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Evaluation on Construction Level of Smart City: An Empirical Study from Twenty Chinese Cities

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Abstract: Currently, the construction of smart cities (SCs) has been booming all over the world and it also acts as a useful tool for the Chinese government to promote the sustainable development of cities. Identifying the aspects of SCs and systematically evaluating the level of smart city construction are significant for urban management and healthy development. Based on the bibliometrics and Chinese experience with smart city construction, this paper firstly proposes dividing the smart city system into four subsystems, that is, smart infrastructure, smart economy, smart governance and smart participation and to establish their corresponding indicator systems. Information entropy method and grey correlation analysis are then adopted to determine the weight of each indicator and evaluate the city smartness level respectively. After that, 20 major cities in China are taken as cases for evaluation. The evaluation is performed on the grey correlation degree of these cities and their variations between 2012 and 2016. Through the further comparison of regional distribution and clustering analysis of these cities, the paper points out the general characteristics and level differences of smart city construction in China. Finally, some policy implications are proposed to improve the smartness level for Chinese cities.

Keywords: smart city; construction level; grey correlation analysis; information entropy

1. Introduction

The world is at an unprecedented level of urbanization [1]. Globally, more people live in urban areas than in rural areas, with 55% of the world's population, 4.2 billion, residing in urban areas in 2018 and 68% of the world's population is projected to be urban by 2050 [2]. With rapid urbanization and urban population growth worldwide, a variety of technical, social, economic and organizational problems have been raised that tend to jeopardize the economic and environmental sustainability of cities [3]. The expansion of cities faces a variety of challenges [4], including difficulty in waste management, scarcity of resources, air pollution, human health concerns, traffic congestion and inadequate, deteriorating and aging infrastructures [5,6]. The unprecedented rate of urban growth creates urgency to finding smarter ways to manage the accompanying challenges [7]. In this context, some debates have emerged on the way new technology-based solutions, as well as new approaches to urban planning and living, can assure future viability and prosperity in metropolitan areas [8,9]. The smart cities (SCs) approach is emerging as a way to solve tangled and wicked problems inherited in the rapid urbanization [10].

The concept of SCs has generally become a new paradigm of smart city development and sustainable socio-economic growth [11], whose origin can be traced back to the Smart Growth Movement of the late 1990s [12]. Despite there is some kind of consensus emphasis the SCs represents innovation in city management, its services and infrastructures, a common definition of this concept has not yet been stated. There is a wide variety of definitions of what a Smart City could be [13]. However, two trends can be clearly distinguished in relation with what are the main aspects that SCs must take into consideration [14]. On the one hand, there is a set of definitions that put emphasis just on one urban aspect (technological, ecological, etc.) leaving apart the rest of the circumstances involved in a city. On the other hand, some authors emphasize how the main difference of the Smart City concept is the interconnection of all the urban aspects. The tangled problems between urbanization are infrastructural, social and institutional at the same time and this intertwining is reflected in the Smart City concept [7,15].

SCs are nowadays widespread all over the world; in all the continents, cities are moving towards smarter urban spaces, using high technologies to face the crucial problems linked with the urban life like traffic, pollution, city crowding, poverty [6]. Some cities are identified to successfully operate in a smarter way to solve concerns. The city of Riverside in California is improving traffic flow and replacing aging water, sewer and electric infrastructure by tech-based transformation. Estonia overcame post-Soviet economic ruin and its capital city Tallinn played as a center to economic development, harnessing information and communication technologies (ICTs). The city developed a large-scale digital skills training program, extensive e-government and an award-winning smart ID card. Taoyuan County in Taiwan is home to the international airport. The Aerotropolis initiative makes its economy more robust and improves quality of living through ICTs. A common fact underlies the practices: that is, those cities are meeting a growing demand for more livable cities. The cities are being labeled with a common phrase: smart city. In the recent years, the SCs has taken on a new dimension of using ICTs to build and integrate critical infrastructures and services of a city. The initiatives of making a city smart have recently emerged as a model to mitigate and remedy current urban problems and make cities better as places to live. Hence some view smart city as an icon of a sustainably livable city [7].

Since 2010, China has been attaching great attention to the construction of SCs. The State Council and the local governments at all levels have released many policies on SCs. As a new pattern of developing and governing a city, SCs have been gradually recognized and accepted by the society. As of the end of 2017, more than 500 pilot cities were under the construction of smart cities in China and such number of cities ranked first in the world. Chinese cities are striving to construct smart cities due to the potential solutions they may offer to a series of problems in the current society. However, the construction of SCs in China started late and local governments did not formulate comprehensive planning for smart city construction. Many cities blindly compare and imitate with each other during the smart construction, which lead to the functional duplication and failure of formulating a complementary relationship between cities. Besides, in the construction process, the cities "attach more importance to construction than to application" and there is also a lack of unified industry standards, construction standards and evaluation standards, resulting in the serious resources waste and the low efficiency construction [16,17]. Therefore, it is necessary to establish an evaluation system that reflects the real situation of smart city construction and better guide its future development.

Defining the concept of SCs is the premise of establishing evaluation system. Due to the inconsistent understanding of SCs, the domains of smart construction usually show great differences. Giffinger et al. explain the term 'smart city' by distinguishing six conceptually distinct characteristics: economy, people, governance, mobility, environment and living [18]. This classification method was also accepted by many following scholars [19–21]. From the perspective of object, the construction of SCs can be divided into hard domains and soft domains. The former includes office and residential buildings, energy grids, natural resources, energy and water management, waste management, environment, transportation, mobility and logistics. In these settings, an improvement in sustainability relies on the deployment of ICT systems, along with the introduction of appropriate policy interventions and urban planning. While the latter include education, culture, policies that foster entrepreneurship, innovation and social inclusion, as well as communication between local public administrations and citizens (e-government).

