An Assessment Model Of Smart City Sustainable Development: Integrating Approach With Z-DEMATEL And Z-TOPSIS-AL

Qi-Gan Shao
Xiamen University of Technology

Chang-Chang Jiang
Xiamen University of Technology

Huai-Wei Lo (w110168888@gmail.com)
Chaoyang University of Technology https://orcid.org/0000-0002-8281-8740

James J. H. Liou
National Taipei University of Technology

Research Article

Keywords: smart city, sustainability, Z-DEMATEL, Z-TOPSIS, performance assessment

Posted Date: March 8th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1210313/v1

An assessment model of smart city sustainable development: integrating approach with Z-DEMATEL and Z-TOPSIS-AL

Qi-Gan Shao[1], Chang-Chang Jiang[1], Huai-Wei Lo[2*], James J. H. Liou[3]

[1]School of Economics & Management,
Xiamen University of Technology, Xiamen, China
[2*]Department of Business Administration,
Chaoyang University of Technology, Taichung, Taiwan
[3]Department of Industrial Engineering and Management,
National Taipei University of Technology, Taipei, Taiwan

Abstract

With the intensification of urbanization, the application of contemporary technology to make cities smarter is the key to their sustainable development (SD). This study aims to propose a comprehensive assessment framework for the SD of smart cities. First, an assessment system with 5 dimensions and 25 indicators is proposed in this paper. Second, a Z fuzzy-based multiple criteria decision-making (MCDM) model is developed to clarify the internal influence of the indicators and to determine the SD performance of smart cities. The Z-DEMATEL (decision-making trial and evaluation laboratory) technique was used to determine the mutual influence relationship of the indicator and their influence weights. Moreover, this paper selected one well-known city in China as a case study and used the Z-TOPSIS-AL (technique for order preference by similarity to ideal solution based on aspiration level) approach for analysis. The results demonstrate that quality of life, per capita GDP, and GDP growth rate are the top three indicators, which means that decision-makers should pay more attention to these indicators when constructing and managing a smart city. This study provides a reference for follow-up related research, and the management findings provide a basis for managers to make decisions on the development of smart cities.

* Corresponding author: Huai-Wei Lo, e-mail: w110168888@gmail.com

E-mail addresses:
qgshao@xmut.edu.cn (Q.G. Shao), ccjiang630@163.com (C.C. Jiang),w110168888@gmail.com (H.W. Lo), jamesjhliou@gmail.com (J.J.H. Liou)

Keywords: smart city, sustainability, Z-DEMATEL, Z-TOPSIS, performance assessment

Introduction

The deterioration of the global climate has also led to various extreme weather threats to the safety and health of urban residents, such as the once-in-a-century torrential rains and floods that occurred in Germany on July 13, 2021 and in Henan Province, China on July 20, 2021. Although cities occupy only 3% of the Earth's area, they account for approximately 55% (4.2 billion) of the world's population and 80% of the world's GDP (Mokarrari & Torabi, 2021). Moreover, the urbanization process has been accelerating. By 2050, the urban population will account for 69% (6.7 billion) of the world's total population (Benites & Simoes, 2021). These cases fully illustrate that the intelligent development of cities is the key to solving urban crises. To some extent, urban sustainable development (SD) determines global sustainable performance.

Measuring urban sustainability not only focuses on the economic dimension but also considers various aspects, such as society, the environment, technology, culture, etc. (Steiniger et al., 2020). With the population of information and communications technology (ICT) applications, there are growing calls for the use of 5G, the artificial intelligence (AI), internet of things (IoT), and other technologies to manage cities; and the urbanization process can lead to smart cities (Bibri, 2018b). Smart cities mean that urban public transportation is smarter, urban medical care is more convenient, resource utilization is better, etc. (Yigitcanlar et al., 2019). Macke et al. (2019) evaluated the sustainability of smart cities from the perspective of urban community residents. However, a large amount of the current literature is devoted to studying urban sustainability assessment or smart city assessment (Yi et al., 2021a; Zhou et al., 2021; Yi et al., 2021b; Ozkaya & Erdin, 2020), and few studies address the sustainability assessment of smart cities. In addition to focusing on the three pillars of economic aspect, environmental aspect, and social aspect, the assessment of smart cities also has requirements for the city's architectural form and the level of infrastructure construction (Bibri, 2018a; Sharma et al., 2020). Therefore, the objective of this paper is to determine the indicators that affect the SD of smart cities, clarify the influence relationships among the indicators and the degree of importance of the indicators, and demonstrate the application value and rationality of the assessment model through case studies.

Exploring the sustainability of smart cities involves multiple dimensions, which makes it a multiple criteria decision-making (MCDM) issue. The main components of applying MCDM to solve the sustainability problems of smart cities are as follows:

(i) Establishing a SD indicator system of smart cities,

(ii) Determining the influence relationship between dimensions,
(iii) Determining the dimension and indicator weights,
(iv) Ranking the SD levels of indicators, and
(v) Determining SD performance of smart cities in Xiamen.

The advantage of MCDM is that it integrates multiple indicators as much as possible to perform comparisons of the SD levels of multiple cities (Yi, et al., 2021a). The prerequisite for assessing the SD effects of smart cities is to build a complete evaluation index system. The indicators contained in this system should be distinguishable and multilevel, and there may be mutual influence relationships among indicators. From the perspective of ICT, Akande et al. (2019) merged 32 indicators into four components by using hierarchical clustering and principal component analysis (PCA) and ranked the level of sustainability and intelligence of approximately 28 European capital cities. Yigitcanlar et al. (2019) proposed a multidimensional smart city framework based on the economy, governance, environment and society; and they strengthened the difference and connections between sustainable cities with smart cities. Neves et al. (2020) presented an evaluation framework with 27 factors and six dimensions of smart cities from the perspective of open data initiatives. Yan et al. (2020) thought that smart devices are components of a smart city, and they proposed a smart city assessment system based on self-organization theory. A seven-dimensional evaluation system including a smart economy, smart environment, smart governance, smart living, smart energy, smart mobility, and smart people is proposed to assess the smart city performance of small- and medium-sized cities in northern Italy (Dall'O' et al., 2017). Mokarrari and Torabi (2021) ranked five important cities in Iran based on their intelligence by using six-dimensional and 20-subdimensional assessment systems. The above analysis shows that different practical contexts require using different assessment dimensions. Economic, environmental, and social perspectives are the basic pillars and guarantees for the development of smart cities. The architectural form and infrastructure of a city affect the scale and level of urban wisdom. In this study, an assessment system including 25 indicators from the five dimensions of built form (D_1), urban infrastructure (D_2), environmental sustainability (D_3), social sustainability (D_4), and economic sustainability (D_5) was established to measure the sustainability of smart cities.

After the assessment system is constructed, the sustainability quality of a smart city can be considered by analyzing indicator data. As a subdiscipline of operations research, MCDM is considered an effective model to solve the problem of projects such as assessment, ranking, selection, classification, etc. under multiple conflicting objectives. Some studies have used the MCDM method to survey sustainable cities. Koca et al. (2021) used the decision-making trial and evaluation laboratory (DEMATEL) model to find the causer and receiver effects of smart city assessment. Ozkaya and Erdin

(2020) evaluated the smart and sustainability level of cities around the world by combining the analytic network process (ANP) with the technique for order preference by similarity to ideal solution (TOPSIS); and they found that Tokyo, London and New York had high overall performance. Peng et al. (2021) discuss the sustainability level of 15 subprovincial cities in China based on grey relational analysis (GRA); and they found that Shenzhen, Guangzhou, and Hangzhou were the top three cities in the overall ranking. Li et al. (2021) measured sustainability, obtained the linchpin factors of Shenyang city in China by combining GRA with sequential relationship analysis (SRA), and found that the economy had the highest relationship with city sustainability. Yi et al. (2021a) assess the sustainable performance of first-tier cities in China based on GRA, and they concluded that most cities' sustainability was not ideal, but nearly all cities showed optimistic development prospects. However, MCDM aggregates a cluster of methods, and new methods are constantly being added. It is difficult to judge which model is the best. Therefore, using new methods to comprehensively assess the sustainability of smart cities is a beneficial supplement to existing research.

In this study, we propose a hybrid MCDM model based on Z fuzzy theory in which Z-DEMATEL is used to identify and determine the mutual influential relationships of the indicators and generate their influence weights. Furthermore, Z-TOPSIS based on the aspiration level (AL) concept (called Z-TOPSIS-AL) is used to determine the SD performance of smart cities. Since we incorporate the concept of the AL into the proposed hybrid model, this model can be used for analysis regardless of how many indicators are assessed. Furthermore, Z fuzzy theory not only considers information ambiguity and assessment environment uncertainty but also measures the confidence of experts/decision-makers in the assessment (Hsu et al., 2021). The proposed model has not been proposed in other articles. The advantages and contributions of this paper are as follows:

(i) This study takes the influence relationships among the indicators and visually displays them through graphics.
(ii) This study comprehensively uses and compares four methods including DEMATEL, fuzzy DANP, grey DEMATEL and Z-DEMATEL to measure the weights of indicators. This provides a practical demonstration program for the methodology of the smart city sustainability assessment system.
(iii) This study conducted case analysis of four famous second-tier cities in China at the indicator level, dimensional level and overall level.

The remainder of this paper is organized as follows. The relevant literature on the SD of smart cities is introduced in Section 2. Section 3 describes the methodology employed. In Section 4, data and result analysis is conducted. A case study and discussion are conducted in Section 5. Section 6 presents the conclusions and directions of future research related to the model.

Literature review

Urban economic growth has created job opportunities and attracted people to migrate from rural to urban areas. Urbanization has become a global urban development trend. Population growth has placed great pressure on the SD of cities, such as urban space expansion, urban infrastructure construction, environmental issues, and social issues (Ragheb et al., 2021). With the development of ICT, AI, IoT, and other technologies, it is necessary to apply these technologies to urban facilities to enhance the quality of life of residents. These new technologies enable residents to participate more in urban life (Zhang et al., 2021). Cities have also become more sensitive in identifying residents' needs and providing related services and solutions (Keshavarzi et al., 2021). A large number of sensors are used in urban facilities, such as traffic control systems, air pollution monitoring, and water resource management. The concept of smart cities is derived from the application of sensors in urban facilities, which control infrastructures and connected devices and users (Finger & Razzaghi, 2017). The purpose of the SD of smart cities is to use smart technology in urban construction, infrastructure applications, environmental optimization, economic development and the improvement of residents' quality of life (Keshavarzi, 2021). Based on this consideration, the dimensions involved in evaluating the SD of smart cities are also multifaceted.

