2025 European Conference on Computing in Construction
CIB W78 Conference on IT in Construction
Porto, Portugal
July 14-17, 2025

THE ASSEMENT FRAMEWORK AND GREATER IMPACT FACTORS ON SMART CITY CONSTRUCTION — A UNIT STUDY OF SHANGHAI, CHINA

Lijing Sun[1], Diran Yu[2], Weiwei Chen[2,3] and Haolang Zhao[4]
[1]Project Miles Transportation Doo Beograd, Patrijarha Varnave 48, Beograd 11000, SERBIA
[2]The Bartlett School of Sustainable Construction,
University College London (UCL), London WC1E 6BT, UK
[3]Civil Engineering Division, Engineering Department, University of Cambridge,
Cambridge, CB3 0FA, UK
[4]Shanghai Qibao Dwight High School, Minhang District, Shanghai 201101, CHINA

Abstract

Smart city construction is essential for sustainable urban development, particularly in developing countries facing urbanization and resource constraints. Current research is limited by cross-sectional and qualitative approaches. This study introduces a dynamic evaluation framework using a longitudinal case study of Shanghai (2012-2021), applying the entropy weight method to assess nine indicators across technology, economy, and environment. Results show that technological R&D, science and technology expenditure, foreign direct investment, and high-tech industrial output are more crucial contributors. The study offers a quantitative, longitudinal approach to smart city evaluation, providing a practical reference for policymakers in emerging cities of developing countries.

Introduction

Background

In the last few years, the smart city concept has become an important policy agenda in many developing and developed countries (Yigitcanlar, 2017). This concept was first proposed by IBM in 2008 and defined as the application of information and communication technology (ICT) to sense, analyse, and integrate essential data from the core city systems (Palmisano, 2008). Through the digital management of the environment, infrastructure, economy and other networks, urban management and intelligent services are achieved, making modern city operations more efficient (Su, Li and Fu, 2011), stimulating sustainable development (Ahvenniemi *et al.*, 2017) and promoting quality of life (Lee, Hancock and Hu, 2014). Thus, the construction of smart cities is of vital importance.

Nowadays, the construction of smart cities has become a global trend, with over 250 smart cities projects underway in 178 cities worldwide (Yigitcanlar and Kamruzzaman, 2018). Extensive research has been conducted on the development of smart cities in the United States and Europe. However, there are few studies on developing countries due to the limited awareness of sustainability issues or low economic development. In 2014, the Shanghai government proposed a three-year smart city construction plan (2014-2016) to cope with the global information technology revolution and lay a solid foundation for the construction of smart cities (Shanghai Government, 2014). In 2016, A Guideline for Sustainable Urban Development in the 21st Century (Shanghai Handbook) was published by the United Nations, the Shanghai government and some other institutions (Global Times, 2016). This handbook focuses on social inclusion, economic development, green growth, and public services, and lists 29 typical cases to introduce the practice of promoting sustainable urbanization. With the support of global and national policy, Shanghai has become a typical successful example of a smart city in developing countries, which can be used as a case study to provide useful guidance for future city development and cities in other developing countries.

Problem Statement

In the process of traditional urbanization, the urban-rural economic imbalance has led to a high concentration of urban population, and the contradiction between the rapidly developing economy and the carrying capacity of the ecological environment has become increasingly obvious. As densely populated areas, cities are facing problems such as scarcity of resources, environmental damage, and a deteriorating ecological environment. Thus, it is an inevitable trend to construct a smart city. Although more and more researchers study the factors that might affect the development of smart cities, there is little literature that quantifies these indicators. In this context, this paper aims to figure out the degree of influence of different factors on the smart city system through a combination of quantitative and qualitative approaches.

Therefore, this study seeks to answer the following research question: Which factors are more critical to the development of smart cities over time？

Research Objectives

This study seeks to quantitatively identify and assess the more crucial factors driving smart city development by applying the entropy weight method. Shanghai, as a representative example of an advanced smart city within a developing country context, is selected to examine the relative significance of technological, economic, and environmental indicators over a ten-year period (2012–2021). By refining and extending an existing evaluation framework, this research adopts a dynamic, longitudinal approach to capture the temporal evolution of smart city progress. The findings aim to offer actionable insights and serve as a reference model for other emerging cities in developing countries pursuing effective and sustainable smart city strategies.