Building a comprehensive model to evaluate the effectiveness of smart city initiatives is a difficult task, mainly because smart city is a multifaceted, multi-technical approach that covers a wide range of cities and requires a number of initiatives [22]. Starting from the concept of integrated data management, Wolisz et al. used a City District Information Model (CDIM) to simulate a sustainable management strategy for energy in future smart city [23]. Calvillo et al. used a linear programming model to evaluate the most common distributed generation (DG) in current and future SCs by taking Madrid, Spain as an example [24]. Mummolo et al. developed a Decision Support System (DSS) tool for configuring an environmental compliant Integrated Waste Management System (IWMS) of a smart city in Southern Italy [25]. Shi et al. used Analytic Hierarchy Process (AHP), AHPBP (Back Propagation) and AHP-ELM (Extreme Learning Machine) models to evaluate the smartness level of 151 cities [26]. Similarly, Xiang and Ren [27] used analytic network process to construct the network diagram of smart city evaluation system and use the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) to measure the smartness level of different cities. Based on AHP, Wang & Duan [28] and Liu & Zhu [29] evaluated the smartness level of Chinese cities from different perspectives. Yang et al. [30] analyzed the input elements and output achievements of smart city construction and proposed the input-output model. Caponio [31] and Sun et al. [32] used system dynamics (SD) model to simulate the construction of SCs in China and foreign countries. In short, the evaluation of SCs by foreign researchers usually focus on one aspect of city construction, such as energy, construction, transportation and environmental protection, while Chinese scholars are more concerned about the indicator system for evaluating the smartness level of a city. However, most of the proposed indicators are related to informatization level, which is difficult to reflect the real situation of a SCs. Besides, the weight calculation of indicator mainly depends on expert scoring and the evaluation results are therefore highly subjective. In addition, previous studies have paid little attention to the smartness level and dynamic variations of multiple cities at the same time and there are limitations on the policy implications for the smart city construction at the regional or national level.

Based on the above introduction and the Chinese experience of smart city construction in recent years, this paper modifies the existing evaluation system of SCs based on the criterion of real "smartness". The indicators adopted in this paper are more specific, measurable, achievable, realistic and timely [33], so as to evaluate the smart city construction closer to the real situation. Furthermore, the method we used in this paper regard the SCs as a complex system and all the indicators are highly interconnected, which can not only avoid the limitations of previous indicator set but also expand to multiple cities and even show their dynamic variations. Under the foregoing description, the rest of the paper is structured as follows. In Section 2, the concept and aspect of smart city is clarified by bibliometrics and four subsystems and forty indicators are presented. Section 3 uses information entropy method to calculate the weight of each indicator and constructs a model for evaluating the level of smart city construction by using grey correlation analysis. In Section 4, 20 cities in China are selected as cases to evaluate the smartness level during 2012 to 2016. We not only compare the ranking changes and regional distribution of these cities but also use the clustering analysis to divide them into five levels. Section 5 is the conclusion of whole paper and some policy implications are suggested for the Chinese smart city construction in the future.

2. Establishment of Indicator System

It has been nearly 10 years since IBM proposed the concept of a smart city. During this period, the discussion on SCs has become increasingly fierce and the published papers have also increased dramatically. Figure 1 shows the changes in the number of research papers on the "Smart City" in the core collection of Web of Science from 2008 to 2017. Obviously, this trend is almost exponentially increasing and some of them focus on smart city indicators or evaluation system. We selected the top 100 most relevant papers and used Vosviewer to visualize their content (see Figure 2). The deeper the background color for an indicator, the higher the frequency of the discussion, such as smart governance, smart environment, smart mobility and participation. This work provides an important reference for the establishment of China's smart city evaluation system.

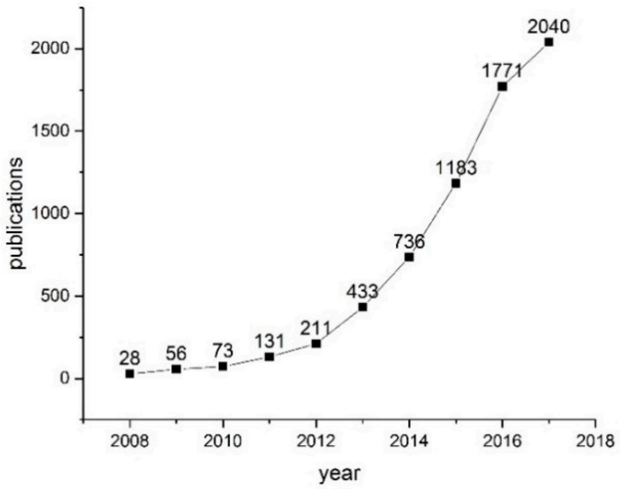

Figure 1. The trend of researches on the "smart city".

Based on the researches aforementioned and the actual situations of China's smart city construction [34], this paper divides the smart city system into four subsystems (see Figure 3). The smart economy and smart governance can be regarded as the Target Layer, because both of them are the goals of smart city construction and their improvement will contribute to the construction of smart infrastructure and smart participation. Likewise, smart infrastructure and smart participation belongs to the Support Layer. They not only relatively independent but also act as the foundations of Target Layer. The relations between these two Layers are not subordinate but parallel and interact.

The indicators for each subsystem are shown in Table 1.

(1) Smart infrastructure [4], the support system of a city. Smart infrastructure, like the bones of human, supports the development of a city. When constructing SCs, the infrastructure including transportation and information should be improved to maintain the stability of a smart city system.
(2) Smart economy [35], the power system of a city. In order to promote the development of smart economy, great efforts should be made to develop smart industry, improve innovation ability and promote Internet applications, to provide sustained power for smart city construction.
(3) Smart governance [36,37], the balance system of a city. To achieve the smart governance of a city, attention should be paid to constructing smart government, smart medical care and smart environment to achieve a balance between economy, society and environment.
(4) Smart participation [38], the participation system of a city. The main participants of smart city construction include government, enterprises and public. The construction of SCs requires diversified participants and the goal of smart city construction can be achieved through the extensive participation of multiple parties.

Table 1. Indicator system for evaluating the smartness level.

Subsystem	Primary Indicators	Secondary Indicators
Smart infrastructure	Network facility	Digital TV penetration (X1) Internet speed (X2) Internet penetration (X3) Wireless Internet penetration (X4)
	Smart transportation	Average daily volume of public transport (X5) Length of rail transit (X6) Average travel speed (X7) Traffic congestion delay indicator (X8) Energy consumption of public transport (X9) Average travel costs of public transport (X10)
	Digital environment	Cloud platform penetration (X11) Information database coverage (X12) Fiber optic coverage (X13)
Smart economy	Innovation vitality	Net population inflow (X14) Num. of patent applications per unit of GDP (X15) Num. of authorized patents per unit of GDP (X16) House price to income ratio (X17)
	Internet applications	E-commerce turnover (X18) Satisfaction for e-commerce service (X19)
	Smart industry	Num. of high-tech enterprises (X20)
Smart economy	Smart industry	Num. of employees (X21) Energy consumption of industrial output value (X22) Per capita industrial output value (X23)
Smart governance	Smart government affairs	Online processing rate of government affairs (X24) Disclosure rate of government information (X25) Daily visits to government websites (X26) Satisfaction for government websites (X27)
	Smart environment	The sound level of environmental noise (X28) Green rate of built-up region (X29) Num. of days with up-to-standard air quality (X30)
	Smart medical care	Per capita number of grade A class 3 hospitals (X31) Coverage of basic medical insurance (X32)
Smart participation	Government support	Planning documents on smart city (X33) Performance appraisal of SCs construction (X34) Percent of S&C expenditure in fiscal (X35) Percent of education expenditure in fiscal (X36)
	Smart population	Smartphone penetration (X37) Usage rate of mobile payment (X38)
	Enterprise investment	Proportion of R&D expenditure in GDP (X39) Proportion of scientific research personnel with doctor's degree (X40)