Technology is the driving force that supports the SD of the urban environment, economy and society. Therefore, the SD of smart cities must consider the three perspectives of environmental sustainability, economic sustainability, and social sustainability (Akande et al., 2019; Yigitcanlar et al., 2019). The construction of a smart city is based on the city's existing planning, urban density, and land use patterns rather than overthrowing the existing patterns with new architectural forms (Bibri, 2018a; Shamsuzzoha et al., 2021). Urban transportation, ICT, logistics distribution networks and other technologies constitute urban infrastructure; and they are the core of supporting urban "smartness". Therefore, this study takes urban infrastructure as an important indicator to consider the SD of smart cities.

In summary, this study believes that measuring the SD of smart cities involves five dimensions, including urban built forms, urban infrastructure construction, environmental sustainability, social sustainability, and economic sustainability. **Table 1** shows the smart city sustainability assessment system formed by these five dimensions and their corresponding indicators.

Table 1 The assessment system for the sustainability of the smart city

Dimensions	Indicators	Descriptions	References

Built form (D_1)	Building densities (C_{11})	The ratio of building area to the entire city area.	Song et al. (2020); Bibri (2018a); Macke et al. (2018)
	Land use patterns (C_{12})	Types of urban land, such as the distribution of cultivated land, garden land, and forestland.	Höffken & Limmer (2019); Bibri (2018a); Yigitcanlar & Kamruzzaman (2018)
	Block sizes and shapes (C_{13})	The sizes, styles and spatial layouts of urban blocks.	Höffken & Limmer (2019); Huovila et al. (2019); Bibri (2018a)
	Public space arrangement (C_{14})	Outdoor and indoor spaces publicly used by citizens in daily life and social life.	Chen & Zhang (2020); Zhang et al. (2019); Bibri (2018b)
	Smart material (C_{15})	A new type of functional material that can perceive external stimuli, can judge and process appropriately, and is executable by itself.	Mishra & Gangele (2020); Sadowski & Maalsen (2020); Zhu et al. (2019)
Urban Infrastructure (D_2)	Smart transportation (C_{21})	Collect traffic information through high-tech means and provide traffic information services using real-time traffic data.	Sharma et al. (2020); Yigitcanlar et al. (2020); Bibri (2018b)
	ICT systems (C_{22})	The infrastructure and components that realize modern computing.	Sharma et al. (2020); Akande et al. (2019); Bibri (2018b)
	Distribution networks (C_{23})	Interconnected nodes distributed in different locations and with multiple terminals	Makhdoom et al. (2020); Sharma et al. (2020); Yahia et al. (2019)
	Data Sharing system (C_{24})	Citizens can read the desensitization data released by the city and perform various operations, calculations and analyses.	Makhdoom et al. (2020); Yahia et al. (2019); Reyna et al. (2018)
	Public safety and civil security (C_{25})	The stable external environment and order required for citizens to engage in normal life, work, study, entertainment and communication	Feizi et al. (2020); Makhdoom et al. (2020); Ejaz & Anpalagan (2019)
	Medical and health systems (C_{26})	Build a network system for hospitals and establish an enterprise-level application system based on it so as to realize the smooth circulation and high sharing of various information such as information	Sharma et al. (2020); Sadoughi et al. (2020); Bibri et al. (2017)

		on people, finances, and things.	
Environmental sustainability (D_3)	Wastewater treatment (C_{31})	Use physical, chemical, and biological methods to treat wastewater to purify wastewater and decrease pollution so as to achieve wastewater recycling and reuse and make full use of water resources.	Prasad et al. (2020); Akande et al. (2019); Zhu et al. (2019)
	Air pollution control (C_{32})	Pollutant emission control technologies and pollutant emission control policies adopted to handle city air pollutants	Feizi et al. (2020); Akande et al. (2019); Yigitcanlar et al. (2019)
	Solid waste treatment (C_{33})	Concentrate various wastes in the city and combine various waste treatment processes into a system according to the characteristics of solid wastes so that the materials and energy obtained from each process can be reasonably used.	Gopikumar et al. (2020); Ferronato et al. (2019); Zhu et al. (2019)
	Ratio of green coverage (C_{34})	The ratio of the total green coverage area in a city to the total area of the region is an important indicator reflecting the status of the ecological and environmental protection in a country or region.	Höffken & Limmer (2019); Zhu et al. (2019); Macke et al. (2018)
	Energy efficiency (C_{35})	Reflects the level of urban energy consumption and utilization effect	Akande et al. (2019); Zhu et al. (2019); Deakin & Reid (2018)
Social sustainability (D_4)	Population growth rate (C_{41})	The rate of population growth of a city caused by natural population changes and migration changes in a certain period of time (usually within 1 year).	Ahad et al. (2020); Macke et al. (2018); Yigitcanlar et al. (2018)
	Quality of life (C_{42})	Comparison between the higher living standards of citizens and the satisfaction of social and spiritual needs	De Guimarães et al. (2020); Feizi et al. (2020); Macke et al. (2018)
	Equality and social inclusion (C_{43})	Pays attention to the rights and interests of more different groups of citizens and attaches importance to the empowerment of the urban bottom groups and disadvantaged groups.	Ahad et al. (2020); Hatuka and Zur (2020); Macke et al. (2018)
	Government governance capacity (C_{44})	The government's ability to govern public affairs	Sharma et al. (2020); Huovila et al. (2019); Yigitcanlar et al. (2018)
Economy Sustainability	E-commerce development	The degree of development of urban e-commerce and related industries.	Chen and Zhang (2020); Xu et al. (2020);

(D_5)	(C_{51})		Akande et al. (2019)
	Per capita GDP (C_{52})	The value of the city's gross domestic product achieved in one year compared to the permanent population (or registered population).	Chen and Zhang (2020); Yi et al. (2019a); Zhang et al. (2019)
	GDP growth rate (C_{53})	The ratio of the city's GDP growth in that year compared to the previous year.	Chen and Zhang (2020); Yi et al. (2019a); Yi et al. (2019b)
	Tertiary industry per GDP (C_{54})	Per capita GDP of the tertiary industry.	Chen and Zhang (2020); Yi et al. (2019a); Yi et al. (2019b)
	Number of patents filed (C_{55})	The number of approved patent applications and the status of patent conversion in a certain period of time (1 year) in a city.	Hall et al. (2019); Khurana et al. (2019); Marco et al. (2019)

The proposed Z fuzzy-based MCDM model

We describe the proposed methodology in this Section. First, we introduced the concept and calculation program of Z-numbers. We developed complete assessment scales for Z-DEMATEL and Z-TOPSIS-AL. Then, the operating process of the improved Z-DEMATEL and Z-TOPSIS-AL techniques were introduced.

Principles and calculation of Z-numbers

Z-numbers is a fuzzy theory concept that is used to conduct calculations for an environment with incomplete reliable or confidence information (Zadeh, 2011). In short, Z-numbers involve two types of fuzzy element: assessment scores and reliability. The level of certainty of a fuzzy problem could be gauged using the machine rate and reliability. Then, Z-numbers could transform the two types of information into fuzzy numbers. It is having been proposed that Z-numbers and MCDM can be integrated to evaluate alternatives (Hsu et al., 2021). To further illustrate the concept, this study reveals the principles of converting fuzzy numbers to Z-numbers, and the specific implementation details are as follows.

Assume there is a Z-number is $Z=\left(\tilde{F},\ \tilde{R}\right)$, where $\tilde{F}$ is the assessment score and $\tilde{R}$ is the reliability degree of $\tilde{F}$. $\tilde{F}=\left(f,\ \mu_{\tilde{F}}\right)\middle|x\in\left[0,\ 1\right]$ and $\tilde{R}=\left(x,\ \mu_{\tilde{R}}\right)\middle|x\in\left[0,\ 1\right]$ are both trigonometric membership functions. A crisp score can be obtained by Eq. 1.

$$\alpha = \frac{\int^{x} \mu_{\tilde{R}}\ dx}{\int^{\mu_{\tilde{R}}} dx} \tag{1}$$

Next, the weight α of the reliability is employed to the evaluation score $\tilde{F}$, and the weighted Z-numbers can be calculated according to Eq. 2.

$$Z^{\alpha} = \left\{ \left(x,\ \mu_{\tilde{F}^{\alpha}} \right) \middle| \mu_{\tilde{F}^{\alpha}}(x) = \alpha \mu_{\tilde{F}}(x),\ x \in \sqrt{\alpha} x \right\} \tag{2}$$

A set of Z-number linguistic variables can be integrated according to the assessed score linguistic variables (**Table 2**) and reliability variables (**Table 3**). Here, we assume that an evaluation system has *n* indicators, and $c_i = \{c_1,\ c_2, \ldots,\ c_n\}$. The indicators must be used for pairwise comparisons to explore the interaction between the indicators, that is, to assess the degree of impact of c_i on c_j. The evaluation scale includes "equal influence (EI)", "weak influence (WI)", "fair influence (FI)", "very high influence (VI)", and "absolute influence (AI)". These linguistic variables will be converted to the corresponding membership function (fuzzy number). The transformation rules are shown in **Table 2**.

Table 2 Assessment scale and corresponding membership function of DEMATEL

Linguistic variable	Code	Membership function
Equal influence	EI	(0, 0, 1)
Weak influence	WI	(0, 1, 2)
Fair influence	FI	(1, 2, 3)
Very high influence	VI	(2, 3, 4)
Absolute influence	AI	(3, 4, 4)

Next, the experts were asked to construct a level of confidence in their responses, that is, the reliability of their assessments. The assessment scale includes "very low (VL)", "low (L)", "medium (M)", "high (H)", and "very high (VH)". **Table 3** lists the reliability rating scale.