Literature Review

The rapid expansion of smart cities, coupled with rising concerns about sustainability, has led to increased scholarly focus on various determinants of smart city development.

Technology

Technological advancement and smart city development are mutually reinforcing processes. As innovation propels urban transformation, the emergence of smart cities simultaneously drives the evolution of technological applications. Over the past decade, a substantial body of research has investigated how emerging technologies are embedded into smart systems to improve urban services and enhance sustainability, while also critically assessing the broader implications of these innovations.

Early studies demonstrated the value of Internet of Things (IoT) technologies in promoting urban sustainability and delivering enhanced citizen services (Zanella *et al.*, 2014; Hashem *et al.*, 2016). With further advancements, scholars identified the convergence of multiple cutting-edge technologies—such as hierarchical fog computing (Tang *et al.*, 2017), artificial intelligence (AI), wireless sensor networks, autonomous vehicles, and IoT—as instrumental in optimizing intelligent city systems (Ahad *et al.*, 2020; Yigitcanlar, Kankanamge and Vella, 2021). During this period, a substantial workforce has been directed toward the high-tech industry, while the government has simultaneously increased its expenditure on scientific and technological development. Notably, during the COVID-19 pandemic, technologies like digital twins and cloud-IoT integration played a critical role in real-time monitoring, public health management, and urban resilience (Lv, Chen and Lv, 2022; Shorfuzzaman, Hossain and Alhamid, 2021). The achievements of high-tech development are fully demonstrated at this stage.

Looking ahead, scholars such as Allam and Jones (2021) forecast the integration of 6G, digital twins, and extended reality (XR) as transformative forces in the next generation of smart cities, aligning with the United Nations' Sustainable Development Goal 11. However, technical barriers such as data security, privacy, and ethical governance also remain pressing concerns (Lim, Kim and Maglio, 2018; Javed *et al.*, 2022).

Environment

The environment constitutes a fundamental dimension of smart city development, influencing both strategic priorities and implementation outcomes. Neirotti et al. (2014) emphasized that the local environmental context significantly shapes a city's trajectory toward becoming smart, underscoring the interplay between ecological conditions and urban intelligence.

With the proliferation of digital technologies, many researchers have begun to explore how innovation can be harnessed to promote environmental sustainability. For example, blockchain has been deployed to optimize energy distribution in smart grids (Guan et al., 2018), while machine learning and computational intelligence have facilitated energy management in public services and infrastructure (Zekic-Susac, Mitrovic & Has, 2021). Further, data-driven applications have enhanced efficiency in transportation systems and the built environment (O'Dwyer et al., 2019; Lin et al., 2022). These efforts contribute not only to improved operational performance but also to healthier urban ecosystems by promoting sustainable energy use, enabling renewable resource management, and reducing emissions to enhance environmental quality.

Economy

Economic development is a core enabler of smart city transformation, serving both as a catalyst for technological innovation and as a beneficiary of smart infrastructure investment. Numerous studies have highlighted the critical role of high-tech industries, foreign direct investment (FDI), and research and development (R&D) in fostering economically resilient and technologically advanced urban environments.

Aldieri and Vinci (2018) noted the employment multiplier effect of technological innovation in urban economies and Jin and Li (2023) further emphasized that investment in R&D institutions by large enterprises contributes directly to the expansion of high-tech sectors, generating employment and stimulating innovation-driven growth. Moreover, foreign investment has also emerged as a significant economic driver in smart cities. Harvey and Rabetti (2024) observed that international capital not only brings in financial resources but also facilitates knowledge transfer and global integration. This contributes to the diffusion of best practices and the acceleration of technology adoption, positioning cities as competitive hubs in the global economy.

In conclusion, while scholars employ a range of assessment methods to evaluate smart cities, most consistently emphasize three core dimensions: technology, economy, and environment.