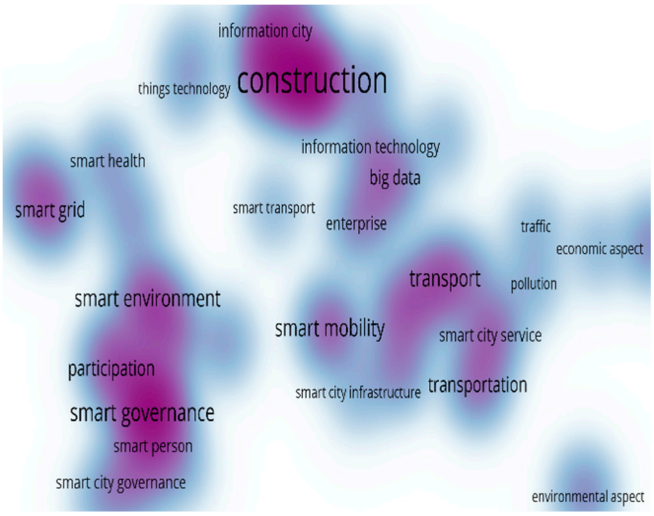

Figure 2. Research hotspots of SCs evaluation.

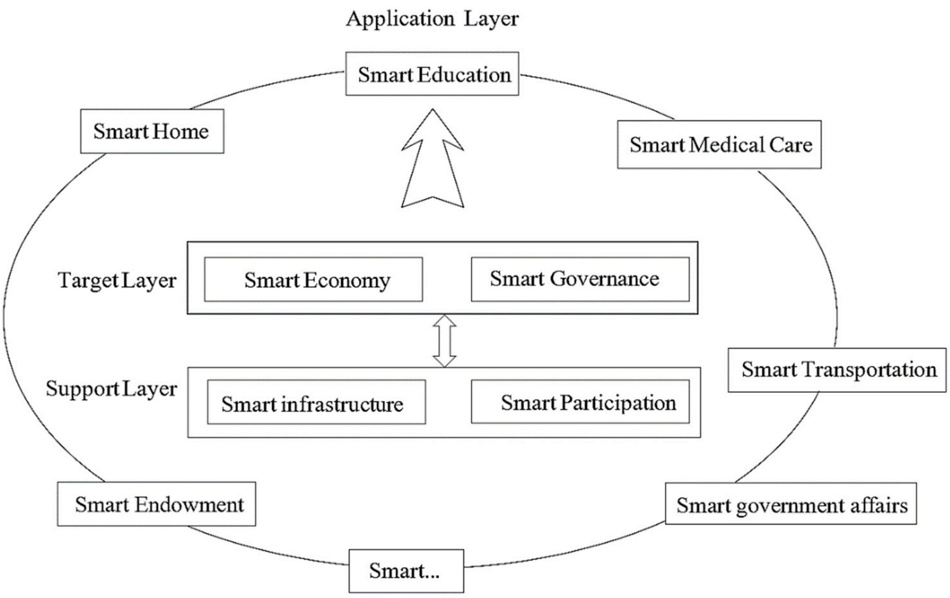

Figure 3. Framework of smart city system.

3. Grey Correlation Method

Smart city is a complex system [39]. The subsystems within this complex system are closely related and the relationship between the indicators is very complicated. Therefore, there exists great uncertainty and ambiguity in conducting a quantitative evaluation by using some indicators. Considering a system containing knowns and unknowns in time series data, grey correlation analysis is an appropriate method to evaluate the level of smart city construction [40].

3.1. The Weight Determination of Each Indicator

Information entropy method is an objective weighting method widely used in scientific research. The largest advantage of this method is that the decision matrix obtained by this method is directly used to calculate the weight of each indicator, therefore excluding the influence of subjective judgment. The steps to determine the weight of each indicator are as follows.

3.1.1. Dimensionless Processing Is Performed on the Data to Obtain the Calculation Matrix Y_{ij}

$$Y_{ij} = \frac{X_{ij}}{Max(X_j)} \tag{1}$$

If not otherwise specified in this section, the rows in the matrix Y_{ij} represent the number of cities being evaluated and expressed by the letter i, where i = 1, 2, 3. . . , m (m = 20); the columns in the matrix Y_{ij} represent the number of indicators and expressed by letter j, where j = 1, 2, 3, . . . , n (n = 40). X_{ij} and $Max(X_j)$ represent the data matrix of ith city and jth indicator and maximum value of the jth indicator respectively. The entropy value obtained for calculating the indicator weight is a relative value, which reflects the importance of the indicator in the whole evaluation system. The dimensionless processing of the data does not affect the calculation of entropy value, that is, does not reduce the amount of information in the data and the dimensionless processing makes the indicators additive and comparable.

3.1.2. Calculate the Characteristic Weight Matrix of the Data Matrix

$$P_{ij} = \frac{X_{ij}}{\sum\limits_{i=1}^{m} X_{ij}} \tag{2}$$

3.1.3. Calculate the Entropy Value E_j of the jth Indicator

$$E_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} p_{ij} \ln(p_{ij}) \tag{3}$$

where p_{ij} is the ith city data of the jth indicator in the characteristic weight matrix.

3.1.4. Calculate the Difference Coefficient D_j of Each Indicator

$$D_j = 1 - E_j \tag{4}$$

where D_j is called the difference coefficient and is used to measure the degree of consistency of information contributed by each city being evaluated.

3.1.5. Calculate the Weight Coefficient W_j of Each Indicator

$$W_j = \frac{D_j}{\sum\limits_{j=1}^{\mathrm{m}} D_j} \tag{5}$$

where W_j is the weight coefficient of the jth indicator.

