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City Intelligence Quotient Evaluation System Using Crowdsourced Social Media Data: A Case Study of the Yangtze River Delta Region, China

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Abstract: Despite the trending studies on smart city development, how to evaluate the smartness of a city remains unclear. This research aimed to design a smart city evaluation system, named the City Intelligence Quotient (CityIQ) evaluation system, which considers both the hard (e.g., physical infrastructure) and soft sides (e.g., citizens' perspectives) of smart city development. Based on the two-level structure of the CityIQ evaluation system (i.e., five dimensions and twenty indicators), a list of keywords was defined for automated information scraping in leading social media platforms to obtain volunteered geographic information. Semantic analysis was then used to update the CityIQ evaluations in a timely manner. Fifteen major cities in the Yangtze River Delta region, China, were selected for the empirical study, in which their smartness indices were calculated, traced and compared. Finally, suggestions for collaborative smart agglomerations were put forward. With the CityIQ evaluation system, policy makers can be informed of up-to-date changes in urban smartness levels and, thus, design context-specific collaborative policies to promote smart agglomerations.

Keywords: smart city; evaluation system; social media data; crowdsourcing; citizens

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1. Introduction

Smart cities can be seen as a powerful incentive to explore the future of cities through the perspective of emerging technologies [1]. The advancement of a new generation of information technology, including the integration of the internet of things, cloud computing and other innovations provide solutions for future city development [2]. The advances of this technology have exhibited a strong potential and tendency of improving human life, which will not only enhance the quality of life, but also influence the way people live, work and socialize [3].

Smart city evaluation systems are important to measure the intelligence of cities. However, despite the booming wave of smart city construction worldwide, there is little research on the evaluation of outcomes in smart cities [4] and there is also no official evaluation criterion accepted worldwide to measure city performance [5]. Some evaluations being used do not even consider the smartness levels of the indicators [6]. Based on a comprehensive perception of the city, building an authoritative smart city evaluation index system can make more scientific and appropriate judgments and responses to the current urban development.

This study aims to design a smart city evaluation system which considers both the hard and soft sides of smartness. In addition to the conventional statistics for hard smartness measurement, this research proposes a novel method to collect real-time public opinions for soft smartness measurement. A smart city is not only equipped with advanced high-tech facilities, but also with higher satisfaction of citizens. Therefore, timely and accurately evaluating results could provide a solid theoretical basis for the future development of smart cities. This study aims to answer the research question: how can public opinion obtained from location-based social media data be used to measure the smartness of cities?

2. Literature Review

2.1. Concept of "Smart Cities"

The "smart city", known as a prevalent vision of future cities, has been adopted globally to pursue urban sustainability [7]. Although the popularity of smart city construction is evident and an extensive array of relevant literature is available, the specific concept of a "smart city" remains vague [8]. "Smartness", which is a generalized concept of computational urbanisms, increasingly refers to urban sustainability strategies that are linked to various fields of application [9]. As a result, the meaning of a smart city is multifaceted and can inadvertently bring together different aspects of urban life [10].

Nevertheless, from the literature analysis, definitions with shared features and overlaps are found through theory development [11]. Initially, a smart city clearly adopts new technologies associated with utilizing urban infrastructure functions to improve efficiency and achieve sustainable development [12]. Hollands suggested that the validity of smart city must be based on something more than its use of information and communication technologies (ICT) [13]. Many elements and dimensions, which characterize a smart city, have emerged from the analysis of existing literature [14]. Giffinger proposed that a smart city is a smart society in which people are involved within a smart infrastructure [15]. In a comprehensive definition, a smart city is considered an advanced model that utilizes information communication technology to improve the quality of life and ensure environmental sustainability [2]. Rooted in a critically aware knowledge base and in a further realistic understanding, cities become smart(er) [16].

Many new categories of "cities" have entered the policy discourse: "sustainable cities", "green cities", "digital cities", "smart cities", "intelligent cities", "eco cities", "low carbon cities" and "livable cities" [17]. The multidimensional definition of smart city differentiates it from these concepts, despite the similarities in the technology basis [18]. For example, ICT is the foundation of smart city and digital city [19]. However, ICT is the core component of a digital city and other aspects play less proactive roles [20]. Meanwhile, the smart city is a more comprehensive goal, which also focuses on environmental aims and the quality of life related to citizens and communities [7]. The present concept of a smart city merges the technology requirements of a digital city and citizens' attitudes of sustainable development in the environment and society [21].

2.2. Prevalent Evaluation Systems of Smart Cities

Given the large number of smart cities operating worldwide to fulfill the goal of city sustainability [3], an approach to measure the state of smart city operation is necessary. The creation of a successful smart city calls for an organic integration of multiple complex urban components [8]. Therefore, a consensus suggests that the smart city evaluation systems should be multidimensional, spanning multiple fields and integrating into complex systems [22].

Some previous studies on smart city evaluation have concentrated on the importance of the hardware side, such as ICT, and focused on the field of technology-oriented implementation [12]. They attempted to provide an evaluation and investigate how they can best support the ICT solutions for modern infrastructure [19]. Researchers support the integration of different dimensions of urban contexts with the assessment of technological development. However, a real smart city relies on its citizens [23]. Whether quality of life can be a separate dimension remains controversial [24]; nevertheless, a consensus suggests that a smart city should emphasize the improvement of urban living [25] where 'citizens' are the key element of the smart city evaluation through continuous interactions. A solid understanding of contexts of smart cities, administration models and public value is required to create practical approaches [8].

Although multiple intelligent city evaluation systems and evaluation research are being introduced in different areas of smart city development for evaluation purposes [26], there is still a gap between accurate, timely measuring approach and the reality. In 2010, the Centre for Regional Science at the Vienna University of Technology proposed six main components of smart city evaluation systems to measure the state of a smart city [15]: smart economy, smart mobility, smart environment, smart people, smart living and smart governance. Given that the role of the citizen in the context of cities is becoming increasingly prominent [26], indicators such as education, innovation, citizen participation and management have increasingly received further attention as basic components in building smart city evaluation systems [12]. Moreover, smart city evaluation systems are at the behest of local residents, rather than outside actors, and should be designed to emphasize the daily experiences of the community [27]. Abu-Rayash and Dincer (2021) proposed that a smart city consists of eight main dimensions, including economy, society, environment, energy, governance, transportation, infrastructure and pandemic resiliency [28]. In 2021, Milad Pira examined soft aspects of smart sustainable cities by including socio-cultural, economic, environmental and governance dimensions with a set of indicators [29].