Table 3 Assessment scale of the reliability and corresponding membership function in expert assessment

Linguistic variable	Code	Membership function
Very low	VL	(0, 0, 0.3)
Low	L	(0.1, 0.3, 0.5)
Medium	M	(0.3, 0.5, 0.7)
High	H	(0.5, 0.7, 0.9)

Very high	VH	(0.7, 1, 1)

Suppose there is the following set of assessment terms: "the assessment grade is medium impact (M), and the reliability is medium (M)". Then, the corresponding Z-number, $Z=\left(\tilde{F}=M,\ \tilde{R}=M\right)$, is calculated as follows:

$$Z=\left[(1,\ 2,\ 3),\ (0.3,\ 0.5,\ 0.7)\right]$$

According to Eq. 4, the membership function of reliability is converted into a crisp score.

$$\alpha=\frac{\int^{x}\mu_{\tilde{R}}dx}{\int^{\mu_{\tilde{R}}}dx}=\frac{\int_{0.3}^{0.5}x\left(\frac{x-0.3}{0.5-0.3}\right)dx+\int_{0.5}^{0.7}x\left(\frac{0.7-x}{0.7-0.5}\right)dx}{\int_{0.3}^{0.5}\left(\frac{x-0.3}{0.5-0.3}\right)dx+\int_{0.5}^{0.7}\left(\frac{0.7-x}{0.7-0.5}\right)dx}=0.4998$$

Then, α is added to the assessment score $\tilde{F}=M$.

$$Z^{\alpha}=\left\{(1,\ 2,\ 3)\middle|\alpha=0.4998\right\}$$

Finally, the weighted Z-number can be converted to the regular fuzzy number.

$$Z'=\left(\sqrt{0.4998}\cdot 1,\ \sqrt{0.4998}\cdot 2,\ \sqrt{0.4998}\cdot 1\right)=(0.707,\ 1.414,\ 2.121)$$

Other examples of Z-number calculations can be seen in Zadeh (2011).

Based on **Tables 2** and **3**, a total of 25 combinations of Z-numbers can be generated. According to the same calculation method, the semantic variable of Z-numbers and its membership function can be generated, as shown in **Table 4**.

Table 4 Z-DEMATEL semantic variables and membership functions

	Impact assessment				
Reliability	N	L	M	H	VH
VL	(0, 0, 0.316)	(0, 0.316, 0.632)	(0.316, 0.632, 0.949)	(0.632, 0.949, 1.265)	(0.949, 1.265, 1.265)
L	(0, 0, 0.548)	(0, 0.548, 1.096)	(0.548, 1.096, 1.644)	(1.096, 1.644, 2.192)	(1.644, 2.192, 2.192)
M	(0, 0, 0.707)	(0, 0.707, 1.414)	(0.707, 1.414, 2.121)	(1.414, 2.121, 2.828)	(2.121, 2.828, 2.828)
H	(0, 0, 0.837)	(0, 0.837, 1.673)	(0.837, 1.673, 2.510)	(1.673, 2.510, 3.347)	(2.510, 3.347, 3.347)
VH	(0, 0, 0.949)	(0, 0.949, 1.897)	(0.949, 1.897, 2.846)	(1.897, 2.846, 3.795)	(2.846, 3.795, 3.795)

In the performance assessment, the assessment scale used is shown in **Table 5**. Similarly, we continue the above Z-DEMATEL concept of membership function establishment and import it into TOPSIS technology so as to construct the semantic variable of Z-TOPSIS-AL and its corresponding membership function. The results are

shown in **Table 6**.

Table 5 Assessment scale and corresponding membership function of TOPSIS

Linguistic variable	Code	Membership function
Very poor	VP	(0, 1, 2)
Poor	P	(2, 3, 4)
Fair	F	(4, 5, 6)
Good	G	(6, 7, 8)
Very good	VG	(8, 9, 10)

Table 6 Z- TOPSIS-AL semantic variables and membership functions

	Performance assessment				
Reliability	**VP**	**P**	**F**	**G**	**VG**
VL	(0, 0.316, 0.632)	(0.632, 0.949, 1.265)	(1.265, 1.581, 1.897)	(1.897, 2.214, 2.530)	(2.530, 2.846, 3.162)
L	(0, 0.548, 1.096)	(1.096, 1.644, 2.192)	(2.192, 2.740, 3.288)	(3.288, 3.836, 4.384)	(4.384, 4.932, 5.480)
M	(0, 0.707, 1.414)	(1.414, 2.121, 2.828)	(2.828, 3.535, 4.242)	(4.242, 4.949, 5.655)	(5.655, 6.362, 7.069)
H	(0, 0.837, 1.673)	(1.673, 2.510, 3.347)	(3.347, 4.183, 5.020)	(5.020, 5.857, 6.693)	(6.693, 7.530, 8.367)
VH	(0, 0.949, 1.897)	(1.897, 2.846, 3.795)	(3.795, 4.743, 5.692)	(5.692, 6.641, 7.589)	(7.589, 8.538, 9.487)

Improved Z-DEMATEL model

Applying DEMATEL method could determine the interactive influence relationship among indicators and help decision-makers know which indicators are the main indicators influencing other indicators and which indicators are the affected indicators through an influential network relation map. It is difficult for decision-makers to reflect their true feelings in a complex and uncertain appraisal environment with using crisp scores. Several fuzzy theoretical approaches have been mixed with DEMATEL to reflect uncertainties (Gul, 2019). Unfortunately, these methods slight confidence degree that decision-makers have in their estimates. In this study, Z-numbers were introduced into DEMATEL so that the reliability of the decision group during the process of assessment could be known. A triangular fuzzy number was retained to conduct the operation to reduce the loss of information. In this study, an improved Z-DEMATEL method, which able to generate a set of indicators influential weights, is described below.

Step 1. Develop a set of evaluation indicators.

A group of experts is formed to establish an appropriate set of indicators $c_i = \{c_1, c_2, \ldots, c_n\}$.

Step 2. Establish the direct relation matrix $\otimes \boldsymbol{A}$.

Each decision-maker will assess the direct impact of indicator i on indicator j according to the assessment level in **Table 2** and check their confidence level according to the reliability level in **Table 3**. In this step, a DEMATEL questionnaire which involves a Z-number is distributed to experts to fill in.

An improved model which can be seen in Eq.3 is revealed to yield group judgments to reduce distorting the assessment results.

$$\min\ z=\sum_{k=1}^{K}\left(l_{ij}-l_{ij}^{k}\right)^{2}+\sum_{k=1}^{K}\left(m_{ij}-m_{ij}^{k}\right)^{2}+\sum_{k=1}^{K}\left(u_{ij}-u_{ij}^{k}\right)^{2}$$

$$s.\ t.\begin{cases}\min_{k}\ l_{ij}^{k}\le l_{ij}\le\max_{k}\ l_{ij}^{k},\\ \min_{k}\ m_{ij}^{k}\le m_{ij}\le\max_{k}\ m_{ij}^{k},\\ \min_{k}\ u_{ij}^{k}\le u_{ij}\le\max_{k}\ u_{ij}^{k},\\ l_{ij}\le m_{ij}\le u_{ij}.\end{cases}\tag{3}$$

where k is the decision-maker and k = 1, 2, …, K, and l_{ij}, m_{ij}, and u_i are respectively represented as the minimum, median, and maximum elements of the group judgment. Eq. 4 can be generated by partial differential of l_{ij}.

$$\frac{\partial z}{\partial l_{ij}}=2\sum_{k=1}^{K}\left(l_{ij}-l_{ij}^{k}\right)\cdot 1=0$$

$$l_{ij}=\frac{\sum_{k=1}^{K}l_{ij}^{k}}{K}\tag{4}$$

Similarly, m_{ij} and u_{ij} use the same program to generate Eqs. 5 and 6.

$$m_{ij}=\frac{\sum_{k=1}^{K}m_{ij}^{k}}{K}\tag{5}$$

$$u_{ij}=\frac{\sum_{k=1}^{K}u_{ij}^{k}}{K}\tag{6}$$

All decision-maker opinions are unified into a group's direct relation matrix through Eq. 3-6, as shown in Eq. 7.

$$\otimes\boldsymbol{A}=\left[\otimes a_{ij}\right]_{n\times n}=\begin{bmatrix}\otimes a_{11} & \otimes a_{12} & \cdots & \otimes a_{1j} & \cdots & \otimes a_{1n}\\ \otimes a_{21} & \otimes a_{22} & \cdots & \otimes a_{2j} & \cdots & \otimes a_{2n}\\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots\\ \otimes a_{i1} & \otimes a_{i2} & \cdots & \otimes a_{ij} & \cdots & \otimes a_{in}\\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots\\ \otimes a_{n1} & \otimes a_{n2} & \cdots & \otimes a_{nj} & \cdots & \otimes a_{nn}\end{bmatrix}_{n\times n},i=j=1,\ 2,\ldots,\ n.\tag{7}$$

where $\otimes a_{ij}=\left(a_{ij}^{L},\ a_{ij}^{M},\ a_{ij}^{U}\right)$. The diagonal element in matrix A must be 0, that is,

$\otimes a_{ij} = 0$ (when $i = j$).

Step 3. Generate the normalized direct relation matrix $\otimes \boldsymbol{Y}$.