Research Gaps

While existing studies—both qualitative and quantitative—have made substantial contributions to identifying various factors that influence smart city development, most have primarily examined these factors in isolation or assessed their general impact based on national contexts. In particular, considerable attention has been paid to the role of environmental sustainability in shaping smart city trajectories. However, a significant gap persists in the literature, as few studies—if any—have undertaken a systematic comparison of the relative importance of these influencing factors. Given that many cities, especially in developing countries, face constraints in terms of funding and skilled human capital, it is essential to quantitatively evaluate and prioritize the key drivers of smart city development. Such an approach would enable more efficient resource allocation and targeted policymaking.

Research Methodology

To identify the more important impact factors of the smart city and study how to promote the smart city better, the author adopts a mixed-method approach to conduct the research, including qualitative and quantitative methods. Since the qualitative analysis cannot measure and compare the importance of different indexes on the smart city system, this paper applies qualitative methods to analyze and adapt existing smart city frameworks proposed by other scholars and then uses the quantitative methods to calculate the weights of different indexes on the framework of the smart city, which enables the results to be more intuitive and comparable. In addition, Shanghai, China is selected as the case study to put forward some new suggestions for countries that attempt to take measures to promote smart city development.

Entropy method

When it comes to determining the weights of indexes, there are two kinds of methods, namely subjective fixed weight methods like the analytic hierarchy process method (AHP) and objective fixed weight methods, like the entropy method (Li *et al.*, 2011). Compared with subjective fixed weight methods, objective fixed weight methods are to calculate the weights of indicators based on the intrinsic information of indexes, which can avoid the interference of human factors (Ding *et al.*, 2017) and improve the objectivity of decision-making and evaluation results (Taheriyoun, Karamouz and Baghvand, 2010). The smaller the entropy value of an index, the greater the variation degree of the index value and the more information it provides, and the greater the role it plays in the comprehensive evaluation system, the greater the weight of the index should be. Thus, the entropy method is used to determine the weights of indicators of the smart city in this paper.

Data Source

The data used in this case study are secondary sources collected from various official government websites between 2012 and 2021. These sources include the *China Statistical Yearbook, China City Statistical Yearbook, China Information Industry Yearbook, and Shanghai Statistical Yearbook*. In terms of reliability, comprehensiveness, and accessibility, government-published data are subject to strict quality control and verification processes. Therefore, the results demonstrate enhanced credibility due to the robustness of the methodology and the reliability of the data sources.

Data Processing

Building upon the existing literature, this study identifies technology, economy, and environment as the three fundamental dimensions of the smart city system. To ensure a comprehensive and systematic evaluation framework, the author adopts and refines the model proposed by Li et al (2019), which has been recognized as effective and successfully applied by scholars at Central China Normal University and the Hong Kong Polytechnic University (see *Table 1*). The adaptation of Li et al.'s framework is driven by the need to better align it with the specific characteristics of Shanghai, a representative case of a high-level smart city in China. Li et al.'s model, which assesses the development patterns of 35 smart cities in China across five different development tiers using six dimensions and twenty-two indices, provides a robust analytical foundation. However, to make it more applicable to the unique dynamics of Shanghai's smart city evolution, the framework has been tailored to incorporate a longitudinal perspective, capturing the city's development trajectory over a ten-year period. This adaptation ensures a more relevant and precise evaluation of the factors influencing Shanghai's smart city development.

Note

[1] Labour employment in information transmission, computer services and software: It refers to the number of people working in companies related to information transmission, computer services and the software industry.

[2] Science and technology expenditure: It refers to the government's annual expenditure on science and technology.

[3] High-tech industrial output from principal business: It refers to the output or value of the high-tech industry in the main business field of the enterprise.

[4] Technological R&D institutions funded by large enterprises: It refers to the number of R&D institutions that are invested by companies with above-average revenue.

[5] Number of Projects for Contracted Foreign Direct Investment: It refers to enterprises set up by juridical persons and natural persons from foreign countries, Hong Kong, Macao and Taiwan in mainland China by way of investment in cash, physical objects, intangible assets and equity, of which all the investments made by foreign investors in unlisted companies and in listed companies in which the proportion of equity held by a single foreign investor is not less than 10 per cent.