The smart city is an entity which combines hard and soft smartness together, and the measurement of soft smartness is becoming increasingly more important. Hard smartness represents the physical development of smart city, such as infrastructure, environment, economy, industry, etc. [10,30]. Conversely, soft smartness represents management, services, public opinion, etc. [31,32]. The conventional evaluation systems mostly focus on analyzing the key factors in the field of ICT. Nowadays, governments and organizations worldwide have gradually increased their attention to soft smartness, which is related to the transformation of smart cities from focusing on the sustainable impacts of ICT to achieving sustainable urban development with positive social impacts on citizens [33]. However, most mainstream evaluation systems of smart cities and its indicators fail to reflect the soft smartness of cities explicitly because they do not consider citizens' opinions [12].

2.3. Evaluations Using Crowdsourced Public Opinion Data

At present, most of the data sources of smart city evaluation are government statistics, which are static. Updating static data is time-consuming, and unable to reflect the real-time status of cities; additionally, it is difficult to form a unified evaluation standard for different cities [34]. Involvement of citizens in smart city evaluation is critical to the full transparency of the evaluation process and its broader societal impacts [35]. Meanwhile, citizens with mobile phones worldwide have become prevalent public opinion information resources through a network of social sensors, which can be obtained every day [36]. Crowdsourced location-based social media data could provide data on public opinion by using geotags [37]. Public opinion data reflect people's comments on urban issues, including smart city development. Therefore, it is necessary and possible to include real-time dynamic data in the smart city evaluation system.

Social media data have both strengths and weaknesses. Compared to conventional statistical data, social media data could update on a real-time basis, which reflects changes with a fine temporal granularity. In addition, social media data can reflect real opinions of the public towards the intelligent city. One weakness of social media data is that social media users are mainly young people, and the sampling might be biased.

3. Research Methodology

This study establishes a City Intelligence Quotient (CityIQ) evaluation index system. The creation of the system was based on the concept of treating a city as an intelligent, living being [38], using innovative methods to achieve a dynamic analysis of the intelligent city development process. Based on a systematic review of some existing major intelligent city evaluation systems globally (Table 1), this research compares the indicator systems in terms of the supporting theories, technical approaches, scale structuring and indicator selection. CityIQ innovatively introduced the 'satisfaction rate' of city users to evaluate a city's smartness level as reflected by public opinions from social media regarding a city's intelligent development.

Table 1. Some of the existing major intelligent city evaluation systems.

No.	Intelligent City Evaluation Systems	Year	Research Team	Number of Primary Dimensions	Content of Primary Dimensions	Number of Secondary Indicators
1	TU Wien System [25]	2007	Rudolf Giffinger	6	Intelligent economy, intelligent people, intelligent governance, intelligent mobility, intelligent environment and intelligent living	31
2	Intelligent Community Forum System [39]	2001	Intelligent Community Forum Institute	4	Broadband, innovation, digital inclusion, marketing and advocacy	18
3	Comparative European Smart City System [40]	2012	Karima Kourtit, Peter Nijkamp, Daniel Arribas	3	Prosperous commerce and social-cultural attraction, labor and municipal facility capacity and high-end e-service usage	0
4	Int'l Digital Corporation Smart City Index [41]	2011	Int'l Digital Corporation	5	Government, buildings, transportation, energy, environment and service	23
5	IBM Evaluation Matrix [42]	2010	IBM Corporation	7	Transportation, communication, water, energy, city service, citizens and commerce	0
6	Shanghai Pudong Smart System [43]	2012	Shanghai Pudong Smart City Research Institute	5	Infrastructure, public management and service, information service for economic development, humanity and science attainment and citizen awareness	18
7	European Smart Cities 4.0 [44]	2015	Rudolf Giffinger, Hans Kramar, Gudrun Haindlmaier, Florian Strohmayer	6	Smart Economy, smart mobility, smart environment, smart people, smart living and smart governance	27
8	Integrated Sustainability Smart City System [28]	2021	AzzamAbu-Rayash, Ibrahim Dincer	8	Economy, environment, society, governance, energy, infrastructure, transportation and pandemic resiliency	32
9	Smart Sustainable City System [29]	2021	Milad Pira	4	Socio-cultural, economic, environmental and governance	28

The CityIQ evaluation index system has a two-level structure: the primary level emphasizes a top-down policy design, including five dimensions. The five primary dimensions are 'Intelligent Construction and Environment', 'Intelligent Governance and Services', 'Intelligent Economy and Industry', 'Intelligent Hardware Construction' and 'Residents' Intelligent Capacity'. The secondary level has twenty indicators, which are the specific systems within the five first-level primary dimensions that touch on all aspects of intelligent city development (Table 2). The overall CityIQ score is the average value of the scores of all five dimensions, which have equal weights, and the score of each dimension is the average value of all scores of the four indicators in each dimension, which have equal weights. Equal weights are used because the balance among five dimensions and the twenty indicators has already been considered in the design of the evaluation index system according to the expert seminars and Delphi method [33,38]. Expertise of prominent experts and their subjective evaluations are combined.

Table 2. The CityIQ evaluation index system.

Primary Dimensions	Secondary Indicators
(1) Intelligent Construction and Environment	Environmental monitoring Pollution monitoring Intelligent construction Green energy
(2) Intelligent Governance and Service	E-government Emergency alerts Smart transportation Smart health care
(3) Intelligent Economy and Industry	Smart agriculture Smart industries Innovative ideas Entrepreneurial support
(4) Intelligent Hardware Construction	Wireless network Broadband speed Data centers Smart grid
(5) Residents' Intelligent Capacity	Public participation Digital libraries Tertiary education Talent policy

The primary dimensions stress a top-level policy design in terms of an intelligent city with five dimensions [25]:

(1) Intelligent Construction and Environment;
(2) Intelligent Governance and Service;
(3) Intelligent Economy and Industry;
(4) Intelligent Hardware Construction;
(5) Residents' Intelligent Capacity.

The secondary indicators reflect the overall evaluation of a smart city with twenty indicators.

3.1. Using Public Opinion to Replace Statistical Data

The conventional methods based on statistical data have several limitations. First, the categories and content of the indicators in conventional evaluation systems may not be unified because statistical data are defined by the governments of different cities and, thus, may have different definitions. Second, the statistical data based on conventional evaluations are unable to obtain timely information about smart city development [45]. Social media have become an emerging alternative for reflecting public opinion. Social media data with city-level geotags provide new perspectives through the public expressing their opinions on different aspects of city development [46]. Social media data with volunteered geographic information have very fine temporal granularity and geographic coverage. Users from different cities might appear on social media at different times of the day.