Since the range of $\otimes a_{ij}$ is from 0 to 4, we can convert this assessment score from 0 to 1 by means of normalization (Eqs. 8 and 9).

$$\otimes \boldsymbol{Y} = \left[\otimes y_{ij}\right]_{n\times n} = \begin{bmatrix} \varepsilon\cdot\otimes a_{11} & \varepsilon\cdot\otimes a_{12} & \cdots & \varepsilon\cdot\otimes a_{1j} & \cdots & \varepsilon\cdot\otimes a_{1n} \\ \varepsilon\cdot\otimes a_{21} & \varepsilon\cdot\otimes a_{22} & \cdots & \varepsilon\cdot\otimes a_{2j} & \cdots & \varepsilon\cdot\otimes a_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \varepsilon\cdot\otimes a_{i1} & \varepsilon\cdot\otimes a_{i2} & \cdots & \varepsilon\cdot\otimes a_{ij} & \cdots & \varepsilon\cdot\otimes a_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \varepsilon\cdot\otimes a_{n1} & \varepsilon\cdot\otimes a_{n2} & \cdots & \varepsilon\cdot\otimes a_{nj} & \cdots & \varepsilon\cdot\otimes a_{nn} \end{bmatrix}_{n\times n} \tag{8}$$

where $\otimes y_{ij} = \left(y_{ij}^{L},\ y_{ij}^{M},\ y_{ij}^{U}\right)$. $\varepsilon = \min\left\{\dfrac{1}{\max_i \sum_{j=1}^{n} a_{ij}^{U}}, \dfrac{1}{\max_j \sum_{i=1}^{n} a_{ij}^{U}}\right\}$ (9)

Step 4. Generate the total impact matrix $\otimes \boldsymbol{T}$.

The normalized direct relation matrix can be calculated according to Eqs. 10-12, and the specific calculation process can be referred to Hsu et al. (2021).

$$\otimes \boldsymbol{T} = \left[\otimes t_{ij}\right]_{n\times n} = \begin{bmatrix} \otimes t_{11} & \otimes t_{12} & \cdots & \otimes t_{1j} & \cdots & \otimes t_{1n} \\ \otimes t_{21} & \otimes t_{22} & \cdots & \otimes t_{2j} & \cdots & \otimes t_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes t_{i1} & \otimes t_{i2} & \cdots & \otimes t_{ij} & \cdots & \otimes t_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes t_{n1} & \otimes t_{n2} & \cdots & \otimes t_{nj} & \cdots & \otimes t_{nn} \end{bmatrix}_{n\times n} \tag{10}$$

where $\otimes t_{ij} = \left(t_{ij}^{L},\ t_{ij}^{M},\ t_{ij}^{U}\right)$.

$$\otimes \boldsymbol{T} = \otimes \boldsymbol{Y} + \otimes \boldsymbol{Y}^{2} + \cdots + \otimes \boldsymbol{Y}^{\infty} \tag{11}$$

$$\begin{aligned} \otimes \boldsymbol{T} &= \otimes \boldsymbol{Y} + \otimes \boldsymbol{Y}^{2} + \cdots + \otimes \boldsymbol{Y}^{\infty} = \otimes \boldsymbol{Y}\left(\boldsymbol{I} + \otimes \boldsymbol{Y} + \otimes \boldsymbol{Y}^{2} + \cdots + \otimes \boldsymbol{Y}^{\infty-1}\right) \\ &= \otimes \boldsymbol{Y}\left(\boldsymbol{I} - \otimes \boldsymbol{Y}^{\infty}\right)\left(\boldsymbol{I} - \otimes \boldsymbol{Y}\right)^{-1} = \otimes \boldsymbol{Y}\left(\boldsymbol{I} - \otimes \boldsymbol{Y}\right)^{-1} \end{aligned} \tag{12}$$

where $\otimes \boldsymbol{Y}^{\infty} = [0]_{n\times n}$ and $\boldsymbol{I}$ is the identity matrix.

Step 5. Establish the influence relationship map (INRM) to find the interactive relationships between the indicators.

Eqs. 13 and 14 are used to sum each column of the matrix $\otimes \boldsymbol{T}$ to generate $\otimes \boldsymbol{r}$. Similarly, the sum of each row is calculated to generate $\otimes \boldsymbol{s}$ according to Eqs. 15 and

16.

$$\otimes \boldsymbol{r} = \left[\otimes r_i\right]_{n\times 1} = \left(\otimes r_1,\ \otimes r_2, \ldots,\ \otimes r_i, \ldots,\ \otimes r_n\right) \tag{13}$$

$$\left[\otimes r_i\right]_{n\times 1} = \left[\sum\nolimits_{j=1}^{n} \otimes t_{ij}\right]_{n\times 1} \tag{14}$$

$$\otimes \boldsymbol{s} = \left[\otimes s_j\right]_{1\times n} = \left(\otimes s_1,\ \otimes s_2, \ldots,\ \otimes s_j, \ldots,\ \otimes s_n\right)^T \tag{15}$$

$$\left[\otimes s_j\right]_{1\times n} = \left[\sum\nolimits_{i=1}^{n} \otimes t_{ij}\right]_{1\times n} = \left[\otimes s_i\right]_{n\times 1}^T \tag{16}$$

where "superscript T" is the transpose of the matrix, , $\otimes r_i = \left(r_i^L,\ r_i^M,\ r_i^U\right)$ and $\otimes s_i = \left(s_i^L,\ s_i^M,\ s_i^U\right)$.

$\otimes r_i + \otimes s_i$ is the index of the strength of influences given and received. Conversely, $\otimes r_i - \otimes s_i$ represents the net influence. A larger $\otimes r_i + \otimes s_i$ represents a greater impact of indicator *i* on the assessment system. If $\otimes r_i - \otimes s_i > 0$ (is positive), it indicates that indicator *i* has a significant influence on others. If $\otimes r_i - \otimes s_i < 0$ (is negative), it indicates that indicator *i* is affected by other indicators.

Here, the centroid method is used to defuzzy the score ($\otimes \lambda = \left(\lambda^L,\ \lambda^M,\ \lambda^U\right)$) to generate the crisp score (λ), as in Eq. 17

$$\lambda = \frac{\lambda^L + \lambda^M + \lambda^U}{3} \tag{17}$$

Next, $\otimes r_i$ and $\otimes s_i$ can generate r_i and s_i, respectively, through the defuzzing program of Eq. 17. The matrix $\otimes \boldsymbol{T}$ is used to recognize the influence between each indicator and draw arrows (indicating the direction of influence) to get an INRM.

Step 6. Generate the impact weight of development indicators

Here, $r_i + s_i$ reflects the total impact of the indicator on the assessment system. Therefore, the impact weight of an indicator can be constructed by using Eq. 18, $w_i = \left\{w_1,\ w_2, \ldots,\ w_n\right\}$. Here, the sum of weights is required to be 1 (Lo et al., 2019)

$$w_i = \frac{\left(r_i + s_i\right)}{\sum\nolimits_{i=1}^{n}\left(r_i + s_i\right)} \tag{18}$$

Z-TOPSIS-AL approach

The TOPSIS model is one of useful MCDM approaches to integrate performance scores. The approach is mainly used to find positive and negative ideal solutions (PIS and NIS) in combinations of projects and to determine the relative gap of each project by determining the gap between each project and the PIS and NIS (Gul et al., 2021). The best project is the one closest to the PIS and the one furthest from the NIS. TOPSIS approach is meant to comprehend and operate and have been used in miscellaneous decision issues (Rani et al., 2020; Zhan et al., 2020). In this paper, TOPSIS is combined with fuzzy theory to reflect the uncertainty of the practical assessment environment, and a relatively good solution is replaced by the AL (Liou et al., 2012). The detailed TOPSIS procedure is described as follows.

Step 1. Define symbols

Suppose there are m projects $A_i = \{A_1, A_2, \ldots, A_m\}$ and n indicators $c_j = \{c_1, c_2, \ldots, c_n\}$, and the weight of the indicators is defined as $w_j = \{w_1, w_2, \ldots, w_n\}$. Each decision-maker D_k (k = 1, 2, …, p) assesses the performance of project A_i according to indicator c_j. **Table 6** shows the performance assessment scale.

Step 2. Build the initial fuzzy decision matrix (FDM) $\otimes \boldsymbol{D}$.

Decision-maker D_k assesses all projects against the scales in **Table 6**. In this paper, the arithmetic mean is used to aggregate the assessment scores of all decision-makers to generate the initial assessment FDM, as shown in Eq. 19.

$$\otimes \boldsymbol{D} = \left[\otimes d_{ij}\right]_{m\times n} = \begin{bmatrix} \otimes d_{11} & \otimes d_{12} & \cdots & \otimes d_{1j} & \cdots & \otimes d_{1n} \\ \otimes d_{21} & \otimes d_{22} & \cdots & \otimes d_{2j} & \cdots & \otimes d_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes d_{i1} & \otimes d_{i2} & \cdots & \otimes d_{ij} & \cdots & \otimes d_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes d_{m1} & \otimes d_{m2} & \cdots & \otimes d_{mj} & \cdots & \otimes d_{mn} \end{bmatrix} \tag{19}$$

Here $\otimes d_{ij} = \left(d_{ij}^{l}, d_{ij}^{m}, d_{ij}^{u}\right)$, where i = 1, 2,…, m and j = 1, 2,…, n; and $d_{ij}^{l} = \frac{1}{p}\sum_{k=1}^{p} d_{ijk}^{l}$, $d^{m} = \frac{1}{p}\sum_{k=1}^{p} d_{ijk}^{m}$, and $d^{u} = \frac{1}{p}\sum_{k=1}^{p} d_{ijk}^{u}$, where k = 1, 2,…, p.

Step 3. Compute a normalized FDM $\otimes \tilde{\boldsymbol{X}}^{*}$.

The aim of normalization is to unify the units of all assessment indicators and make the scores in the matrix bound between 0 and 1. The normalized fuzzy matrix is

$\otimes \boldsymbol{D}^{*} = \left[\otimes d_{ij}^{*} \right]_{m \times n}$. The conventional normalized method takes the best performance score in the project as the denominator, as shown in Eq. 20.

$$\otimes d_{ij}^{*} = \frac{\otimes d_{ij}}{\max_{j} \left\{ \otimes d_{ij} \right\}} \tag{20}$$

In this paper, the concept of the AL is introduced into this step, and the modified formula is shown as Eq. 21.

$$\otimes d_{ij}^{*} = \frac{\otimes d_{ij}}{d^{aspire}} \tag{21}$$

where $x^{aspire} = 10$ (the highest level of the assessment scale).

Step 4. Obtain a weighted formalized FDM $\otimes \tilde{\boldsymbol{X}}^{**}$.