Table 1: Systems for the Smart City (Adapted by the author)

System	Factor Level	Explanatory Level	Index	Nature
Smart city	Smart Technology	Innovative Resource	Labour Employment in Information Transmission, Computer Services and Software[1]	+
			Science and Technology Expenditure[2]	+
		Innovative Output	High-tech Industrial Output from Principal business[3]	+
	Smart Economy	Sustainable Productivity	Per Capita GDP	+
		Enterprise Investment	Technological R&D Institutions Funded by Large Enterprises[4]	+
		Global Interconnectedness	Number of Projects for Contracted Foreign Direct Investment[5]	+
			Export Value of High-tech Enterprises	+
	Smart Environment	Renewable Management	Environmental Protection Investment	+
		Environmental Quality	Rate of Good Ambient Air Quality	+

By applying Shanghai's data from 2012 to 2021 to the adapted framework, the author evaluates the indicators' weights using SPSS. The specific calculation steps of the entropy method are as follows:

a. Standardization of indexes

By standardizing each index, the errors caused by different units are reduced. U_i (i=1) is set as the comprehensive evaluation values of the smart city system, that is, the comprehensive development level. U_{ij} ($0 < U_{ij} < l$) refers to the significance of the j index to the i system (j=1, 2, …, m). The larger the value of U_{ij}, the higher the importance. The specific calculation method is as follows:

$$U_{ij} = \begin{cases} (X_{ij} - X_{min})/(X_{max} - X_{min}), \\ if\ U_{ij}\ is\ the\ positive\ \text{index} \\ (X_{max} - X_{ij})/(X_{max} - X_{min}), \\ if\ U_{ij}\ is\ the\ negative\ \text{index} \end{cases} \tag{1}$$

b. Determination of entropy values and weights

The formulas of the entropy value of E_j and the weight of λj are as follows:

$$E_j = -k \sum_{i=1}^{m} U_{ij} \ln U_{ij} \tag{2}$$

$$\lambda_j = (1 - E_j)/(n - \sum_{j=1}^{n} E_j)\ and\ \sum_{j=1}^{n} \lambda_j = 1 \tag{3}$$

In these two equations, m is the total number of the year, n is the total number of indexes, and k= -1/ lnm.

c. Determination of the evaluation indexes of the two systems

As illustrated above, U_1 represents the comprehensive evaluation of the smart city system, namely the development level of the system. The formula is as follows:

$$U_i = \sum_{j=1}^{n} \lambda_j U_{ij} \tag{4}$$

Results

Through the entropy method, the results addressing the research question are presented in *Table 2*. In the smart city evaluation framework composed of technological, economic and environmental perspectives, four out of nine indicators have weights exceeding 11.11%, the threshold that represents the average value of these weights of indexes, and they are technological R&D institutions funded by large enterprises (18.50%), science and technology expenditure (12.01%), number of Projects for Contracted Foreign Direct Investment (11.78%) and high-tech industrial output from principal business (11.15%) respectively. In other words, at the technological level, when much innovative resource like science and technology expenditure is allocated by the government and innovative output like the high-tech industrial output from principal business is increasing, the smart city will be better constructed. At the economic level, if an increasing number of enterprises invest more funds into the establishment of technological R&D institutions, there will be further breakthroughs in many technologies, which promote the advancement of the smart city. Besides, when more projects are set up or invested by foreign companies, the global interconnectedness of the city will be stronger, which may result in technology iteration and industrial upgrading, and contribute to the city's smart transformation.

Table 2: Weights of different indexes of the smart city system (Source: the author's elaboration)

Factor Level	Explanatory Level	Index	Weight	Nature
Smart Technology	Innovative Resource	Labour Employment in Information Transmission, Computer Services and Software	10.99%	+
		Science and Technology Expenditure	12.01%	+
	Innovative Output	High-tech Industrial Output from Principal Business	11.15%	+
Smart Economy	Sustainable Productivity	Per Capita GDP	9.66%	+
	Enterprise Investment	Technological R&D Institutions Funded by Large Enterprises	18.50%	+
	Global Interconnectedness	Number of Projects for Contracted Foreign Direct Investment	11.78%	+
		Export Value of High-tech Enterprises	8.51%	+
Smart Environment	Renewable Management	Environmental Protection Investment	9.84%	+
	Environmental Quality	Rate of Good Ambient Air Quality	7.57%	+