In this study, we use Weibo (Chinese Twitter) as the data source, because it is the most popular social media in China with a wide coverage of users (i.e., 511 million monthly live users and 224 million daily live users). The social media datasets mainly consist of user-generated content, with people sharing their daily thoughts related to various dimensions of the intelligent cities in which they live. It is considered that the generated posts could largely reflect people's real experiences and evaluations on intelligent cities. Therefore, public opinions obtained from social media data that reflect social sentiment were used in this study to replace government statistics. The large sample and the timely public opinion data were fully used to reflect the smartness of cities and reflect the effectiveness of smart city construction and operations.

This study employed two methods to classify the geographic locations of social media data from Weibo. One was social media geo-tag posts generated by users with coordinates, and the specific location data collected are classified at the city level. The other was location recognition from social media posts by semantic analysis. The locations were classified to city level when names of places or cities appear in the posts.

The process of the sentiment analysis is as follows:

i. Collection of a raw labeled dataset for sentiment analysis. The raw social media datasets with the keywords were collected. The plain texts were collected from Weibo posts (in Chinese) before data cleaning.
ii. Preprocessing of the texts. After data cleaning, text preprocessing was carried out, transforming Chinese texts with sentiment into mathematical matrixes. Word to vector technology predicted the word vectors of feature words according to their contexts. The strong correlation between synonyms was maintained, and the contexts could be speculated according to the feature words.
iii. Numerical encoding of texts. The text sentiment analysis technology based on active learning was adopted to analyze social media posts [47], to determine whether a given text in the data was positive, negative or neutral by extracting the meaning from the natural language and assigning it a numerical score from 0 to 100. This study chose a custom-trained supervised machine learning model and the active learning model for sentiment analysis. Text sentiment analysis and self-learning classification based on a small number of text labels were used.
iv. Choosing the appropriate machine learning algorithm. After obtaining the text vector, the next step was to train the classifier. The active learning method was employed, which can obtain more valuable label samples with less labor cost and better generalization performance. In the active learning model, we used a random forest classifier as the classification model.
v. Hypertuning and training machine learning model.
vi. Prediction. The efficiency of the active learning algorithm lied in the use of specific strategies to minimize the number of samples that needed to be labeled in the supervised process and to reduce labor cost from labeling useless samples. Active learning was essentially part of a supervised process, and it could compress training samples to a tenth or less of their original size to achieve similar training effects. This was essential to train a robust machine learning model. The machine learning model would learn various patterns in the dataset and could predict sentiment for a given unseen text. We collected the raw labeled dataset for sentiment analysis before building the active learning model. The training was carried out based on a raw labeled dataset consisting of about 20,000 social media posts in Chinese. A total of 2000 texts were used for initialization, and training iterations were 50–100 times. Finally, the accuracy of the training results was 75–80%.

3.2. Analytical Framework

The CityIQ evaluation system uses the public opinion data from social media to measure city smartness. The analytical framework is shown in Figure 1.

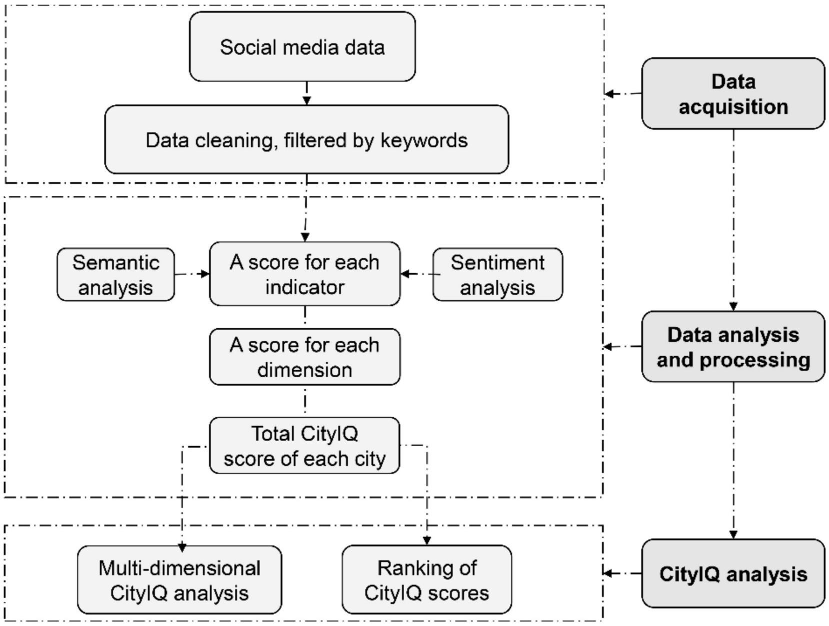

Figure 1. Analytical framework of the CityIQ evaluation system.

The semantic analysis and text sentiment analysis model is based on machine learning [48,49]. The public opinion data are converted into a corresponding score index through semantic analysis [50]. The data are all objective public opinion attitudes toward certain aspects of the city to ensure an objective and timely evaluation. The CityIQ evaluation index system uses online public opinion data to measure the intelligent development of the city. The specific analytical framework is as follows.

(1) Data acquisition. The twenty indicators that represent the development of urban intelligence are semantically transformed to form a keyword list for online search purposes. According to the keyword search list formed through intelligent semantic transformation, data from the mainstream social media site Weibo (the equivalent to Twitter in China) were obtained in this research. Weibo means 'microblog', and it provides the most important microblogging service in China [51,52]. The Weibo data were collected from Sina Weibo by using Sina Weibo's application programming interface (http://open.weibo.com/ (accessed on 1 August 2021)). The Weibo user-generated content was cleaned and filtered by the keywords by natural language processing [53]. This method introduced artificial intelligence technologies, such as machine training and semantic association to expand the scope of the meaning of keywords (shown in the Appendix A) and, thus, to obtain more abundant information.

(2) Data analysis and processing. The semantic analysis and text sentiment analysis models are introduced to infer citizens' evaluation of city smartness from different perspectives. The Weibo data scraped by the keywords are converted into the corresponding score index through semantic analysis. Semantic transformation technology is one of the innovations of this index system, which is based on a semantic analysis and text sentiment analysis model. The textual content in social media reflects citizens' sentiments. Text sentiment analysis categorizes texts on a given topic based on the sentimental opinions conveyed, which can be negative, neutral or positive. Based on the text semantic analysis and sentiment analysis results of the keywords [54], the CityIQ scores of twenty indicators are derived. The score of each indicator ranges from 0 to 100.

(3) CityIQ analysis. With the CityIQ scores of twenty indicators, the scores of five dimensions are calculated. The score of each dimension is the average value of the four indicator scores of this dimension, and ranges from 0 to 100. The CityIQ scores of different cities are compared from multi-dimensional perspectives. The time-series

changes of the scores are obtained every week in the CityIQ evaluation system, thus providing a dynamic ranking of each city. Social media geo-tag posts with coordinates generated by social media users and the specific location data collected from city level administrative areas are defined as data of selected cities.