3.2. The Grey Correlation Method for Evaluating Smartness Level

Grey correlation analysis method is the essential of grey system theory. The essence of grey correlation method is to determine a set of reference series, calculate the grey correlation coefficient between corresponding series and reference series for each scheme, then compare their advantages and disadvantages and perform the ranking analysis according to grey correlation degree [41]. Therefore, grey correlation analysis can be used to evaluate the level of smart city construction. To be specific, grey correlation analysis is performed between the data of each subsystem and the optimal indicators in each year. According to the obtained grey correlation values of the four subsystems, as well as the comprehensive grey correlation value of the whole city system, the evaluation can be conducted from the perspectives of infrastructure level, economy level, governance level, participation level and overall smartness level. Specific steps are as follows:

3.2.1. Determine the Reference Series and Comparison Series

The reference series is usually composed of the unit attribute values of the optimal indicators of a subsystem, that is, the maximum value of a positive indicator or the minimum value of a negative indicator. The reference series is recorded as $X_0(j)$, that is, $X_0 = \{X_0(j)\}$. The comparison series is the cities evaluated in a subsystem and is recorded as $X_i = \{X_i(j)\}$. According to the indicator system for evaluating the smartness level established in the previous section, the reference series and comparison series are constructed, namely:

Reference series: $X_0(j) = \{X_0(1), X_0(2), ..., X_0(40)\}$;

Comparison series: $X_y = \{X_0(1), X_0(2), ..., X_0(20)\}$, $y = 1, 2, ..., 5$;

where y is the number of comparison series, that is, the number of years evaluated.

3.2.2. Positive Processing of Negative Indicator

Among the indicators constructed in this paper, several indicators are negative indicators, that is, traffic congestion delay(X8), energy consumption of public transport(X9), average travel cost of public transport(X10), energy consumption per unit of industrial output(X22) and average equivalent sound level of regional environmental noise(X28). Before the negative indicators go through dimensionless processing, they need to be adjusted to be the positive. This paper adopts the reciprocal method to implement the positive processing:

$$X_{ij}{}' = \frac{1}{X_{ij}} \tag{6}$$

where X_{ij} represents the specific data of the above five indicators.

3.2.3. Dimensionless Processing for Reference Series and Comparison Series

The difference in the dimension of these indicators makes it impossible to directly compare these indicators. Therefore, it is necessary to carry out dimensionless processing on the collected data before evaluation. This paper uses the dimensionless processing of extremum method and its calculation formula is as follows:

$$C_{yj} = \frac{X_{yj}}{X_{0j}}, y = 0, 1, ..., 5; \tag{7}$$

where C_{0j} represents the standard value after the non-dimensionalization of the reference series, with $C_{0j} = 1$; C_{yj} represents the standard value of the jth indicator in the yth year after the dimensionless processing; X_{0j} represents the optimal value of the jth indicator within 5 years.

3.2.4. Calculate the Grey Correlation Coefficient for 40 Indicators

On the basis of the dimensionless processing of the raw data, the grey correlation coefficient of each indicator in each year is calculated by:

$$\xi_{yj} = \frac{\text{minmin}|C_{0j} - C_{yj}| + p\text{maxmax}|C_{0j} - C_{yj}|}{|C_{0j} - C_{yj}| + p\text{maxmax}|C_{0j} - C_{yj}|} \tag{8}$$

where ξ_{yj} represents the grey correlation coefficient of the jth indicator in the yth year and its numerical meaning is the relative difference between the standard value of the comparison curve and that of the reference curve of the jth indicator in the yth year; p represents the resolution coefficient, being in [0, 1] and its role is to reduce the influence of extreme values on the calculation results. p is generally taken as 0.5.

3.2.5. Calculate the Grey Correlation Degree of Each Subsystem and Whole Smart City System

$$
\begin{aligned}
R_{ky} &= \sum_{j=1}^{40} w_{kj} \times \xi_{yj} \\
R_y &= \sum_{k=1}^{4} W_k \times R_{ky}
\end{aligned}
\tag{9}
$$

where w_{kj} represents the evaluation weight of the jth indicator of the kth evaluation subsystem and k represents the four subsystems, that is, smart infrastructure, smart economy, smart governance and smart city construction support, R_{ky} represents the grey correlation degree of the kth subsystem in the yth year, that is, the scores of the four subsystems in the yth year. The higher the score, the better the performance of the city presents in the subsystem; R_y represents the overall grey correlation degree of the smart city in the yth year, that is, the score of the level of smart city construction in the yth year. The higher the score, the higher the overall intelligence level of the city.

4. Smartness Evaluation on 20 Chinese Cities

4.1. City Selection and Data Source

This paper selects 20 cities as evaluation cases, that is, Beijing (BJ), Tianjin (TJ), Shanghai (SH), Shenzhen (SZ), Guangzhou (GZ), Guiyang (GY), Hefei (HF), Lanzhou (LZ), Chengdu (CD), Wuhan (WH), Kunming (KM), Wuxi (WX), Nanjing (NJ), Qingdao (QD), Hangzhou (HZ), Chongqing (CQ), Xiamen (XM), Urumqi (UR), Yinchuan (YC) and Nanning (NN). The reasons why these cities are selected are that they are in the pilot list of SCs in China with a rich experience in smart city construction and that most of them are the major cities in each province or region with relatively complete data.

The data of this paper are sourced from the *China City Statistical Yearbook*, the statistical bulletin of national economic and social development of these cities, China Informatization Report, *Statistical Report on the Development of China's Internet* and A*nnual Report of China Urban Rail Transit*, the annual *Traffic Analysis Report of Chinese Major Cities* issued by Gaode Transportation, *the Development Report of China's Smart Cities* issued by Guomai Internet, *the China Urban Land Price Indicator Report* and *the Development Indicator Report of Chinese E-Commerce Demonstration Cities*, *China High-tech Statistical Yearbook*, Development Research Report of Chinese Government Websites, *Urban Environmental Status Bulletin* and other related reports.

Considering that China's smart city construction started in a year after 2010 and it usually takes at least two years to observe the construction effect, we choose the year of 2012 as the starting point for observation; the latest data available so far is until the year of 2016. Thus, the time span of this research is 5 years from 2012 to 2016.

4.2. The Weight Determination of Indicator

According to the weight determination of indicator by information entropy method, the original data is first dimensionless and then the characteristic weight, entropy and difference coefficient of each indicator are calculated by relevant equation. Finally, the corresponding weights are obtained, as shown in Table 2.

Table 2. The weight determination for 40 indicators in 2012–2016.