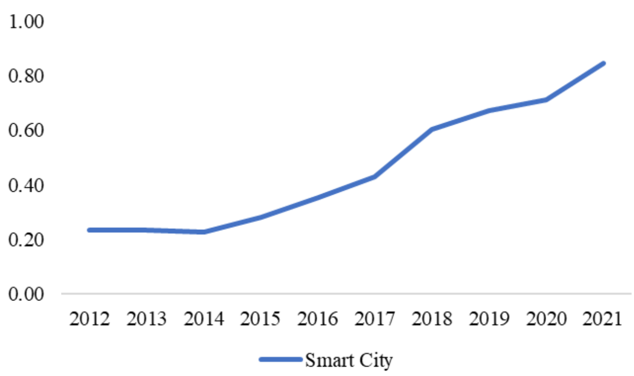

Figure 1: The trend for the comprehensive evaluation values of the smart city from 2012 to 2021 (Source: the author's elaboration)

In *Figure 1*, a noticeable surge in Shanghai's intelligence and digitalization is observed in 2014, coinciding with the Shanghai government's introduction of its smart city construction plan. The index subsequently reached 0.85, indicating a significant improvement in the city's overall smart city score, where a higher index reflects greater progress in smart city development.

Discussion

At the technological level, as future smart cities aim to meet the growing demands of urban populations, advancements in information and communication technologies (ICT) are expected to play a pivotal role in enabling more efficient and responsive resource management (Javed et al., 2022). Accordingly, increased investment in science and technology is essential to support the development and deployment of advanced technologies that are integral to smart city initiatives. In recent years, an increasing number of countries have recognized the critical role of technological innovation in infrastructure development and the creation of sustainable urban environments. As a result, many have begun leveraging technological interventions to support and sustain smart ecosystems (Ahad *et al.*, 2020). For example, Energy Management Systems have made substantial progress by incorporating cutting-edge technologies such as artificial intelligence (AI), machine learning, and the Internet of Things (IoT) to optimize energy consumption, reduce operational costs, and minimize environmental impact—thereby contributing significantly to smart city construction (Ur Rehman *et al.*, 2023).

At the economic level, growing corporate attention to technological research and development (R&D) institutions has helped strengthen high-tech industries, which in turn stimulate economic growth (Zheng, Cheng and Li, 2020), generate employment opportunities (Aldieri and Vinci, 2018), and increase tax revenues that can be reinvested into smart city projects. Moreover, in the context of a robust economy, foreign direct investment brings in not only capital but also new technologies, technical expertise, and additional financing channels (Harvey and Rabetti, 2024). Such international cooperation facilitates knowledge exchange and the adoption of global best practices in smart city development.

In light of the findings, both governments and enterprises, as primary drivers of smart city construction, should actively support technological innovation and upgrades while prioritizing economic development. These two pillars—technology and economy—play a foundational role in advancing smart city strategies and achieving long-term sustainability.

Similarities and Differences with Previous Literature

Compared to previous studies, this paper adopts a quantitative approach to identify the key factors that play a more significant role in the development of smart cities. While most existing literature tends to emphasize qualitative analysis, or at best offers limited quantitative assessments, few have directly compared the relative importance of different influencing factors. For instance, Fernandez-Anez et al. (2018) proposed that smart cities were composed of "governance", "economy", "environment", "mobility", "people" and "living" based on the work of (Giffinger *et al.*, 2007) qualitatively, while Zhang and Chen (2021) chose indicators in the three dimensions of resource consumption, ecological restoration, and socioeconomic development to assess urban sustainability by taking 17 cities in China as an example quantitatively. In this essay, by modifying and refining the analytical framework established by Li et al (2019), this study selects Shanghai—a representative high-level smart city—as the case study, and aims to identify the more significant influencing factor on the smart city construction, which promotes research on the determinants of smart city development and is expected to offer practical insights for other well-developed cities in developing countries seeking to advance their own smart city strategies.

In addition, in the tailored evaluation model developed specifically for Shanghai, a dynamic time-series dataset spanning ten years is analyzed to capture its longitudinal development trajectory through the entropy method. While the original framework created by Li et al (2019) was designed to assess 35 Chinese cities across five development tiers in a cross-sectional manner using the principal component analysis (PCA) and back propagation (BP) neural network techniques, it lacked the capacity to evaluate the temporal evolution of smart city development within individual cities. This study addresses that gap by optimizing the framework and using the entropy method to incorporate a longitudinal perspective, thereby enriching the overall understanding of urban smart development over time.