3.3. Study Area and Data Processing

3.3.1. Study Area

The Yangtze River Delta region is located in eastern China and is the largest urban agglomeration in China, with the highest density and urbanization rates in China. It is a strategically important region, as it is the location where the One Belt One Road initiative and the Yangtze River Economic Belt meet (Figure 2). With the national strategy of modernization and comprehensive opening up, this region has become the most important city cluster in China. In this research, fifteen major cities in the Yangtze River Delta region were selected, which may generally represent intelligent city development in this agglomeration.

Figure 2. Location of the study area in China.

3.3.2. Data Processing

The twenty indicators of the CityIQ evaluation system are semantically transformed to form a keyword list for an online search (shown in the Appendix A). According to the keyword search list formed by intelligent semantic transformation, the Weibo data are obtained with a weekly granularity, to evaluate citizens' opinions on smart city development.

Artificial intelligence technologies, such as machine training and semantic association, were employed to extract the information with the target keywords and the machine-trained related word library. Based on intelligent semantic transformation of the list of keywords used for searching social media data, it is possible to obtain dynamic observations of smart city development.

The CityIQ indices of many Chinese cities are available to the public at the Intelligent City Knowledge Service System (iCity) website (http://icity.ikcest.org/ (accessed on 1 August 2021)). iCity is one of the service systems of the International Knowledge Centre for Engineering Sciences and Technology (IKCEST) under the auspices of UNESCO.

4. Case Study

4.1. CityIQ Analysis of the Yangtze River Delta Cities

Taking Shanghai as an example, the temporal variations of the twenty indicators of CityIQ from September to October 2019 are shown in Figure 3. Most indicators fluctuated dramatically, although they were updated every week. The CityIQ evaluation system could capture citizens' evaluation toward the smart city dynamic development in a timely manner.

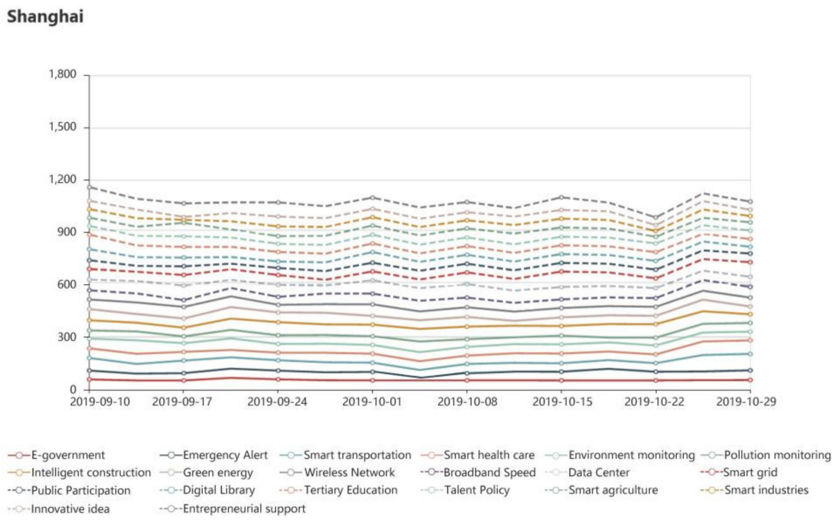

Figure 3. Temporal variations in CityIQ scores with twenty indicators, taking Shanghai as an example.

With the historical CityIQ scores for the five dimensions and twenty indicators of different cities, it is possible to analyze the advantages and disadvantages for each city. Since the values of CityIQ are updated weekly, the average CityIQ scores of the major fifteen cities in the Yangtze River Delta from April to October 2019 were selected (Figure 4).

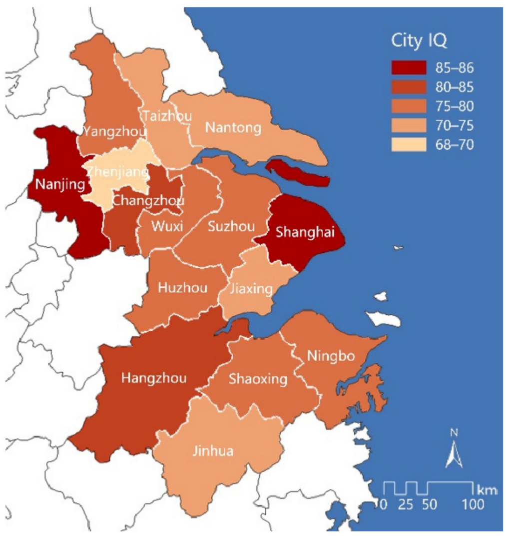

Figure 4. CityIQ scores of the fifteen major cities in the Yangtze River Delta region, China.

Based on the historical scores and indicators of the cities evaluated in the database, and the comparisons according to various dimensions, disadvantages in the construction of intelligent cities can be derived. The ranking presents overall information about the intelligent development of these fifteen cities in the Yangtze River Delta based on the five-dimensional indicators (shown in different colors in the histogram in Figure 5). Shanghai tops the list with 86.0 points. In general, the provincial capital cities have higher CityIQ scores than non-provincial ones, but the strengths and weaknesses of each city are noticeably different.

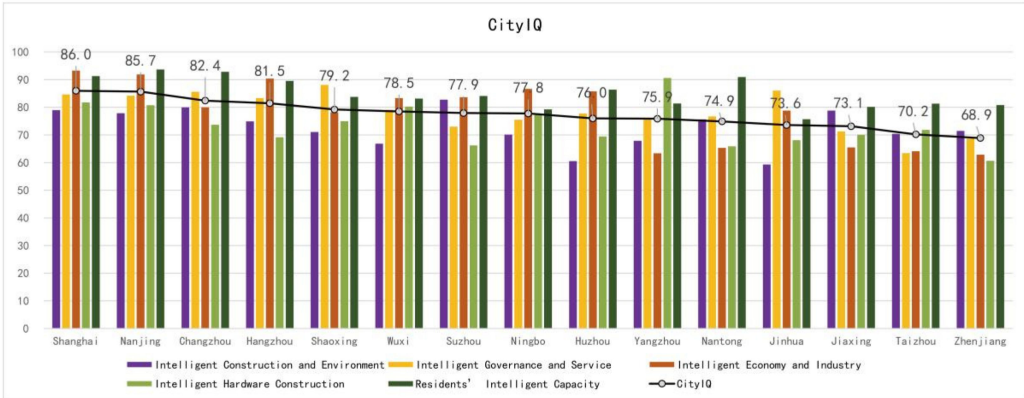

Figure 5. Overall CityIQ scores of the fifteen major cities in the Yangtze River Delta region, China.