Indicator	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
2012	0.0035	0.0004	0.0064	0.002	0.1374	0.0085	0.0005	0.001	0.0329	0.0092
2013	0.0033	0.0004	0.0044	0.0016	0.1372	0.0084	0.0005	0.001	0.0328	0.0091
2014	0.0022	0.0006	0.0043	0.0009	0.1438	0.0096	0.0006	0.0011	0.0359	0.01
2015	0.0025	0.0004	0.0077	0.0068	0.1572	0.0113	0.0007	0.0008	0.0412	0.0115
2016	0.0029	0.0015	0.0062	0.0068	0.1434	0.0127	0.001	0.0013	0.0472	0.0131
Indicator	**X11**	**X12**	**X13**	**X14**	**X15**	**X16**	**X17**	**X18**	**X19**	**X20**
2012	0.0036	0.0033	0.0035	0.0459	0.014	0.0337	0.0114	0.0102	0.1778	0.1007
2013	0.0036	0.0033	0.0329	0.0022	0.0121	0.0269	0.0125	0.0102	0.1775	0.0924
2014	0.004	0.0037	0.0176	0.0023	0.0108	0.0251	0.0128	0.016	0.1943	0.1044
2015	0.0163	0.0043	0.0098	0.0028	0.012	0.0254	0.0192	0.0124	0.0846	0.1175
2016	0.0134	0.0046	0.0112	0.0032	0.0165	0.0257	0.0297	0.0118	0.0864	0.1319
Indicator	**X21**	**X22**	**X23**	**X24**	**X25**	**X26**	**X27**	**X28**	**X29**	**X30**
2012	0.0843	0.0723	0.0592	0.0027	0.0028	0.0118	0.0086	0	0.001	0.0036
2013	0.0803	0.0742	0.0529	0.0591	0.0025	0.0133	0.0041	0.0001	0.0006	0.005
2014	0.0809	0.0872	0.0532	0.0063	0.0109	0.0016	0.0028	0.0001	0.0012	0.0038
2015	0.0934	0.0736	0.0588	0.0231	0.0118	0.0081	0.0069	0.0001	0.0039	0.0034
2016	0.107	0.0638	0.06	0.0117	0.0061	0.0134	0.0084	0.0001	0.0044	0.0033
Indicator	**X31**	**X32**	**X33**	**X34**	**X35**	**X36**	**X37**	**X38**	**X39**	**X40**
2012	0.0175	0.0095	0.0314	0.0098	0.0171	0.001	0.009	0.0109	0.0249	0.0167
2013	0.0167	0.0151	0.0114	0.0057	0.0255	0.0018	0.0062	0.0108	0.0249	0.0171
2014	0.0424	0.0123	0.0064	0.0076	0.0169	0.0014	0.0077	0.0119	0.0266	0.0189
2015	0.0241	0.0184	0.0121	0.0327	0.0213	0.0033	0.0064	0.008	0.0297	0.0169
2016	0.0282	0.0161	0.0088	0.0041	0.0243	0.0037	0.0073	0.0038	0.0321	0.0228

4.3. Results of the Smart City Construction Evaluation

By using grey correlation model, the smartness level of 20 cities is evaluated from 2012 to 2016, which aims to reflect the status quo and development trend of China's smart city construction. The steps of the evaluation are as follows. Firstly, the optimal value of each indicator is taken as the value of reference series; secondly, dimensionless processing is performed on the indicator values of reference series and comparison series and the grey correlation coefficient of each indicator is calculated; thirdly, the obtained grey correlation coefficient is combined with the weight determined by information entropy method to calculate the grey correlation coefficient between the Primary indicators as well as the grey correlation value between the subsystems. Finally, the comprehensive grey correlation degree of smartness is obtained. The comprehensive grey correlation degrees of each city from 2012 to 2016 are shown in Table 3.

The rankings and its changes of smartness level for 20 cities from 2012 to 2016 are shown in Figure 4. BJ, SH, HZ, GZ and SZ rank the top five and their rankings have little change. For other cities, TJ, GY, HF, CD, WX, QD, CQ, XM and UR all shows an upward trend, while LZ, WH, KM, NJ, YC and NN shows a downward trend in 2012–2016. Among these cities, CD is rising most obvious, thanks to its' stable performance in the field of smart infrastructure and smart economy; and YC's ranking dropped the most significant, due to the smart decline of its industrial economy both in unsuccessful transformation and the loss of labour forces, which leads to the decline of city innovation ability.

Table 3. Comprehensive grey correlation degree of 20 cities in 2012–2016.

NO.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
City	**BJ**	**SH**	**SZ**	**HZ**	**GZ**	**XM**	**WX**	**NJ**	**CD**	**TJ**
2012	0.56	0.48	0.42	0.45	0.43	0.40	0.40	0.41	0.38	0.39
2013	0.57	0.49	0.43	0.44	0.42	0.39	0.41	0.41	0.38	0.39
2014	0.62	0.50	0.43	0.44	0.42	0.40	0.41	0.42	0.38	0.39
2015	0.67	0.55	0.48	0.54	0.47	0.44	0.44	0.43	0.41	0.41
2016	0.67	0.52	0.51	0.49	0.47	0.44	0.44	0.44	0.42	0.41
NO.	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
City	**CQ**	**WH**	**QD**	**HF**	**YC**	**UR**	**LZ**	**GY**	**KM**	**NN**
2012	0.39	0.39	0.37	0.37	0.41	0.37	0.39	0.37	0.37	0.37
2013	0.37	0.38	0.37	0.36	0.39	0.37	0.38	0.36	0.36	0.36
2014	0.38	0.38	0.38	0.37	0.40	0.37	0.38	0.39	0.36	0.36
2015	0.40	0.39	0.39	0.40	0.38	0.38	0.38	0.38	0.37	0.37
2016	0.41	0.41	0.40	0.40	0.38	0.38	0.38	0.38	0.38	0.38

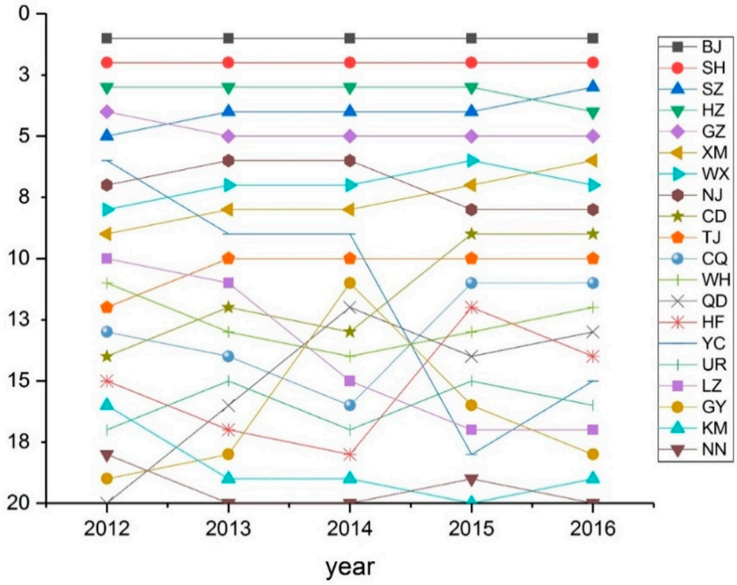

Figure 4. The rankings changes of smart city construction level for 20 cities in 2012–2016.