Considering the different importance of each indicator, the weight (w_j) assessed by the indicator is multiplied by the normalized FDM $\otimes \tilde{\boldsymbol{X}}^{**}$ to generate the weighted normalized FDM. The calculation method is shown in Eq. 22.

$$\otimes \boldsymbol{D}^{**} = \left[\otimes d_{ij}^{**} \right]_{m \times n} = \otimes d_{ij}^{*} \cdot w_j \tag{22}$$

Step 5. Define the fuzzy positive and fuzzy negative ideal solutions (FPIS and FNIS, respectively).

Based on the concept of the desirability level, the normalized scores of the PIS and NIS of the projects should be 1 and 0. Therefore, the fuzzy PIS and fuzzy NIS (A^{aspire} and A^{worst}, respectively) of project solutions are calculated as Eqs. 23 and 24, respectively.

$$A_j^{asprie} = \left(1 \cdot w_1,\ 1 \cdot w_2, \ldots,\ 1 \cdot w_n \right) = \left(w_1,\ w_2, \ldots,\ w_n \right) \tag{23}$$

$$A_j^{worst} = \left(0 \cdot w_1,\ 0 \cdot w_2, \ldots,\ 0 \cdot w_n \right) = \left(0,\ 0, \ldots,\ 0 \right) \tag{24}$$

Step 6. Compute the gap between each project solution and the fuzzy PIS and NIS.

The separation gaps between project i and the PIS and NIS are calculated according to Eqs. 25 and 26. In this step, the fuzzy scores were defuzzy and converted to crisp scores.

$$\varphi_i^{*} = \sum_{j=1}^{n} \sqrt{\left(\frac{\left(A_j^{asprie} - d_{ij}^{**l} \right)^2 + 2 \cdot \left(A_j^{asprie} - d_{ij}^{**m} \right)^2 + \left(A_j^{asprie} - d_{ij}^{**u} \right)^2}{4} \right)} \tag{25}$$

$$\varphi_i^{-} = \sum_{j=1}^{n} \sqrt{\left(\frac{\left(d_{ij}^{**l} - A_j^{worst} \right)^2 + 2 \cdot \left(d_{ij}^{**m} - A_j^{worst} \right)^2 + \left(d_{ij}^{**u} - A_j^{worst} \right)^2}{4} \right)} \tag{26}$$

Step 7. Calculation of the closeness coefficient (CC_i).

The proximity coefficient CC_i is a reliable ranking index. The ranking index considers the gap between all projects and the FPIS and FNIS and overcomes the disadvantages of the traditional TOPSIS ranking index (Kuo, 2017). The approximation coefficient is calculated using Eq. 27.

$$CC_i = w^+\left(\frac{\varphi_i^-}{\sum_{i=1}^{m}\varphi_i^-}\right) - w^-\left(\frac{\varphi_i^*}{\sum_{i=1}^{m}\varphi_i^*}\right), \quad \begin{cases} -1 \le CC_i \le 1 \\ 0 \le w^+ \le 1 \\ 0 \le w^- \le 1 \end{cases}, \quad i = 1, 2, \ldots, m \tag{27}$$

The closer CC_i is to 1, the closer the results are to the desired level. In contrast, the closer CC_i is to -1, the worse the performance.

Case study

Xiamen city, which is located on the southeast coast of China, is a subprovincial city and was selected as the research area. The lack of a scientific and unified understanding of the concept and connotation of smart cities is currently the main challenge for the development of smart cities in Xiamen. With the acceleration of Xiamen's urbanization process, problems such as environmental pollution, traffic jams, and energy shortages have become increasingly prominent and have triggered a wave of smart city construction. Therefore, this study seeks to provide targeted suggestions for the development of Xiamen by constructing an indicator system for evaluating the SD of smart cities.

Problem description and data collection

As mentioned in Section 2, the assessment system of smart cities involves five dimensions of the urban built form, urban infrastructure, environmental sustainability, social sustainability and economic sustainability and a total of 25 indicators under these five dimensions. In order to improve the strategies for the SD of smart cities, this study needs to clarify the dimensions and the influence relationships between the standards under each dimension and clarify the key indicators that promote the SD of China's smart cities. The Z-DEMATEL model, which has been introduced in Section 3.2, is used to explore the internal influence relationships among the dimensions and the indicators under each dimension. Moreover, this model applies Z-technology, which can alleviate the lack of correctness of decision-makers' subjective judgments.

To perform a comprehensive assessment, 12 decision-makers with extensive experience in the field of smart cities or SD are invited to conduct the analysis. The group of decision-makers comprised 6 senior managers engaged in the smart city

industry and 6 professors from the Urban Research Institute of a university in China. The 6 senior managers come from 3 companies in Xiamen, which are engaged in the development of artificial intelligence transportation technology, the provision of smart city technology solutions, and the design of urban architecture. All 6 professors have more than 15 years of experience in urban research and SD. Among these professors, 2 professors are mainly engaged in sustainable city research, 1 professor is engaged in smart environment research, 1 professor is engaged in green building research, and 2 professors are engaged in research in the field of smart cities. This study designs a questionnaire to generate the degree of influence between any two indicators according to **Table 3**. Decision-makers were invited to respond to make pairwise comparisons of the degrees of influence between the indicators. A 25×25 average initial direct relation matrix was calculated by averaging 12 decision-makers' responses.

Identify mutual influence relationships and influence weights

It is difficult to assess the interdependence of the SD indicators of smart cities. By applying DEMATEL, the direct relation matrix can be constructed by comparing indicators pairwise, and then the INRM and indicator weights can be generated. In view of the fuzziness of information and the uncertainty of the assessment environment, this work combines Z fuzzy theory and DEMATEL to strengthen and optimize the analysis model of conventional DEMATEL and measure the reliability of decision-maker assessments.

When quantifying decision-maker judgments, the use of general numerical scores cannot accurately reflect decision-maker judgments. To solve this problem, this paper uses the Z-DEMATEL semantic assessment method provided by Hsu et al. (2021) to find the corresponding Z numbers, as shown in **Table 3**. Taking the questionnaire data provided by one of the decision-makers as an example (**Table 7**), the decision-maker believed that the degree of influence of C_{11} on C_{12} was "absolute influence (AI)", and the reliability of the assessment score was "very high (VH)". Following the same answering method, the entire initial matrix will be transformed into a matrix similar to **Table 7**. The diagonal elements of the direct relation matrix represent the self-influence relations of the indicators. The diagonal elements should be set to 0 according to the requirements of DEMATEL.

Table 7 The direct relation matrix of the decision-maker 1

	C_{11}	C_{12}	C_{13}	C_{14}	⋯	C_{55}
C_{11}	0	(AI,VH)	(AI,H)	(AI,VH)	⋯	(EI,VH)
C_{12}	(AI,VH)	0	(AI,VH)	(AI,H)	⋯	(EI,VH)
C_{13}	(AI,VH)	(AI,VH)	0	(AI,VH)	⋯	(EI,VH)

C_{14}	(AI,H)	(AI,VH)	(AI,VH)	0	⋯	(EI,VH)
⋮	⋮	⋮	⋮	⋮	⋱	(EI,VH)
C_{55}	(FI,VH)	(FI,VH)	(FI,VH)	(FI,VH)	⋯	0

According to the Z-DEMATEL step of Section 3.2, the influence weights of all indicators can be generated, as shown in **Table 8**. The larger the weight of the indicator is, the greater the influence the indicator has on the assessment system. The results show that C_{42} is the most influential indicator; and C_{52}, C_{53}, C_{24}, and C_{22} are the second to fifth indicators, respectively.

Next, the weight of the indicator generated by Z-DEMATEL is used as one of the parameters calculated by Z-TOPSIS-AL.

Table 8 The results of Z-DEMATEL

	r	s	$r+s$	$r-s$	Weight	Rank
C_{11}	1.521	1.341	2.862	0.180	0.041	9
C_{12}	1.388	1.344	2.732	0.044	0.039	15
C_{13}	1.376	1.261	2.638	0.115	0.038	18
C_{14}	1.365	1.487	2.851	-0.122	0.041	10
C_{15}	1.537	1.109	2.646	0.429	0.038	17
C_{21}	1.480	1.617	3.097	-0.137	0.044	6
C_{22}	1.693	1.494	3.187	0.199	0.045	5
C_{23}	1.154	1.525	2.679	-0.371	0.038	16
C_{24}	1.662	1.562	3.224	0.099	0.046	4
C_{25}	0.994	1.883	2.877	-0.889	0.041	7
C_{26}	1.132	1.691	2.822	-0.559	0.040	12
C_{31}	1.224	1.356	2.580	-0.132	0.037	20
C_{32}	1.336	1.471	2.806	-0.135	0.040	14
C_{33}	1.193	1.420	2.613	-0.226	0.037	19
C_{34}	1.247	1.159	2.406	0.087	0.034	22
C_{35}	1.375	1.497	2.871	-0.122	0.041	8
C_{41}	0.984	1.308	2.292	-0.324	0.033	25
C_{42}	1.448	2.040	3.488	-0.592	0.050	1
C_{43}	1.165	1.223	2.389	-0.058	0.034	23
C_{44}	2.015	0.801	2.816	1.214	0.040	13
C_{51}	1.245	1.313	2.558	-0.068	0.036	21
C_{52}	1.749	1.495	3.243	0.254	0.046	2
C_{53}	1.739	1.503	3.242	0.237	0.046	3
C_{54}	1.255	1.587	2.842	-0.331	0.041	11
C_{55}	1.780	0.571	2.351	1.209	0.034	24

The INRM can be drawn using the total impact relationship matrix. The mutual influence between the 5 dimensions can be seen in Figure 1. The most influential

dimension is D_5, which significantly influences other dimensions (D_1, D_2, D_3, and D_4). In addition, D_1 is a secondary influential dimension, and D_2 is a dimension that is easily affected by other dimensions in the assessment system. It is worth mentioning that the internal indicators of D_5, D_1, and D_2 have a mutual influence relationship.