Limitations and Recommendations

The paper still presents certain limitations in terms of research scope and data processing. Regarding the research scope, the current evaluation framework of the smart city is limited to three dimensions: technology, economy, and environment. However, with the increasing research in this field, other critical factors influencing the development of smart cities—such as policy—have attracted increasing attention. Given that the advancement of many industries in developing countries, particularly in China, is heavily policy-driven, the Shanghai government's introduction of its smart city construction plan in 2014 had a significant impact on the city's digitalization and intelligence. This policy shift contributed to a noticeable surge in the smart city index, highlighting the need for future studies to incorporate policy or other contextual factors into the evaluation framework and explore methodologies to quantify political influence.

Moreover, since this study exclusively focuses on Shanghai, its findings are primarily applicable to emerging cities in developing countries that share similar development conditions. Due to significant variations in geography, governance structures, and socio-economic contexts, the proposed framework may not be universally applicable. Future research should aim to include comparative case studies from a broader range of cities and countries to enhance the generalizability and robustness of the model.

In terms of data processing, to improve the quality of the research, secondary data is processed before it is used. For instance, imputation methods were employed to handle missing data. Besides, the author selects data from the last ten years to enlarge the sample size, minimizing the bias. However, data access is restricted by official regulations since the secondary data in this essay can only be released by authorized agencies and are not subject to cross-verification, this may limit the replicability and transparency of the analysis.

Conclusion

This research is pivotal in advancing smart city construction and achieving sustainable development since this paper introduces a novel framework for evaluating which indicators have a greater impact on smart city development, collecting data of from Shanghai, China from 2012 to 2021 and utilizing the entropy method to quantify key driving factors. The finding reveals that technology and economic factors significantly contribute to smart city construction, and suggest that increased investment in science and technology, enhanced innovative output, expanded R&D funding, and improved global connectivity can substantially improve living standards and facilitate smart city progress. From the theoretical perspective, this paper bridges the gap between the previous research and future research as there is little research on this aspect. Additionally, various parties can conduct more detailed research to facilitate the progress of smart cities and perfecting the assessment framework in developing countries according to actual national conditions. From the practical perspective, the different proportions of different impact factors of the smart city system provide suggestions for the rational allocation of resources when the city has limited resource. In Shanghai, the government should make more investments in technological innovation and economic development. With the utilization of digital solutions, like energy-efficient infrastructures and urban sensor networks, technological incomes will be promoted, the living standards of people will be enhanced, and carbon emissions will be lowered. Furthermore, for other emerging cities in developing countries, this framework and the entropy methodology can serve as a valuable blueprint for sustainable smart city development.

References

Ahad, M. A., Paiva, S., Tripathi, G. and Feroz, N. (2020). 'Enabling technologies and sustainable smart cities'. Sustainable Cities and Society. Amsterdam: Elsevier, 61, p. 102301. doi: 10.1016/j.scs.2020.102301.

Ahvenniemi, H., Huovila, A., Pinto-Seppä, I. and Airaksinen, M. (2017). 'What are the differences between sustainable and smart cities?' Cities, 60, pp. 234–245. doi: 10.1016/j.cities.2016.09.009.

Aldieri, L. and Vinci, C. P. (2018). 'Innovation effects on employment in high-tech and low-tech industries: evidence from large international firms within the triad'. Eurasian Business Review, 8 (2), pp. 229–243. doi: 10.1007/s40821-017-0081-9.

Allam, Z. and Jones, D. (2021). 'Future (post-COVID) digital, smart and sustainable cities in the wake of 6G: Digital twins, immersive realities and new urban economies'. LAND USE POLICY, 101. doi: 10.1016/j.landusepol.2020.105201.

Ding, X., Chong, X., Bao, Z., Xue, Y. and Zhang, S. (2017). 'Fuzzy Comprehensive Assessment Method Based on the Entropy Weight Method and Its Application in the Water Environmental Safety Evaluation of the Heshangshan Drinking Water Source Area, Three Gorges Reservoir Area, China'. Water, 9 (5), p. 329. doi: 10.3390/w9050329.