Cities in the Yangtze River Delta region performed well in the dimension of 'Residents' Intelligent Capacity', for which the inter-city gap was relatively small. However, the overall level of 'Intelligent Construction and Environment' in these fifteen cities was poor. There were clear gaps in the indicator of 'Intelligent Hardware Construction' among cities in the Yangtze River Delta (Figure 6).

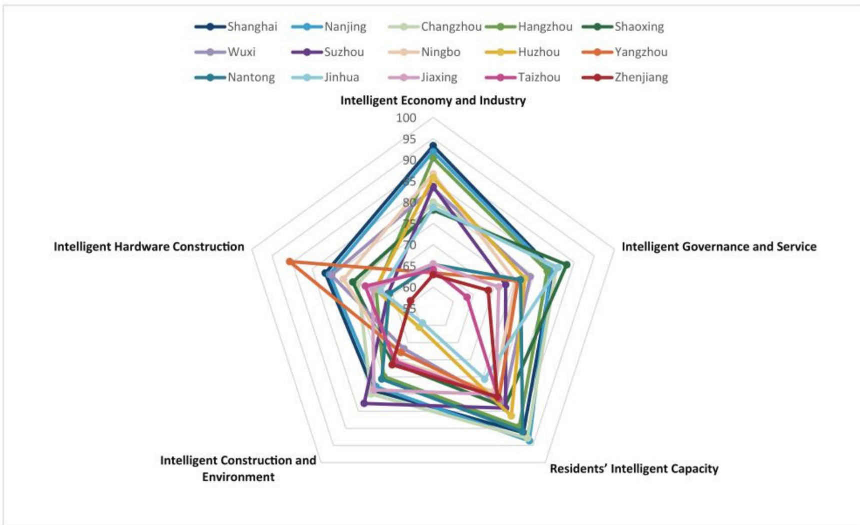

Figure 6. Comparison of the five dimensions of the fifteen major cities in the Yangtze River Delta region, China.

In order to compare these fifteen cities further, their indicator scores for different dimensions were examined. For example, regarding the scores and rankings of these cities in the dimension of 'Intelligent Economy and Industries' (Figure 7), the provincial capitals or municipalities (Shanghai, Nanjing and Hangzhou) were the leading cities. There were large gaps between cities for the indicator of 'Innovative ideas', so these cities need more collaboration.

4.2. Collaborations among the Yangtze River Delta Cities in Terms of Intelligent Development

For intelligent development, agglomerations need more integration and collaboration among the different cities. Intelligent agglomeration helps cities learn from each other and provides a more rational and effective way for improving the competitiveness of the agglomeration as a whole. In order to discover the strengths and weaknesses of the Yangtze River Delta cities, a hierarchical cluster analysis was conducted to analyze the similarities of these cities in terms of their intelligent development, measured through the five dimensions and twenty indicators. The Ward method—prevalently adopted in the urban studies research—was employed to perform the hierarchical cluster analysis. The method has a proven track record of deriving homogeneous and interpretable clusters among different cities or countries [55,56]. In this way, the Yangtze River Delta cities could cooperate in intelligent urban development from different perspectives, to achieve collaborative development as a single intelligent agglomeration.

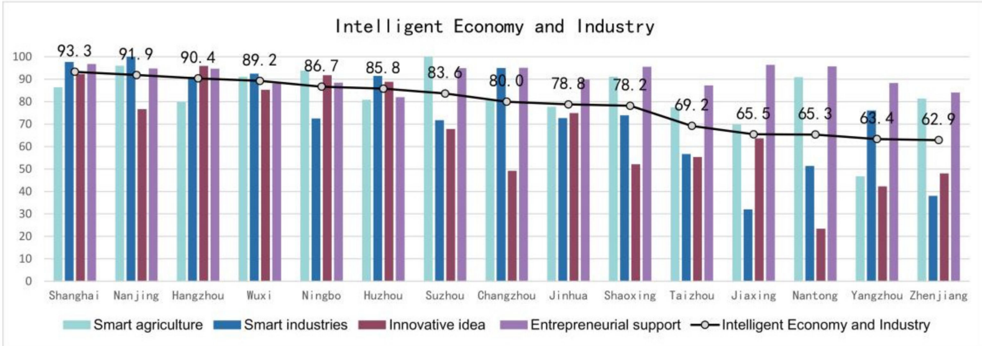

Figure 7. CityIQ scores for the 'Intelligent Economy and Industry' dimension of the fifteen major cities in the Yangtze River Delta region, China.

The hierarchical cluster analysis differentiated these fifteen cities into three groups with distinct strengths and weaknesses in terms of their intelligent development (Figure 8). In the first-tier cities, Shanghai, Nanjing, Changzhou, Hangzhou and Suzhou rank highly in their CityIQ scores, with excellent performance in the aspects of Residents' Intelligent Capacity, Intelligent Economy and Industry and Intelligent Construction and Environment. Although its average CityIQ scores for the five dimensions are not high, Suzhou has similar strengths, so it belongs to the first tier. The second-tier cities are weaker than the first-tier cities in several aspects. The third-tier cities are weak in the dimensions of 'Intelligent Governance and Service', 'Intelligent Hardware Construction' and 'Intelligent Economy and Industry' in particular, according to their CityIQ scores.

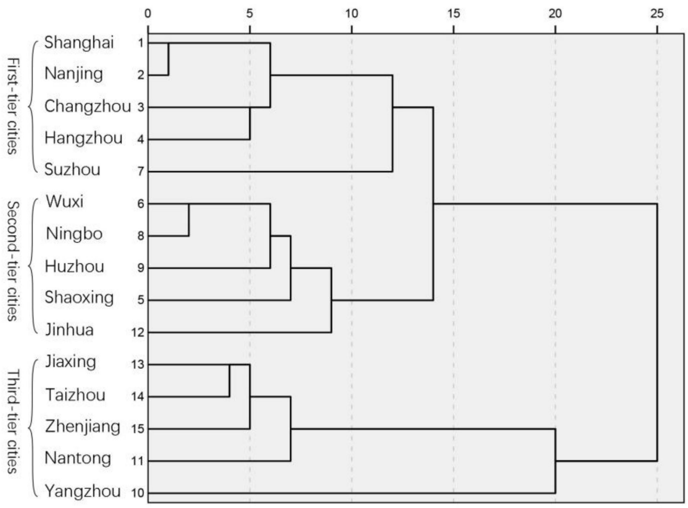

Figure 8. Cluster analysis of the overall CityIQ scores of these fifteen cities.