4.4. Further Analysis of Evaluation Results

4.4.1. Comparative Analysis by Regional Distribution

Under the geographical distribution and economic characteristics, the 20 cities can be divided into four categories: North China urban economic zone (BJ, TJ, QD), Yangtze River city belt (SH, HZ, WX, NJ, HF, WH, CQ, CD), Southern China urban agglomeration (SZ, GZ, XM) and Western China urban economic zone (GY, LZ, KM, UR, YC, NN). Combining the comprehensive grey correlation degree, the trend of smartness level changes for different city categories can be compared. Figure 5 shows the fluctuation of smartness level to some extent in 20 cities between 2012 and 2016. Except for LZ and YC, all cities have shown a growth. The smartness level between, and in, each category is also quite different. The cities that located in north China, south China and Yangtze river regions are significantly higher than the city in West China and the city belongs to first-tier cities (BJ, SH, GZ, SZ) is higher than the other cities within each category.

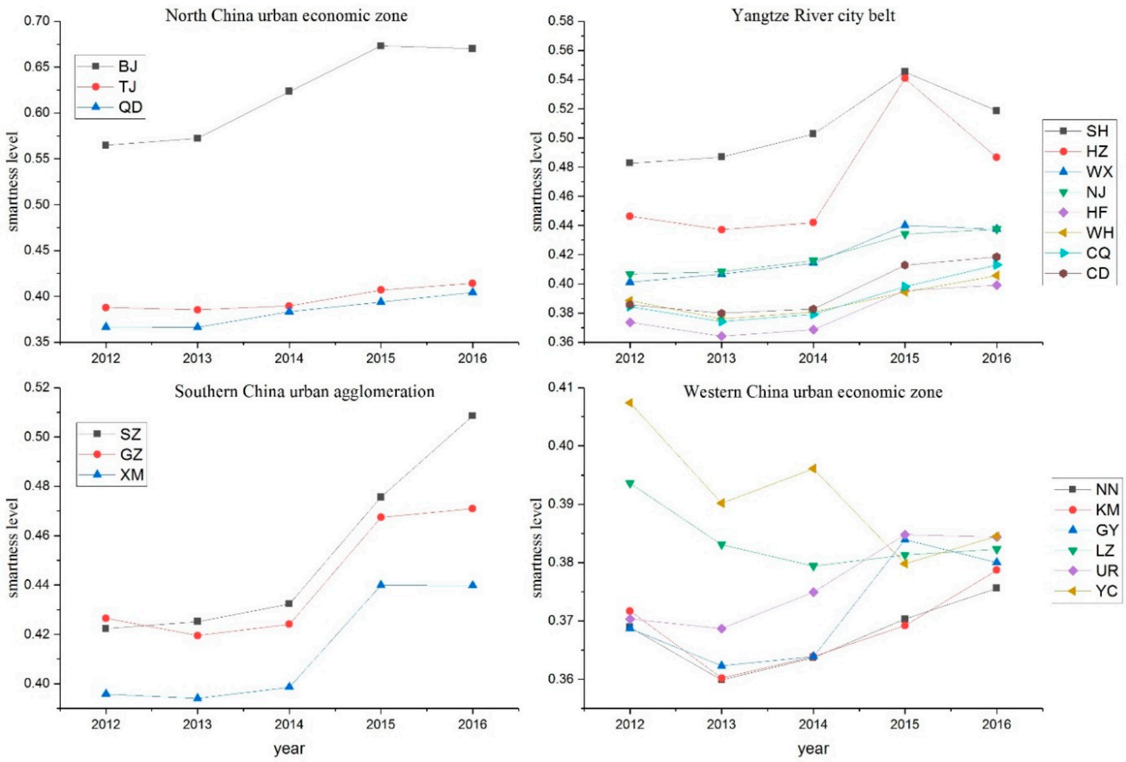

Figure 5. The fluctuation of smartness level four categories cities in 2012–2016.

From the perspective of regional locations, the overall smartness level in north China cities has gained an increase during the five years but the internal differences are large. The smartness level of BJ has increased from 0.56 to 0.67, being the highest in the region and even in China both in terms of growth rate and the growth of absolute smartness level, which is closely related to its status of being the capital. For TJ, which is also a municipality directly governed under the central government, the smartness level of this city is not only low (0.41 in 2016) but also slower (an increase of 0.03 in the five years), basically maintaining a similar level with QD. The smartness level of south China cities has increased the most. For example, SZ increased from 0.42 to 0.51, XM and GZ both increased by 0.04 but the gap in the level of smart city construction within this city agglomeration gradually expanded.

The Yangtze River city belt contains more cities. Although the smartness level of each city in this city agglomeration has large fluctuations, growths can be found any way. The largest increase is observed in SH, HZ and WX, with an increase of 0.04 and other cities are between 0.02–0.03. It is puzzling that the smartness level of SH and HZ has decreased in 2016 compared with that in the previous year, down by 0.03 and 0.05 respectively. This is mainly because the urban traffic in the two cities became more crowded in 2016, with the indicator X8 increasing from 0.391 and 0.363 to 0.777 and 0.798 and the congestion severity increasing from No. 17 and No. 19 to No. 4 and No. 6, respectively in the 20 cities. In addition, the number of patent applications per unit of GDP (X15) and the number of authorized patent per unit of GDP (X16) of HZ have dropped significantly, ranking from No. 3 and No. 1 in the previous year to No. 19 and No. 18, which explain the obvious decrease of the smartness level. It can also be seen that from the lower reaches to the upper reaches of the Yangtze River, the smartness level in descending order, which is related to the convenience of city transport and the level of opening up. The cities that are geographically close to each other also have the similar smartness level and development trends, such as WX and NJ, CQ and CD.