Fernandez-Anez, V., Miguel Fernandez-Guell, J. and Giffinger, R. (2018). 'Smart City implementation and discourses: An integrated conceptual model. The case of Vienna'. Cities. Oxford: Elsevier Sci Ltd, 78, pp. 4–16. doi: 10.1016/j.cities.2017.12.004.

Giffinger, R., Christian Fertner, Hans Kramar, Robert Kalasek, Nataša Pichler-Milanović and Evert Meijers. (2007). Smart cities ranking of European medium-sized cities. Available at: https://www.smart-cities.eu/download/smart_cities_final_report.pdf.

Global Times. (2016). The Publication of Shanghai Handbook (2016). 环球网. Available at: https://www.huanqiu.com/article/9CaKrnJYiHN (Accessed: 14 August 2023).

Harvey, C. R. and Rabetti, D. (2024). 'International business and decentralized finance'. Journal of International Business Studies, 55 (7), pp. 840–863. doi: 10.1057/s41267-024-00705-7.

Hashem, I. A. T., Chang, V., Anuar, N. B., Adewole, K., Yaqoob, I., Gani, A., Ahmed, E. and Chiroma, H. (2016). 'The role of big data in smart city'. International Journal of Information Management. Oxford: Elsevier Sci Ltd, 36 (5), pp. 748–758. doi: 10.1016/j.ijinfomgt.2016.05.002.

Javed, A., Shahzad, F., Rehman, S., Bin Zikria, Y., Razzak, I., Jalil, Z. and Xu, G. (2022). 'Future smart cities requirements, emerging technologies, applications, challenges, and future aspects'. CITIES, 129. doi: 10.1016/j.cities.2022.103794.

Jin, C. and Li, D. (2023). 'Study on the impact of R&D input intensity on technological innovation output - Based on data from China's high technology industry'. PLOS ONE. Edited by C. Shen, 18 (10), p. e0292851. doi: 10.1371/journal.pone.0292851.

Li, X., Fong, P. S. W., Dai, S. and Li, Y. (2019). 'Towards sustainable smart cities: An empirical comparative assessment and development pattern optimization in China'. Journal of Cleaner Production, 215, pp. 730–743. doi: 10.1016/j.jclepro.2019.01.046.

Li, X., Wang, K., Liu, L., Xin, J., Yang, H. and Gao, C. (2011). 'Application of the Entropy Weight and TOPSIS Method in Safety Evaluation of Coal Mines'. Procedia Engineering, 26, pp. 2085–2091. doi: 10.1016/j.proeng.2011.11.2410.

Lim, C., Kim, K.-J. and Maglio, P. P. (2018). 'Smart cities with big data: Reference models, challenges, and considerations'. Cities. Oxford: Elsevier Sci Ltd, 82, pp. 86–99. doi: 10.1016/j.cities.2018.04.011.

Lv, Z., Chen, D. and Lv, H. (2022). 'Smart City Construction and Management by Digital Twins and BIM Big Data in COVID-19 Scenario'. Acm Transactions on Multimedia Computing Communications and Applications. New York: Assoc Computing Machinery, 18 (2), p. 117. doi: 10.1145/3529395.

Palmisano, S. J. (2008). A Smarter Planet: The Next Leadership Agenda.

Shanghai Government. (2014). Plan of Smart City Construction in Shanghai(2014-2016). Available at: https://app.sheitc.sh.gov.cn/zxgh/665205.htm (Accessed: 14 August 2023).

Shorfuzzaman, M., Hossain, M. S. and Alhamid, M. F. (2021). 'Towards the sustainable development of smart cities through mass video surveillance: A response to the COVID-19 pandemic'. Sustainable Cities and Society. Amsterdam: Elsevier, 64, p. 102582. doi: 10.1016/j.scs.2020.102582.

Su, K., Li, J. and Fu, H. (2011). 'Smart city and the applications'. in 2011 International Conference on Electronics, Communications and Control (ICECC). 2011 International Conference on Electronics, Communications and Control (ICECC), pp. 1028–1031. doi: 10.1109/ICECC.2011.6066743.