In order to further differentiate these fifteen cities in the five dimensions, a cluster analysis was conducted based on the scores of the four indicators in each dimension. In the dimension of 'Intelligent Economy and Industry', for example (Figure 9), the first-tier cities include Shanghai, Hangzhou, Wuxi, Huzhou, Nanjing, Ningbo and Jinghua, which perform well in all four indicators. The third-tier cities have disadvantages in several indicators, especially 'Innovative ideas' and 'Smart industries', according to their CityIQ scores.

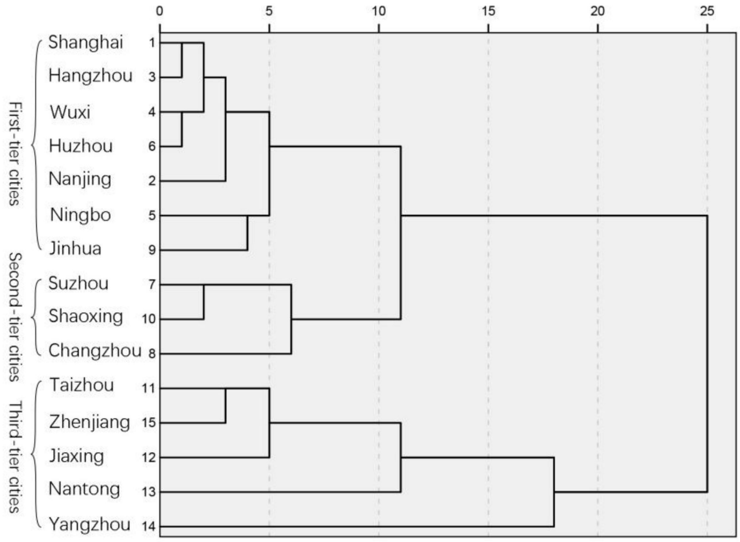

Figure 9. Cluster analysis of the dimension of 'Intelligent Economy and Industry'.

In order to further analyze the disparity among these fifteen cities in different indicators, a cluster analysis was conducted based on their scores for one indicator. For the indicator of 'Intelligent industries', for example (Figure 10), these fifteen cities were clustered into three groups.

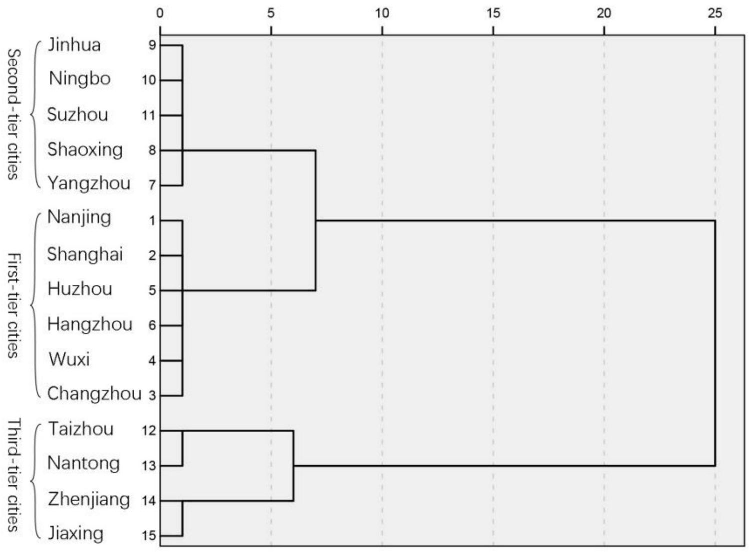

Figure 10. Cluster analysis of the 'Smart industry' indicator.

Based on the above analysis, each city in the Yangtze River Delta region has its own advantages and disadvantages regarding smart development. The intelligent development of different cities needs more integration and collaboration, according to their strengths and weaknesses in the five dimensions and twenty indicators. In the future, attention should be paid to regional cooperation, so that the allocation of resources can be continuously adjusted, reorganized and optimized. Understanding the advantages and disadvantages of smart development in different cities helps to promote the construction of smart infrastructure and the integration of industrial development and environmental protection to realize high-efficiency governance and the sustainable development of smart cities in the Yangtze River Delta.

5. Conclusions

This study developed a CityIQ evaluation system based on crowdsourced social media data, which covers five dimensions and twenty indicators of smart city development. Taking fifteen cities in the Yangtze River Delta region, China, as an example, the degree of city smartness in the five dimensions and twenty indicators was compared.

CityIQ achieves real-time information updates through the use of crowdsourced user-generated contents and innovative searching of a massive amount of online information regarding perspectives on the smartness of cities. It effectively solves the difficulty of obtaining large amounts of real-time data encountered in traditional evaluation index systems and establishes standards to measure the smartness level and public response of the citizens.

The theoretical advancement and practical innovation of smart cities are of great significance to urban construction and planning. Mutual comparisons and cooperation are important for regional collaborations and development [30]. According to the CityIQ evaluation system, cities' smart development levels in terms of five dimensions and twenty indicators are dynamically evaluated, so we can shape targeted policies to provide rational support for the development of smart cities. CityIQ could help to guide cities to achieve smart development through collaborative regional resources.

This study is an initial exploration of measuring smart cities by using public opinion data. Further studies are needed in the future. First, the temporal dynamics of CityIQ could be examined over time to support smart city collaborations over time. Second, it may be possible to compare smart city development in Western cities by using crowdsourced Twitter data. Third, sensitivity tests can be further employed to validate the analytical results. For instance, the results from the cluster analysis are subject to change when different cluster methods are applied.

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Appendix A

Table A1. Keywords for the twenty indicators.

Primary Dimension	Indicator	Keywords
Intelligent Construction and Environment	Environment monitoring	Air quality, air pollution index, AQI, fog and haze, PM 2.5 real-time monitoring, atmospheric pollution, air monitoring, air purifier, suspended particles
	Pollution monitoring	Atmospheric pollution, air pollution, PM 2.5, water pollution, solid waste pollution, soil pollution, chemical pollution, coal-fired, nitrogen oxides, carbon monoxide, noise pollution
	Intelligent construction	Internet of things, 5G, smart transportation, unmanned driving, artificial intelligence, cloud computing, big data, scientific and technological innovation, VR, virtual reality, BIM, CIM, smart life, intelligent manufacturing
	Green energy	Low carbon, clean energy, renewable energy, green industry, solar energy, new energy, wind energy, nuclear energy, biological energy

