHTZI has the next highest importance for PE and D projections and both have a small difference of around 20%. In Figure 5(a), E has the least impact at 10.8%. The importance of E and NHTZI on M in Figure 5(b) is 3.9% and 3.3% respectively. In Figure 5(c), both T and E have a predicted importance of nearly 20% for G, while NHTZI has the most 11.7%. In Figure 5(d) both E and T are no more than 10% important for the prediction of D, at 9.1% and 5.1%, respectively.

6. Conclusion

This paper first constructed NHTZI and SSCI and measured related indicators, selected CRITIC method to calculate the weight of each indicator of NHTZI and SSCI respectively, and then used ANN model to analyze the impact of NHTZI on SSCI, and concluded as follows.

(1) Beijing was the best performing city in both the NHTZI and SSCI measures.

(2) Through linear regression analysis, it is concluded that high-tech zone development is closely related to the sustainability and intelligence of the city. And the increase in the level of high-tech zones promotes the development of sustainable smart cities.

(3) The ANN model analysis revealed that the impact of the total value of NHTZI on SSCI is minimal. This suggested that the combined impact of NHTZI could be diluted by its constituent components.

(4) The secondary indicator Scale(S), which constitutes the NHTZI, is the most important for SSCI prediction, indicating that among the secondary indicators that constitute the NHTZI the indicator of size has a greater impact on the development of sustainable smart cities. So, in order to improve the SSCI level, the emphasis on size in the NHTZI needs to be strengthened.

References

[1] World Cities Report 2020: The Value of Sustainable Urbanization[R].2020

[2] Paris Agreement, C.N.63. 2016.TREATIES-XXVII.7. d.2016

[3] Wu, M., Huang, J.L. Provincial development zones, leading industries and county industrial development. econ. perspect. 2017, 52-61. (In Chinese)

[4] Wang Q, Yang R, Zhao R, Wang C. Does State-level Upgrade of High-tech Zones Promote Urban Innovation Efficiency: Evidence from China. Sustainability. 2019; 11(21):6071.

[5] Wang, X., Feng, Y. The effects of National High-tech Industrial Development Zones on economic development and environmental pollution in China during 2003–2018. Environ Sci Pollut Res 28, 1097–1107 (2021).

[6] Yang S, Liu W, Zhang Z. The Dynamic Value of China’s High-Tech Zones: Direct and Indirect Influence on Urban Ecological Innovation. Land. 2022; 11(1):59.

[7] M.-L. Marsal-Llacuna, J. Colomer-Llinàs, J. Meléndez-Frigola Lessons in urban monitoring taken from sustainable and livable cities to better address the Smart Cities initiative Technological Forecasting and Social Change, 90 (B) (2015), pp. 611-622, 10.1016/j.techfore.2014.01.012

[8] A. Caragliu, C. del Bo, P. Nijkamp Smart cities in Europe 3rd Central European Conference in Regional Science -CERS, Centre for Regional Science (2009) (2007) Smart cities final report

[9] The Climate Group, ARUP, Accenture, Horizon Information Marketplaces: The New Economics of Cities

[10] Cities of tomorrow - Challenges, visions, ways forward.2011.10

[11] Bhattacharya, T.R.; Bhattacharya, A.; McLellan, B.; Tezuka, T. Sustainable smart city development framework for developing countries. Urban Res. Pract. 2018, 13, 180-212.

[12] Carli, R.; Dotoli, M.; Pellegrino, R. Multi-criteria decision making for sustainable metropolitan cities assessment. j. Environ. Manag. 2018, 226, 46-61.

[13] International Organization for Standardization (ISO). Sustainable Development of Communities-Indicators for City Services and Quality of Life; ISO 37120:2014; ISO: Geneva, Switzerland, 2014.

[14] International Organization for Standardization (ISO). Sustainable Cities and Communities—Indicators for City Services and Quality of Life; ISO 37120:2018; ISO: Geneva, Switzerland, 2018.

[15] International Telecommunication Union Focus Group on Smart Sustainable Cities (ITU-T FG-SSC). Key Performance Indicators Related to the Use of Information and Communication Technology in Smart Sustainable Cities; ITU-T Y.4901/L.1601; ITU-T FG- SSC; United Nations: Geneva, Switzerland, 2016.

[16] International Telecommunication Union Focus Group on Smart Sustainable Cities (ITU-T FG-SSC). Key Performance Indicators Related to the Sustainability Impacts of Information and Communication Technology in Smart Sustainable Cities; ITU-T Y.4902/L.1602; ITU-T FG-SSC; United Nations: Geneva, Switzerland, 2016.

[17] International Telecommunication Union Focus Group on Smart Sustainable Cities (ITU-T FG-SSC). Key Performance Indicators for Smart Sustainable Cities to Assess the Achievement of Sustainable Development Goals; ITU-T Y.4903/L.1603; ITU-T FG-SSC; United Nations: Geneva, Switzerland, 2016.

[18] Standardization Administration of the P.R.C. Evaluation Indicators for New-Type Smart Cities; GB/T 33356-2016; China National Information Technology Standardization Network: Beijing, China, 2016. (In Chinese)

[19] Research on the Structural Characteristics of Regional High-tech Industrial Cluster Innovation Network-the Empirical Analysis of Hunan Province [J]. Finance Theory and Practice,2021,42(04):123-130.

[20] National High-tech Industrial Development Zone Comprehensive Evaluation Index System Released. Henan Science and Technology (15), 2. (2021).

[21] Zhang XM & Tang QY. (2013). Research on the development evaluation of national high-tech industrial development zones. World Geography Research (01), 114-120.

[22] Liu Yingbing, Du Wenying, Chen Nengcheng & Wang Xiaolei. (2020). Construction and Evaluation of the Integrated Perception Ecological Environment Indicator (IPEEI) Based on the DPSIR Framework for Smart Sustainable Cities. sustainability (17).

[23] Konstantinos A. Komnitsas. (2011). Potential of geopolymer technology towards green buildings and sustainable cities. procedia Engineering(C).