As for the cities in west China urban economic zone, their smartness level is the lowest and even there is a decline (YC and LZ) in the past five years. The rest of the cities in this region have only increased by 0.01, reflecting the slow growth of their smart city construction in recent years. As time goes by, the smartness level of the six western cities gradually converges, all reaching 0.38 in 2016.

4.4.2. Clustering Analysis for 20 Cities

More deeply, we adopt the clustering analysis to calculate the distance of grey correlation degree of 20 cities from 2012 to 2016. The dendrogram generated by average linkage clustering is shown in Figure 6. It is obvious that the clustering results will be different when the clustering criteria (standardized distance) changes. As the distance criteria narrows gradually, the number of clusters obtained will increase. We think that the appropriate classification distance should not be too wide or too narrow, so we chose the line close to 0.75, which divide 20 cities into 7 categories. On the other side, giving the three types of cities of HZ, GZ and SZ, SH are relatively close in standardized distance and their actual level of smart construction shows less difference. Therefore, we classify them into one category and finally get five types of cities.

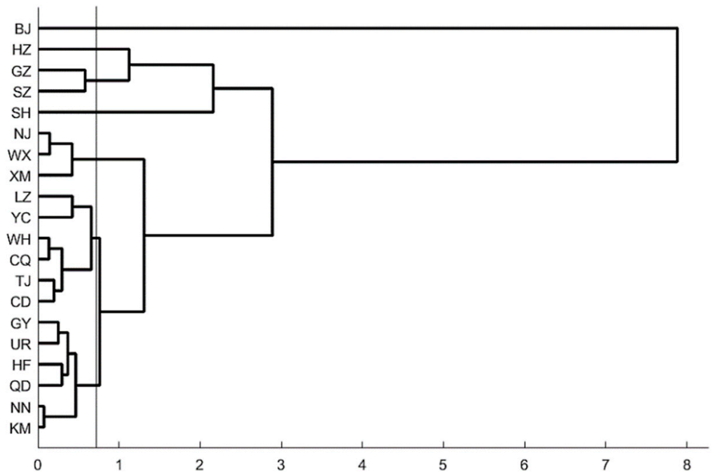

Figure 6. Dendrogram of clustering analysis.

Obviously, whether the results of comprehensive gray correlation degree value or the dendrogram of clustering analysis, the smartness level is quite different among the 20 cities, with the distribution of a "pyramid" pattern. The 20 cities also can be divided into five classes as shown in Table 4.

Table 4. Classes of the 20 cities.

Class	**I**	**II**	**III**	**IV**	**V**
City	BJ	HZ, GZ, SZ, SH	NJ, WX, XM	LZ, YC, WH, CQ, TJ, CD	GY, UR, HF, QD, NN, KM

Class I: highest-level smart city. Only one city, BJ. The comprehensive grey correlation degree of BJ reached 0.67 in 2016, far ahead of other cities. In fact, the goal of building a smart city in BJ can be traced back to 2009. As the capital of China, BJ has achieved a huge leap from "Digital Beijing" to "Smart Beijing" with its unique resource endowment. By making full use of the local IT infrastructure and rich data resources, BJ has greatly enhanced the urban comprehensive service capabilities and industrial integrating innovation have also made enormous achievements.

Class II: higher-level smart city. HZ, GZ, SZ and SH. From a spatial point of view, the above-mentioned cities belong to the core cities of the Yangtze River Delta and the Pearl River Delta. The comprehensive grey correlation degrees of the four cities are range from 0.47 to 0.52 with mean value of 0.4975 in 2016, classing to higher-level smart city. HZ and SH mainly rely on their performance on smart economy. For example, the emerging large high-tech enterprises such as Hangzhou Alibaba e-commerce and Shanghai smart industry parks are making outstanding contributions to the SCs construction. The smart city of SZ focuses on smart infrastructure construction, such as big data platform and unified government cloud platform and has formulated smart industry represented by Tencent and Huawei. GZ makes great efforts to develop smart traffic sensing network and strives to improve urban traffic conditions, while strengthening technology expenditure to promote smart healthcare and smart city management.

Class III: medium-level smart city. NJ, WX and XM. Next to BJ, SH, GZ and SZ, these cities have been considered as new first tier cities in 2016. Among them, NJ and WX belong to Jiangsu Province, which economy is developed and total GDP is second only to Guangdong Province. In 2011, the Jiangsu provincial government and local telecommunications companies reached a cooperation to promote the unified gateway construction for SCs and "Smart Jiangsu" began. In addition, the Yangtze River City Group, including NJ and WX, is gradually achieving "intelligence interoperability". At present, the focus of the SCs construction in Jiangsu is reflected in the integration of two industries (high-level integration of informatization and industrialization), urban government affairs, people's livelihood and other smart industries. XM is one of the earliest special economic zones in China with high degree of openness to the world. Its smart city construction mainly involves smart medical care, such as the establishment of a citizen health information system, a grading diagnosis and treatment collaboration platform, smart education and smart social security and so forth.

Class IV: lower-level smart city. LZ, YC, WH, CQ, TJ, CD. Some of them are provincial capital, like LZ, YC, WH and CD but located in the central or western regions with relatively backward in development level. CQ and TJ are listed in the four municipalities directly under the Central Government and their administrative status is higher than general provincial capitals. However, in terms of the development vitality, they are far less than BJ and SH. The reason lies in the critical stage of economic transformation and the smart economy for most industries are insufficient, which lower the smartness level for these cities.

Class V: lowest-level smart city. GY, UR, HF, QD, NN and KM. All these cities except QD are located in the central or western regions of China, with an average level of smartness only 0.38 in 2016. More specifically, each sub-system of smart construction in these cities are all at low level. It is necessary to formulate the overall urban smart construction plan to realize the comprehensive development of the four subsystems.

In terms of the spatial distribution of SCs (see Figure 7), China's high-level smart cities are mainly distributed in the Beijing, Yangtze River city belt and Southern China urban agglomeration, while the central and western economic zones are generally backward in smart city construction, posing an obvious gap with the eastern cities.