Table A1. *Cont.*

Primary Dimension	Indicator	Keywords
Intelligent Governance and Service	E-government	Informatization, automatic office, intelligent management, smart government, e-commerce
	Emergency alert	Disaster prevention and reduction, meteorological disaster, geological disaster, natural disaster warning, warning system, sensor, emergency response
	Smart transportation	Traffic, transportation, highway traffic, unmanned driving, intelligent transportation, transport facilities, urban transport, public transit, rail transport
	Smart health care	Health, physical health, mental health, smart hospital, smart medical, artificial intelligence doctor, electronic medical record, mobile phone registration
Intelligent Economy and Industry	Smart agriculture	Agricultural big data, modern agriculture, Internet of Things, mechanization, automatic control system
	Smart industries	Internet of Things, intelligent production, 3D Printing, connected factory, smart factory, intelligent manufacturing, Industry 4.0, industrial internet, smart commercial district
	Innovative idea	Business wisdom, cultural creativity, creative industry center, characteristic town, business incubator, creative industry
	Entrepreneurial support	Policy support, fiscal policy, policy support, talent introduction, settlement policy
Intelligent Hardware Construction	Wireless network	Wireless coverage, 5G, broadband, network performance, Wi-Fi, wireless communication
	Broadband speed	Broadband, optical fiber, broadband speed, network speed
	Data center	Data information, data transmission, data processing, data center facilities, big data center, urban brain
	Smart grid	Smart pipeline, oil and gas pipeline facilities, transportation, water supply network, pipeline maintenance
Residents' Intelligent Capacity	Public participation	Public, indirect participation, direct participation, public management, consulting and complaints, public sentiment, public opinion
	Digital library	Resources website, learning resources sharing, digital books, digital library, smart education, smart campus, educational informationization
	Tertiary education	Education, higher education, basic education, universal education, cultural education, elementary education, adult education, continuing education, diploma, training
	Talent policy	Talent policy, innovative talent, talent apartment, professional talent, settlement policy, talent introduction

References

1. Batty, M.; Axhausen, K.W.; Giannotti, F.; Pozdnoukhov, A.; Bazzani, A.; Wachowicz, M.; Ouzounis, G.; Portugali, Y. Smart cities of the future. *Eur. Phys. J. Spéc. Top.* **2012**, *214*, 481–518. [CrossRef]
2. Silva, B.N.; Khan, M.; Han, K. Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities. *Sustain. Cities Soc.* **2018**, *38*, 697–713. [CrossRef]
3. Meijer, A.; Bolívar, M.P.R. Governing the smart city: A review of the literature on smart urban governance. *Int. Rev. Adm. Sci.* **2015**, *82*, 392–408. [CrossRef]
4. Caird, S. City approaches to smart city evaluation and reporting: Case studies in the United Kingdom. *Urban Res. Pract.* **2018**, *11*, 159–179. [CrossRef]
5. Angelidou, M. Smart cities: A conjuncture of four forces. *Cities* **2015**, *47*, 95–106. [CrossRef]
6. Debnath, A.K.; Chin, H.C.; Haque, M.; Yuen, B. A methodological framework for benchmarking smart transport cities. *Cities* **2014**, *37*, 47–56. [CrossRef]

7. Cocchia, A. Smart and Digital City: A Systematic Literature Review. In *Smart City*; Springer International Publishing: Cham, Switzerland, 2014; pp. 13–43. [CrossRef]
8. Meijer, A.J.; Gil-Garcia, J.R.; Bolívar, M.P.R. Smart city research: Contextual conditions, governance models, and public value assessment. *Soc. Sci. Comput. Rev.* **2016**, *34*, 647–656. [CrossRef]
9. Gabrys, J. Programming Environments: Environmentality and Citizen Sensing in the Smart City. *Environ. Plan. D Soc. Space* **2014**, *32*, 30–48. [CrossRef]
10. Albino, V.; Berardi, U.; Dangelico, R.M. Smart Cities: Definitions, Dimensions, Performance, and Initiatives. *J. Urban Technol.* **2015**, *22*, 3–21. [CrossRef]
11. Batty, M. Smart Cities, Big Data. *Environ. Plan. B Plan. Des.* **2012**, *39*, 191–193. [CrossRef]
12. Myeong, S.; Jung, Y.; Lee, E. A Study on Determinant Factors in Smart City Development: An Analytic Hierarchy Process Analysis. *Sustainability* **2018**, *10*, 2606. [CrossRef]
13. Hollands, R.G. Will the real smart city please stand up? *City* **2008**, *12*, 303–320. [CrossRef]
14. Vanolo, A. Smartmentality: The Smart City as Disciplinary Strategy. *Urban Stud.* **2013**, *51*, 883–898. [CrossRef]
15. Giffinger, R.; Gudrun, H. Smart cities ranking: An effective instrument for the positioning of the cities? *ACE Arch. City Environ.* **2010**, *4*, 7–26. [CrossRef]
16. Allwinkle, S.; Cruickshank, P. Creating Smarter Cities: An Overview. *J. Urban Technol.* **2011**, *18*, 1–16. [CrossRef]
17. De Jong, M.; Joss, S.; Schraven, D.; Zhan, C.; Weijnen, M. Sustainable–smart–resilient–low carbon–eco–knowledge cities; making sense of a multitude of concepts promoting sustainable urbanization. *J. Clean. Prod.* **2015**, *109*, 25–38. [CrossRef]
18. Ahvenniemi, H.; Huovila, A.; Pinto-Seppä, I.; Airaksinen, M. What are the differences between sustainable and smart cities? *Cities* **2017**, *60*, 234–245. [CrossRef]
19. Kramers, A.; Höjer, M.; Lövehagen, N.; Wangel, J. Smart sustainable cities—Exploring ICT solutions for reduced energy use in cities. *Environ. Model. Softw.* **2014**, *56*, 52–62. [CrossRef]
20. Dameri, R.P. Searching for Smart City definition: A comprehensive proposal. *Int. J. Comput. Technol.* **2013**, *11*, 2544–2551. [CrossRef]
21. Batty, M. Big data, smart cities and city planning. *Dialog-Hum. Geogr.* **2013**, *3*, 274–279. [CrossRef]
22. Lee, J.H.; Hancock, M.G.; Hu, M.-C. Towards an effective framework for building smart cities: Lessons from Seoul and San Francisco. *Technol. Forecast. Soc. Chang.* **2014**, *89*, 80–99. [CrossRef]
23. Mahizhnan, A. Smart cities: The Singapore case. *Cities* **1999**, *16*, 13–18. [CrossRef]
24. Shapiro, J.M. Smart Cities: Quality of Life, Productivity, and the Growth Effects of Human Capital. *Rev. Econ. Stat.* **2006**, *88*, 324–335. [CrossRef]
25. Giffinger, R.; Fertner, C.; Kramar, H.; Kalasek, R.; Milanović, N.; Meijers, E. *Smart Cities—Ranking of European Medium-Sized Cities*; Centre of Regional Science, Vienna University of Technology: Vienna, Austria, 2007.
26. Schuurman, D.; Baccarne, B.; De Marez, L. Smart Ideas for Smart Cities: Investigating Crowdsourcing for Generating and Selecting Ideas for ICT Innovation in a City Context. *J. Theor. Appl. Electron. Commer. Res.* **2012**, *7*, 11–12. [CrossRef]
27. Shelton, T.; Lodato, T. Actually existing smart citizens. *City* **2019**, *23*, 35–52. [CrossRef]
28. Abu-Rayash, A.; Dincer, I. Development of integrated sustainability performance indicators for better management of smart cities. *Sustain. Cities Soc.* **2021**, *67*, 102704. [CrossRef]
29. Pira, M. A novel taxonomy of smart sustainable city indicators. *Humanit. Soc. Sci. Commun.* **2021**, *8*, 197. [CrossRef]
30. Neirotti, P.; De Marco, A.; Cagliano, A.C.; Mangano, G.; Scorrano, F. Current trends in Smart City initiatives: Some stylised facts. *Cities* **2014**, *38*, 25–36. [CrossRef]
31. Kummitha, R.K.R.; Crutzen, N. How do we understand smart cities? An evolutionary perspective. *Cities* **2017**, *67*, 43–52. [CrossRef]
32. Angelidou, M. Smart city policies: A spatial approach. *Cities* **2014**, *41*, S3–S11. [CrossRef]
33. Huovila, A.; Bosch, P.; Airaksinen, M. Comparative analysis of standardized indicators for Smart sustainable cities: What indicators and standards to use and when? *Cities* **2019**, *89*, 141–153. [CrossRef]
34. Nieminen, M.; Hyytinen, K. Future-oriented impact assessment: Supporting strategic decision-making in complex socio-technical environments. *Evaluation* **2015**, *21*, 448–461. [CrossRef]
35. Joss, S.; Sengers, F.; Schraven, D.; Caprotti, F.; Dayot, Y. The Smart City as Global Discourse: Storylines and Critical Junctures across 27 Cities. *J. Urban Technol.* **2019**, *26*, 3–34. [CrossRef]
36. Rahman, M.; Ali, G.N.; Li, X.J.; Samuel, J.; Paul, K.C.; Chong, P.H.; Yakubov, M. Socioeconomic factors analysis for COVID-19 US reopening sentiment with Twitter and census data. *Heliyon* **2021**, *7*, e06200. [CrossRef] [PubMed]
37. See, L.; Mooney, P.; Foody, G.M.; Bastin, L.; Comber, A.; Estima, J.; Fritz, S.; Kerle, N.; Jiang, B.; Laakso, M.; et al. Crowdsourcing, Citizen Science or Volunteered Geographic Information? The Current State of Crowdsourced Geographic Information. *ISPRS Int. J. Geo-Inf.* **2016**, *5*, 55. [CrossRef]
38. Wu, Z.; Pan, Y.; Ye, Q.; Kong, L. The City Intelligence Quotient (City IQ) Evaluation System: Conception and Evaluation. *Engineering* **2016**, *2*, 196–211. [CrossRef]
39. Intelligent Community Indicators. Available online: https://www.intelligentcommunity.org/method (accessed on 9 June 2021).
40. Kourtit, K.; Nijkamp, P.; Arribas, D. Smart cities in perspective—A comparative European study by means of self-organizing maps. *Innov. Eur. J. Soc. Sci. Res.* **2012**, *25*, 229–246. [CrossRef]