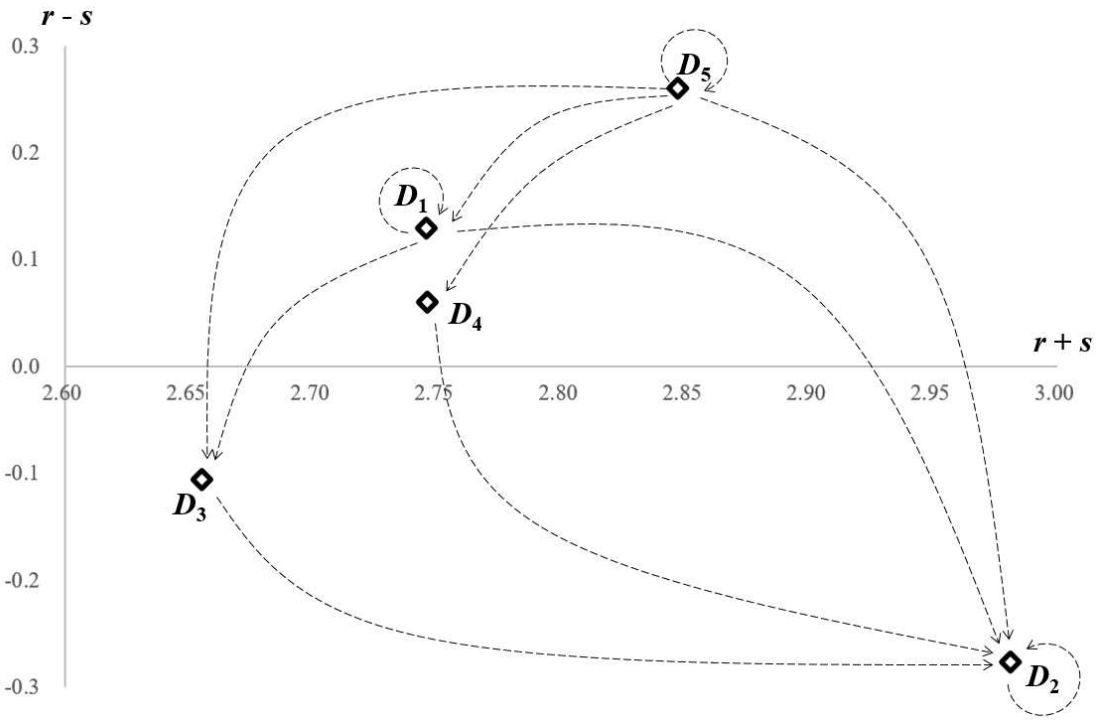

Figure 1 INRM of the dimensions

Determine the performance of the assessed project

This study focuses on the SD performance of smart cities in Xiamen. In this section, we present 8 decision-makers assessing Xiamen's performance in each indicator. For example, decision-maker 1 believes that Xiamen's performance in C_{11} is good (G), and the decision-maker has high confidence (high) in this assessment score. After each decision-maker assesses Xiamen's performance on 25 indicators from C_{11} to C_{55}, **Table 9** will be generated. According to **Table 6**, the translation variables can be converted to Z numbers. Many compromise ranking methods have no way to assess a single project, and the case in this work falls into this situation. To solve this problem, this paper adds the AL concept to the TOPSIS model and regards the desired level and the worst level as two assessed options. This shows that the existing assessed indicators are far from the ALs. **Table 10** shows the gap between Xiamen city and the desired level and the worst level, which are 0.504 and 0.504, respectively. Coincidentally, Xiamen's performance in developing a sustainable smart city is moderate, and it is not biased toward the desired level or the worst level.

Table 9 Xiamen city's SD performance under each indicator

	C_{11}	C_{12}	C_{13}	C_{14}	⋯	C_{55}
Decision-maker 1	(G,H)	(G,H)	(F,H)	(F,H)	⋯	(G,H)
Decision-maker 2	(G,M)	(F,M)	(F,M)	(VG,M)	⋯	(F,M)
Decision-maker 3	(F,VH)	(F,VH)	(F,VH)	(G,VH)	⋯	(F,VH)
Decision-maker 4	(F,H)	(G,H)	(P,H)	(G,H)	⋯	(F,H)
Decision-maker 5	(F,VH)	(P,VH)	(P,VH)	(F,VH)	⋯	(F,VH)
Decision-maker 6	(F,H)	(F,H)	(F,H)	(G,H)	⋯	(G,H)
Decision-maker 7	(G,VH)	(G,VH)	(F,VH)	(G,VH)	⋯	(P,VH)
Decision-maker 8	(F,H)	(F,H)	(F,H)	(G,H)	⋯	(F,H)

Table 10 Analysis results of Z-TOPSIS-AL

	φ^*	φ^-	CC
Options	0.504	0.504	0
Aspiration	0	1	0.333
Worst	1	0	-0.333

Figure 2 shows the performance of Xiamen city's (blue) smart SD in each indicator. The orange bars in Figure 1 indicate the best performance (desired level). Obviously, most of Xiamen's current performance in each indicator is medium. We can determine the gap and ranking of all indicators through **Table 11**; and the higher the indicator ranking is, the more improvement that is needed. C_{53}, C_{52}, C_{15}, C_{42} and C_{22} are the top five indicators most in need of review and drafting improvement plans. Further detailed management implications are discussed in Section 5.

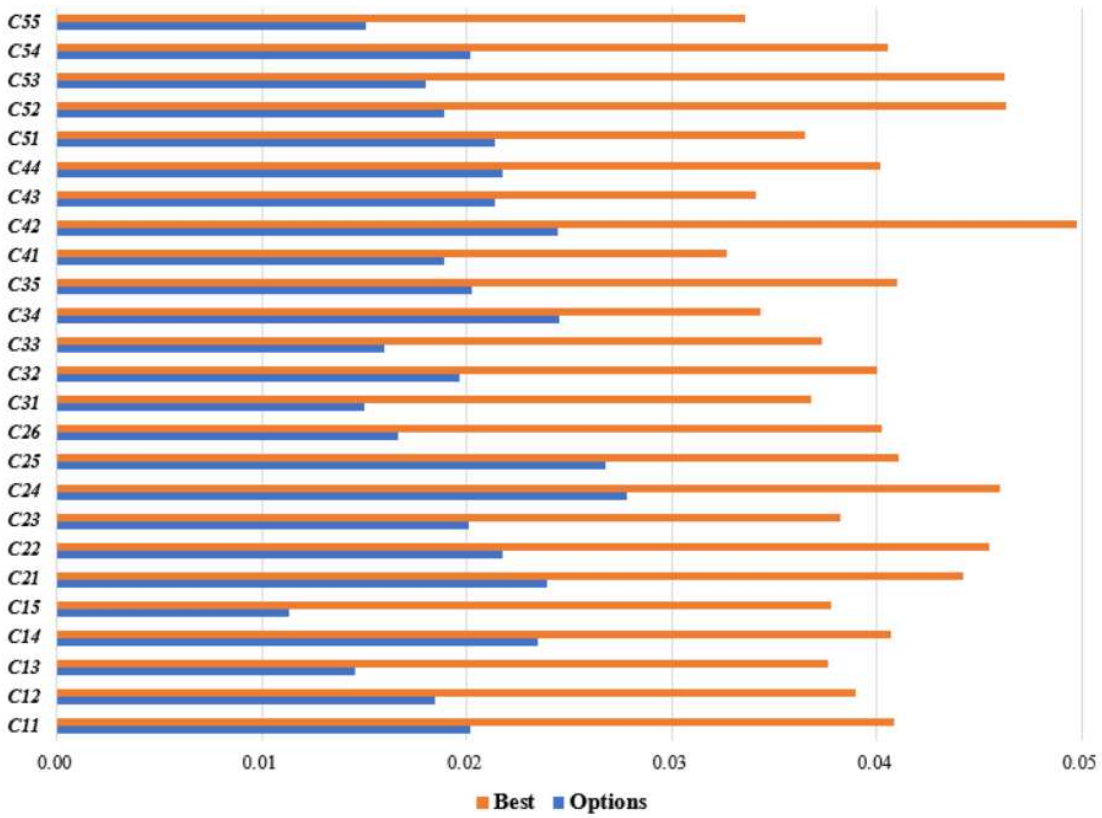

Figure 2 Gap analysis

Table 11 The gaps and rankings that Xiamen city needs to improve under each indicator

	Options	Aspiration	Gap	Rank
C_{11}	0.020	0.041	0.021	11
C_{12}	0.018	0.039	0.021	12
C_{13}	0.015	0.038	0.023	7
C_{14}	0.023	0.041	0.017	20
C_{15}	0.011	0.038	0.026	3
C_{21}	0.024	0.044	0.020	15
C_{22}	0.022	0.045	0.024	5
C_{23}	0.020	0.038	0.018	19
C_{24}	0.028	0.046	0.018	18
C_{25}	0.027	0.041	0.014	22
C_{26}	0.017	0.040	0.024	6
C_{31}	0.015	0.037	0.022	8
C_{32}	0.020	0.040	0.020	14
C_{33}	0.016	0.037	0.021	9
C_{34}	0.024	0.034	0.010	25
C_{35}	0.020	0.041	0.021	10
C_{41}	0.019	0.033	0.014	23
C_{42}	0.024	0.050	0.025	4
C_{43}	0.021	0.034	0.013	24

C_{44}	0.022	0.040	0.018	17
C_{51}	0.021	0.036	0.015	21
C_{52}	0.019	0.046	0.027	2
C_{53}	0.018	0.046	0.028	1
C_{54}	0.020	0.041	0.020	13
C_{55}	0.015	0.034	0.018	16

Discussion and comparisons

In order to illustrate the validity and applicability of the model used in this study, we implemented a number of DEMATEL methods for comparison. **Figure 3** presents the indicator rankings generated by the four DEMATEL methods. Obviously, the DEMATEL method does not consider the problem of information uncertainty, and its results are quite different from those of other methods. However, although fuzzy DEMATEL and grey DEMATEL are integrated into the consideration of uncertain environments, they lack the confidence of measuring decision-makers in the assessment. Z-DEMATEL can satisfy the above three methods, and the generated weight results will be more reasonable.