Taheriyoun, M., Karamouz, M. and Baghvand, A. (2010). 'DEVELOPMENT OF AN ENTROPY- BASED FUZZY EUTROPHICATION INDEX FOR RESERVOIR WATER QUALITY EVALUATION'. Journal of Environmental Health Science & Engineering, 7 (1), pp. 1–14.

Tang, B., Chen, Z., Hefferman, G., Pei, S., Wei, T., He, H. and Yang, Q. (2017). 'Incorporating Intelligence in Fog Computing for Big Data Analysis in Smart Cities'. Ieee Transactions on Industrial Informatics. Piscataway: Ieee-Inst Electrical Electronics Engineers

Inc, 13 (5), pp. 2140–2150. doi: 10.1109/TII.2017.2679740.

Ur Rehman, U., Faria, P., Gomes, L. and Vale, Z. (2023). ‘Future of energy management systems in smart cities: A systematic literature review’. Sustainable Cities and Society, 96, p. 104720. doi: 10.1016/j.scs.2023.104720.

Yigitcanlar, T. (2017). ‘Editorial: Smart cities in the making’.

Yigitcanlar, T. and Kamruzzaman, M. (2018). ‘Does smart city policy lead to sustainability of cities?’ Land Use Policy. Oxford: Elsevier Sci Ltd, 73, pp. 49–58. doi: 10.1016/j.landusepol.2018.01.034.

Yigitcanlar, T., Kankanamge, N. and Vella, K. (2021). ‘How Are Smart City Concepts and Technologies Perceived and Utilized? A Systematic Geo-Twitter Analysis of Smart Cities in Australia’. Journal of Urban Technology. Abingdon: Routledge Journals, Taylor & Francis Ltd, 28 (1–2), pp. 135–154. doi: 10.1080/10630732.2020.1753483.

Zanella, A., Bui, N., Castellani, A., Vangelista, L. and Zorzi, M. (2014). ‘Internet of Things for Smart Cities’. Ieee Internet of Things Journal. Piscataway: Ieee-Inst Electrical Electronics Engineers Inc, 1 (1), pp. 22–32. doi: 10.1109/JIOT.2014.2306328.

Zhang, D. and Chen, Y. (2021). ‘Evaluation on urban environmental sustainability and coupling coordination among its dimensions: A case study of Shandong Province, China’. Sustainable Cities and Society. Elsevier Ltd, 75. doi: 10.1016/j.scs.2021.103351.

Zheng, Y., Cheng, Y. and Li, L. (2020). ‘Factors Affecting Regional Economic Synergy in China – Based on Research on High-Tech Industry’. IEEE Access, 8, pp. 14123–14133. doi: 10.1109/ACCESS.2019.2959409.

Appendix

Table 3: The Values of Different Indexes of the Smart City System from 2012 to 2021

Year	Unit	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Labour employment in information transmission computer services and software	10^4 Number	208.62	253.90	289.94	338.14	381.59	434.15	483.69	591.19	657.13	803.79
Science and technology expenditure	10^8 Yuan	245.43	257.66	262.29	271.85	341.71	389.90	426.37	389.54	406.20	422.70
High-tech industrial output from principal business	10^8 Yuan	6099.44	6292.51	6670.49	6594.43	6951.17	8187.05	9014.65	8507.87	8362.92	8461.85
Per capita GDP	10^8 Yuan	21305.59	23204.12	25269.75	26887.02	29887.02	32925.01	36011.82	37987.55	38963.30	43214.85
Technological R&D institutions funded by large enterprises	Number	1179	1404	818	738	666	621	628	695	805	850
Number of Projects for Contracted Foreign Direct Investment	Number	4043	3842	4697	6007	5153	3950	5597	6800	5751	6708
Export value of high-tech enterprises	10^8 Yuan	309.28	266.40	363.50	455.85	502.95	584.16	588.31	553.96	692.52	737.26
Environmental protection investment	10^8 Yuan	570.49	607.88	699.89	708.83	823.57	923.53	989.19	1079.25	1087.86	1119.86
Rate of Good Ambient Air Quality	%	93.7	66.0	77.0	70.70	75.40	75.30	81.10	84.70	87.20	91.80