41. IDC Launches Smart City Evolution Index. Opens Public Voting to Identify Top Smart City Projects in Asia/Pacific. Available online: https://www.idc.com/ap/pulse/2016-february (accessed on 20 April 2021).
42. Dirks, S.; Keeling, M.; Dencik, J. *How Smart Is Your City?: Helping Cities Measure Progress*; IBM Institute for Business Value, IBM Global Business Services: New York, NY, USA, 2009.
43. Shanghai: Smart City Evaluation Index System 2.0. Available online: http://www.pudong.gov.cn/shpd/news/20121219/006002_1cfd6faf-d6d7-462e-abc5-533b4edf8cea.htm (accessed on 25 August 2021).
44. European Smart Cities 4.0. Available online: http://smart-cities.eu/?cid=2&ver=4 (accessed on 20 September 2021).
45. Kitchin, R. The real-time city? Big data and smart urbanism. *GeoJournal* **2014**, *79*, 1–14. [CrossRef]
46. Gong, Z.; Cai, T.; Thill, J.-C.; Hale, S.; Graham, M. Measuring relative opinion from location-based social media: A case study of the 2016 U.S. presidential election. *PLoS ONE* **2020**, *15*, e0233660. [CrossRef]
47. Lyu, K.; Kim, H. Sentiment Analysis Using Word Polarity of Social Media. *Wirel. Pers. Commun.* **2016**, *89*, 941–958. [CrossRef]
48. Kryvasheyeu, Y.; Chen, H.; Moro, E.; Van Hentenryck, P.; Cebrian, M. Performance of Social Network Sensors during Hurricane Sandy. *PLoS ONE* **2015**, *10*, e0117288. [CrossRef]
49. Allen, C.; Tsou, M.-H.; Aslam, A.; Nagel, A.; Gawron, J.-M. Applying GIS and Machine Learning Methods to Twitter Data for Multiscale Surveillance of Influenza. *PLoS ONE* **2016**, *11*, e0157734. [CrossRef] [PubMed]
50. Ye, X.; Wei, X. Multi-Dimensional Analysis of El Niño on Twitter: Spatial, Social, Temporal, and Semantic Perspectives. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 436. [CrossRef]
51. Liu, J.C.-E.; Zhao, B. Who speaks for climate change in China? Evidence from Weibo. *Clim. Chang.* **2016**, *140*, 413–422. [CrossRef]
52. Liu, X.; Song, Y.; Wu, K.; Wang, J.; Li, D.; Long, Y. Understanding urban China with open data. *Cities* **2015**, *47*, 53–61. [CrossRef]
53. Zhou, X.; Wang, M.; Li, D. From stay to play—A travel planning tool based on crowdsourcing user-generated contents. *Appl. Geogr.* **2017**, *78*, 1–11. [CrossRef]
54. Wang, Z.; Ye, X. Social media analytics for natural disaster management. *Int. J. Geogr. Inf. Sci.* **2018**, *32*, 49–72. [CrossRef]
55. Segev, E. *Google and the Digital Divide: The Bias of Online Knowledge*; Elsevier Science & Technology: Witney, UK, 2010.
56. Yang, T.; Ye, M.; Pei, P.; Shi, Y.; Pan, H. City Branding Evaluation as a Tool for Sustainable Urban Growth: A Framework and Lessons from the Yangtze River Delta Region. *Sustainability* **2019**, *11*, 4281. [CrossRef]