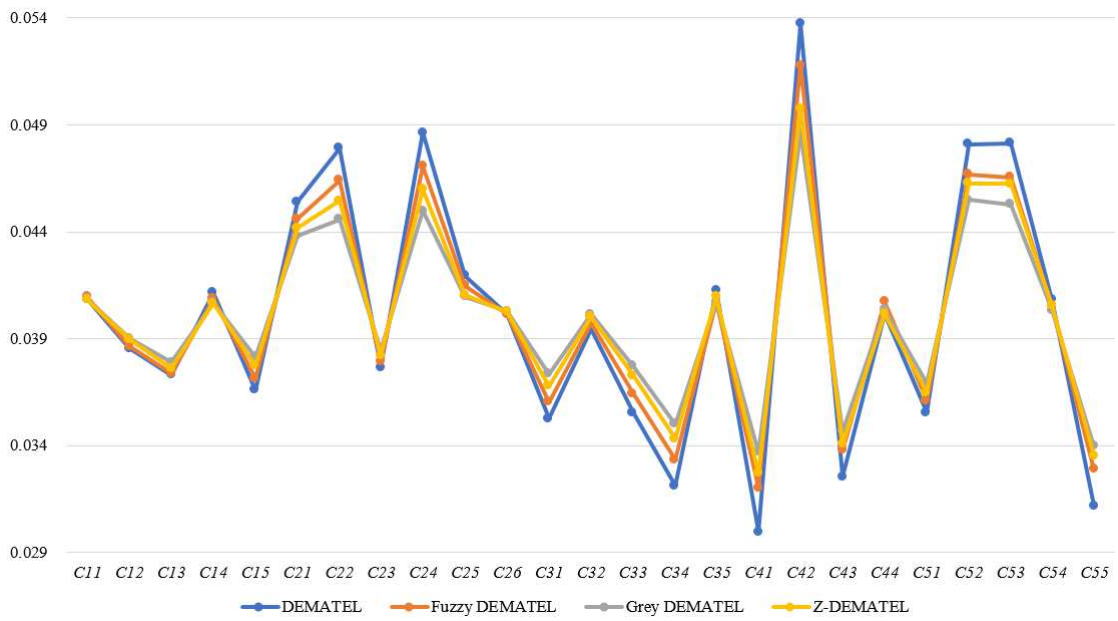

Figure 3 The indicator weights generated by the four DEMATEL methods

As shown in Table 8, quality of life (C_{42}) is the most influential indicator for evaluating the sustainability of smart cities. The per capita GDP (C_{52}), GDP growth rate (C_{53}), data sharing system (C_{24}) and ICT (C_{22}) ranked 2 to 5, respectively. Smart city projects impact the quality of life of citizens by improving the perceived quality of more citizens' services in the fields of transportation, medical care, and the environment.

Citizens positively or negatively evaluate their life experiences and their relationships with the city based on their views on a good and beneficial life (Macke, et al., 2018). Therefore, the improvement of the quality of life is the most intuitive benefit citizens feel regarding the development of smart cities. This is the reason why quality of life (C_{42}) is the most important indicator in the SD level system of smart cites. The per capita GDP (C_{52}) and GDP growth rate (C_{53}) are indicators to measure the status of urban economic development, reflect the citizens' living standards, and provide economic guarantees for the SD of smart cities. From a global perspective, well-developed smart cities are cities with high GDP per capita and faster GDP growth (Alizadeh, 2021). The construction of a smart city requires the government to invest considerable financial, human, and material resources in the fields of transportation, ICT, medical care, and the environment. This requires a city to have high fiscal revenues, and GDP is the most important indicator of the cites' fiscal revenue level. Therefore, the per capita GDP and GDP growth rate rank second and third, respectively, in importance in evaluating the sustainability of smart cities, which has important management implications. Data sharing/openness is considered indispensable for the development of smart cities (Mak & Lam, 2021). Makhdoom et al. (2020) stated that realizing data sharing is an important step in building a smart city construction environment and proposed using blockchain technology to realize the security of data sharing channels. Cao et al. (2020) proposed a trustworthy data sharing platform to enhance the transparency of data usage in smart cities. This paper believes that the application of data sharing systems in transportation, medical, business and other fields will generate strong commercial value; and the facts have also proven that mining the business logic behind big data is the driving force for the promotion of urban economic development. ICT (C_{22}), with the existing traditional infrastructure of the city and the use of digital technology for coordination and management, is the only way to sustain the construction and development of smart cities (Ahad et al., 2020). The core of using ICT technology to achieve "smartness" in cities is the sensors and actuators embedded in smart devices, which perceive the environment to facilitate effective decision-making. Therefore, the SD of smart cities must continue to apply various smart technologies to act as the brain of the city.

With respect to economic sustainability (D_5), e-commerce development (C_{51}) and the number of patents filed (C_{55}) are easily affected by other indicators. The level of urban residents' utilization of e-commerce is greatly affected by the local economic development and the education level of residents; and the per capita GDP, GDP growth rate and tertiary industry per capita GDP are the barometers of urban economic development and education level (Cheba et al., 2021). Therefore, it is easy to see how these three dimensions contribute to the development of e-commerce. For example, Hangzhou, a new first-tier city in China, is known as the e-commerce capital of China.

It is precisely because of Hangzhou's strong economic advantages and developed tertiary industry that e-commerce companies such as Alibaba have been cultivated. The city's sound economic foundation will encourage the government to spend great efforts on the research and development of new technologies, thereby forming sustainable economic development. Therefore, enterprises in economically developed cities will devote their energy to the research and development of new technologies to promote product upgrades and new product development. Shenzhen, known as the fastest-growing smart city, possessed a total of 1,681,566 patents in the first three quarters of 2020, ranking second in China. The intellectual property rights of a city have a significant relationship with its economic development.

As seen in Table 11, the population growth rate (C_{41}) and equality and social inclusion (C_{43}) are the result indicators in the dimension of social sustainability (D_4). The quality of life of urban residents has a significant impact on the growth rate of the urban population (Shi et al., 2021). The improvement of the quality of life of citizens is manifested in the high disposable income of families, transparent government management, perfect urban education system, reliable medical and health conditions, convenient transportation and other areas. These are exactly the goals pursued by smart cities. Most citizens tend to have children without great pressure. Efficient government governance capabilities promote social fairness and tolerance and ease the pressure on residents' lives, which is also an inevitable requirement for the SD of urban society. The ratio of green coverage (C_{43}) is the ratio of the vertical projection area of various types of green space in the city to the total area of the city. Its level is one of the important indicators to measure the quality of the level of urban environment sustainability. Public green space, street green space, and courtyard green space are the main components of urban green areas. When urban air pollution is well controlled and waste and wastewater treatment systems are complete, more land can be used for greening and beautifying the environment.

The aim of this work is to find strategies to improve the sustainability of smart cities based on sustainable indicators. The Z-TOPSIS-AL method is used to assess the sustainability of Xiamen, China. As seen in Table 9, smart materials (C_{15}), ICT systems (C_{22}), quality of life (C_{42}), per capita GDP (C_{52}) and GDP growth rate (C_{53}) are the indicators that have larger gaps compared to the desired level. In Xiamen, a large amount of energy is consumed, and the environment is polluted in various ways. The construction industry, manufacturing industry and even the daily lives of residents all demand smart materials (Balali & Valipour, 2020). It is necessary to accelerate the use of smart materials in the manufacturing industry and construction industry and detect and assess the degree of environmental optimization after the application of smart materials. In the retail industry, the government has increased the use of biodegradable plastic bags to reduce the environmental damage caused by white pollution. As an open

coastal city in China, Xiamen's GDP growth rate is not fast, and the total GDP is insufficiently high. In 2020, the GDP of Xiamen was 638 billion RMB, an increase of 5.7% compared to 2019. Excessive housing prices and low wages are the main reasons why the quality of life of residents in Xiamen has not been high. The improvement of the quality of life perceived by urban residents is a barometer to the SD of smart cities. Economically developed cities often more easily complete the design and construction of smart cities. Therefore, through smart city design, increasing the supply of urban land area, upgrading industrial development through green technology, increasing worker wages, and attracting more talent to work in Xiamen are important strategies to make the city more intelligent and sustainable.

Conclusion

As the most creative urban form, smart cities have become a strategic choice for global urban development. In order to promote the construction and development of smart cities, share successful experiences and summarize the current problems, it is necessary to assess the sustainability of smart city development. Assessing the SD of smart cities involves multiple dimensions. This study is an initial attempt to provide a framework of sustainability indicators for smart city assessment. A smart city sustainability assessment framework with 5 dimensions and 25 indicators, as shown in Table 1, is established in this paper. A hybrid MCDM model combining Z-DEMATEL with the Z-TOPSIS-AL method, which has not been employed in the literature, is proposed in this paper. Building a smart city SD assessment system and employing an intergraded Z-DEMATEL and Z-TOPSIS-AL model are the two contributions of this study.

This paper has some limitations that can provide opportunities for further research. First, this paper provides an in-depth discussion only on the assessment indicators of smart cities. Second, we conducted a case analysis for only the city of Xiamen, and we can sort and compare the degree of smartness and SD of multiple cities in the follow-up. Finally, the fuzzy-DEMATEL, grey-DEMATEL, Z-DEMATEL and rough-DEMATEL methods could be used together to find the best method.

References

Ahad M A, Paiva S, Tripathi G, Feroz N (2020) Enabling Technologies and Sustainable Smart Cities. Sustain. Cities Soc. 61: 102301.

Akande A, Cabral P, Gomes P, Casteleyn S. (2019) The Lisbon ranking for smart sustainable cities in Europe. Sustain. Cities Soc. 44: 475–487.

Alizadeh T (2021) Chapter 1 - *Global trends of smart cities. Global Trends of Smart*

Cities-A Comparative Analysis of Geography, *City Size*, Governance, and Urban Planning. 1–25.

Balali A, Valipour A (2020) Identification and selection of building façade's smart materials according to sustainable development goals. Sustain. Mater. Technol. 26: e00213.

Benites A J, Simoes A F (2021) Assessing the urban sustainable development strategy: An application of a smart city services sustainability taxonomy. Ecol. Indic. 127: 107734.

Bibri S E (2018a) A foundational framework for smart sustainable city development: Theoretical, disciplinary, and discursive dimensions and their synergies. Sustain. Cities Soc. 38: 758–794.