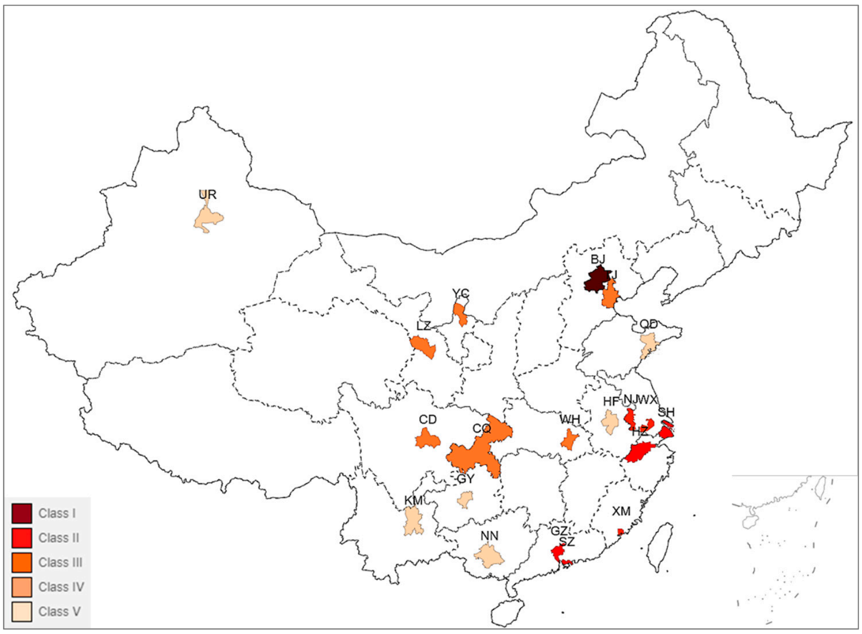

Figure 7. Spatial distribution of 20 Chinese smart city construction in 2012–2016.

5. Discussion

In this paper, an obvious breakthrough is made in terms of specificity, measurability, achievability and reality of the indicators for smart city construction evaluation comparing with the previous studies. Meanwhile, the indicators we selected also can compare the smartness level among different cities, which means it applicable widely. However, with the large-scale promotion of advanced ICT and rapid evolution for smart cities, the indicators that become less smartness is an issue hard to avoid completely. Take smart transportation for instance, the indictors like the average daily volume of public transport ($\times5$) and average travel speed ($\times7$) seems not smart enough, while some new smart indicators are excluded or not considered, such as carpooling in Intelligent Transport Systems (ITS) [42], Electronic Toll Collection (ETC) network [43]. This paper explores the reasons as follows.

First, there are significant gaps in the construction of smart transportation among different cities in China. 20 case cities of this paper, including Guangzhou, Shenzhen, Shanghai, Tianjin, Chongqing and Hangzhou were selected as National ITS (Intelligent Transportation Systems) construction Demo Cities, they began to develop the smart transportation in an earlier time. Another example, Beijing, Xiamen, Guangzhou and Qingdao have taken the lead in installing public transportation intelligent terminal equipment in 2016, which has greatly facilitated their smart transportation. For cities in the western provinces, the indicators with hi-tech are not yet widely available because the high construction investment.

Second, understanding of smart transportation usually vary from one city to another, even though they have some common purposes, like easing the traffic congestion and reducing air pollution. However, cities still have great differences when emphasizing the smart transportation. For example, Beijing recently focus on the interconnection of Beijing-Tianjin-Hebei transportation system and the interconnection of people, vehicles and goods, while Guangzhou vigorously develops the self-driving car systems.

Finally, and most importantly, the limitations of data acquisition. Since China's smart transportation construction is still at the start stage, many regional statistical data do not include enough smart indicators, especially considering 20 cities dispersed throughout China. Hence, there is very few public data available to compare different cities.

Smart city system is a typical complex dynamic system. In future works, it is necessary for us to consider the indicators with greater attribute of smartness, if technological and data conditions permit.

6. Conclusions

Since IBM formally proposed the concept of "smart city" in 2010, SCs have not only became a hot topic for global urban development but also gradually attracted extensive attention from Chinese government and scholars. SCs can be regarded as a potential way to further exploration the urban development pattern and resident lifestyle. It is also expected to make full use of the new round of technological wave to more effectively solve the urban problems, providing people easier access to a high quality of life in the future. Therefore, measuring the effect of smart city construction is a basic and long-term work for the urban sustainable development for all regions.

This paper extracts some hot indicators from the literature about smart city evaluation and then divides the construction of SCs into smart infrastructure, smart economy, smart governance and smart participation according to the current situation of China's smart city construction. On this basis, grey correlation analysis is used to evaluate the level of smart city construction for 20 major cities. Through the regional analysis and clustering analysis of case cities, we conclude that there are some policy implications for China smart city construction in the future.

6.1. Considering the Difference of Cities with Local Characteristics

Cities across China have huge differences in geographical location, development level and planning direction, so it is impossible to carry out smart construction with the same formula. For each city, it should focus on its own resource endowment and future development needs to carry out smart city planning. For example, the smart construction for eastern coastal cities may emphasize social governance, such as strengthening environmental governance and enhancing public service capabilities such as medical care; for remote cities in the west, their smart construction needs to concern more about the network facilities, to improve urban innovation and economic vitality. There are also many cities with local characteristics, such as cultural and eco-tourism cities. In this case, smart city construction should focus on tapping local resources to improve the sustainability of the city.

6.2. Forming the Complementary Network within the Urban Agglomeration

At present, the smartness level in different economic zones or urban agglomerations is uneven, which seriously restricts the coordinated development of cities all over China. In the case of north China, Beijing and Tianjin are adjacent to each other and both are municipalities directly under the central government in terms of administrative levels. However, the level of smart construction varies greatly, which leads to the troubles of information interconnection and business intercommunication between them. The successful one however, in smart construction is that Yangtze River City Group in Jiangsu Province. Eight cities including Nanjing and WuXi have formed smart cooperation in data sharing, industrial collaboration and intra-provincial access. However, this kind of smart interconnection is still limited to a small scale of urban agglomeration. It can be extended to the entire Yangtze River basin urban agglomeration if conditions possess, give full play to the scale effect of urban clusters to reduce the economic cost of "building each other".

6.3. Maintaining Balanced Development among Urban Agglomerations

China's regional development has been unbalanced for a long time and the gap between east, central and western regions is very significant. Therefore, it is necessary to improve the national smart city construction overall planning from top-level design, not only accelerate the smart construction of eastern urban agglomerations but also make full use of the experience and technologies of eastern cities to help the cities that were lagged behind in smart construction. In terms of financial fund allocation, resources should be properly skewed to the backward cities to achieve the relatively balanced development of the SCs construction among different urban agglomerations.

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