Bibri S E (2018b) The IoT for smart sustainable cities of the future: An analytical framework for sensor-based big data applications for environmental sustainability. Sustain. Cities Soc. 38: 230–253.

Bibri S E, Krogstie J (2017) Smart sustainable cities of the future: An extensive interdisciplinary literature review. Sustain. Cities Soc. 31: 183–212.

Cao Q H, Giyyarpuram M, Farahbakhsh R, Crespi N (2020) Policy-based usage control for a trustworthy data sharing platform in smart cities. Futur. Gener. Comp. Syst. 107: 998–1010.

Cheba K, Kiba-Janiak M, Baraniecka A, Kołakowski T (2021) Impact of external factors on e-commerce market in cities and its implications on environment. Sustain. Cities Soc. 72: 103032.

Chen Y, Zhang D (2020) Evaluation of City Sustainability Using Multi-Criteria Decision-Making Considering Interaction among Criteria in Liaoning Province China. Sustain. Cities Soc. 59: 102211.

Dall'O' G, Bruni E, Panza A, Sarto L, Khayatian F (2017) Evaluation of cities' smartness by means of indicators for small and medium cities and communities: A methodology for Northern Italy. Sustain. Cities Soc. 34: 193–202.

De Guimarães J C F, Severo E A, Júnior L A F, Da Costa W P L B, Salmoria F T (2020) Governance and quality of life in smart cities: Towards sustainable development goals. J. Clean Prod. 253: 119926.

Deakin M, Reid A (2018) Smart cities: Under-gridding the sustainability of city-districts as energy efficient-low carbon zones. J. Clean Prod. 173: 39–48.

Ejaz W, Anpalagan A (2019) Internet of things for smart cities: overview and key challenges. In Internet of Things for Smart Cities (pp. 1–15). Springer, Cham.

Feizi A, Joo S, Kwigizile V, Oh J S (2020) A pervasive framework toward sustainability and smart-growth: Assessing multifaceted transportation performance measures for smart cities. J. Transp. Health 19: 100956.

Ferronato N, Ragazzi M, Portillo M A G, Lizarazu E G G, Viotti P, Torretta V (2019)

How to improve recycling rate in developing big cities: An integrated approach for assessing municipal solid waste collection and treatment scenarios. Environ. Dev. 29: 94–110.

Finger M, Razzaghi M (2017) Conceptualizing “smart cities”. Informatik-Spektrum 40: 6–13.

Gopikumar S, Raja S, Robinson Y H, Shanmuganathan V, Rho S (2020) A Method of Landfill Leachate management using Internet of Things for Sustainable Smart city development. Sustain. Cities Soc. 66: 102521.

Gul M (2019) Emergency department ergonomic design evaluation: A case study using fuzzy DEMATEL-focused two-stage methodology. Health Policy Technol. 8(4): 365–376.

Gul M, Lo H W, Yucesan M (2021) Fermatean fuzzy TOPSIS-based approach for occupational risk assessment in manufacturing. Complex Intell. Syst. 7 (5): 2635–2653.

Hall B H, Helmers C (2019) The impact of international patent systems: Evidence from accession to the European Patent Convention. Res. Policy 48(9): 103810.

Hatuka T, Zur H (2020) From smart cities to smart social urbanism: A framework for shaping the socio-technological ecosystems in cities. Telemat. Inform. 55: 101430.

Höffken J I, Limmer A (2019) Smart and eco-cities in India and China. Local Environ. 24(7): 646–661.

Hsu W C J, Liou J J, Lo H W (2021) A group decision-making approach for exploring trends in the development of the healthcare industry in Taiwan. Decis. Support Syst. 141: 113447.

Huovila A, Bosch P, Airaksinen M (2019) Comparative analysis of standardized indicators for Smart sustainable cities: What indicators and standards to use and when? Cities 89: 141–153.

Keshavarzi G, Yildirim Y, Arefi M (2021) Does scale matter? An overview of the “smart cities” literature. Sustain. Cities Soc. 74: 103151.

Khurana S, Haleem A, Mannan B (2019) Determinants for integration of sustainability with innovation for Indian manufacturing enterprises: Empirical evidence in MSMEs. J. Clean Prod. 229: 374–386.

Koca G, Egilmez O, Akcakaya O (2021) Evaluation of smart city: Applying the DEMATEL technique. Telemat. Inform. 62: 101625.

Kuo T (2017) A modified TOPSIS with a different ranking index. Eur. J. Oper. Res. 260(1): 152–160.

Li W W, Yi P T, Zhang D N (2021) Investigation of sustainability and key factors of Shenyang city in China using GRA and SRA methods. Sustain. Cities Soc. 68: 102796.

Liou J J, Tzeng G H (2012) Comments on “Multiple criteria decision making (MCDM)

methods in economics: an overview". Technol. Econ. Dev. Econ. 18(4), 672–695.
Lo H W, Liou J J, Tzeng G H (2019) Comments on "Sustainable recycling partner selection using fuzzy DEMATEL-AEW-FVIKOR: A case study in small-and-medium enterprises". J. Clean Prod. 228: 1011–1012.
Macke J, Casagrande R M, Sarate J A R, Silva K A (2018) Smart city and quality of life: Citizens' perception in a Brazilian case study. J. Clean Prod. 182: 717–726.
Macke J, Sarate J A R, Moschen S D A (2019) Smart sustainable cities evaluation and sense of community. J. Clean Prod. 239: 118103.
Mak H W L, Lam Y F (2021) Comparative assessments and insights of data openness of 50 smart cities in air quality aspects. Sustain. Cities Soc. 69: 102868.
Makhdoom I, Zhou I, Abolhasan M, Lipman J, Ni W (2020) Privacy Sharing: A blockchain-based framework for privacy-preserving and secure data sharing in smart cities. Comput. Secur. 88: 101653.
Marco A C, Sarnoff J D, Charles A W (2019) Patent claims and patent scope. Res. Policy 48(9): 103790.
Mishra A, Gangele A (2020) Smart Materials for Clean and Sustainable Technology for Smart Cities. Materials Today: Proceedings, 29: 338–342.
Mokarrari K R, Torabi S A (2021) Ranking cities based on their smartness level using MADM methods. Sustain. Cities Soc. 72: 103030.
Neves F T, de Castro Neto M, Aparicio M (2020) The impacts of open data initiatives on smart cities: A framework for evaluation and monitoring. Cities 106: 102860.
Ozkaya G, Erdin C (2020) Evaluation of smart and sustainable cities through a hybrid MCDM approach based on ANP and TOPSIS technique. Heliyon 6(10): e05052.
Prasad D, Alizadeh T (2020) What makes Indian cities smart? A policy analysis of smart cities mission. Telemat. Inform. 55: 101466.
Ragheb A, Aly R, Ahmed G (2021) Toward sustainable urban development of historical cities: Case study of Fouh City, Egypt. Ain Shams Eng. J.
Rani P, Mishra A R, Mardani A, Cavallaro F, Alrasheedi M, Alrashidi A (2020) A novel approach to extended fuzzy TOPSIS based on new divergence measures for renewable energy sources selection. J. Clean Prod. 257: 120352.
Reyna A, Martín C, Chen J, Soler E, Díaz M (2018) On blockchain and its integration with IoT. Challenges and opportunities. Futur. Gener. Comp. Syst. 88: 173–190.
Sadoughi F, Behmanesh A, Sayfouri N (2020) Internet of Things in Medicine: A Systematic Mapping Study. J. Biomed. Inform. 103: 103383.
Sadowski J, Maalsen S (2020) Modes of making smart cities: Or, practices of variegated smart urbanism. Telemat. Inform. 55: 101449.
Shamsuzzoha A, Nieminen J, Piya S, Rutledge K (2021) Smart city for sustainable environment: A comparison of participatory strategies from Helsinki, Singapore and London. Cities 114: 103194.

Sharma M, Joshi S, Kannan D, Govindan K, Singh R, Purohit H C (2020) Internet of Things (IoT) adoption barriers of smart cities' waste management: An Indian context. J. Clean Prod. 270: 122047.

Shi T, Zhu W Z, Fu S H (2021) Quality of life in Chinese cities. China Econ. Rev. 69: 101682.

Song J, Chen W, Zhang J, Huang K, Hou B, Prishchepov A V (2020) Effects of building density on land surface temperature in China: Spatial patterns and determinants. Landsc. Urban Plan. 198: 103794.

Steiniger S, Wagemann E, de la Barrera F, Molinos-Senante M, Villegas R, de la Fuente H, ... Barton J R (2020) Localising urban sustainability indicators: The CEDEUS indicator set, and lessons from an expert-driven process. Cities 101: 102683.

Xu B, Huang D, Mi B (2020) Smart city-based e-commerce security technology with improvement of SET network protocol. Comput. Commun. 154: 66–74.

Yahia N B, Eljaoued W, Saoud N B B, Colomo-Palacios R (2019) Towards sustainable collaborative networks for smart cities co-governance. Int. J. Inf. Manage. 56: 102037.

Yan J H, Liu J P, Tseng F M (2020) An evaluation system based on the self-organizing system framework of smart cities: A Case study of smart transportation systems in China. Technol. Forecast. Soc. Chang. 153: 119371.

Yi P, Dong Q, Li W (2019b) Evaluation of city sustainability using the deviation maximization method. Sustain. Cities Soc. 50: 101529.

Yi P, Li W, Zhang D (2019a) Assessment of City Sustainability Using MCDM with Interdependent Criteria Weight. Sustainability 11(6): 1632.

Yi P T, Li W W, Zhang D N (2021a) Measurement of city sustainability based on the grey relational analysis: The case of 15 sub-provincial cities in China. Sustain. Cities Soc. 73: 103143.

Yi P T, Li W W, Zhang D N (2021b) Sustainability assessment and key factors identification of first-tier cities in China. J. Clean Prod. 81: 125369.

Yigitcanlar T, Kamruzzaman M (2018) Does smart city policy lead to sustainability of cities? Land Use Pol. 73: 49–58.

Yigitcanlar T, Kamruzzaman M, Buys L, Ioppolo G, Sabatini-Marques J, da Costa E M, Yun J J (2018) Understanding 'smart cities': Intertwining development drivers with desired outcomes in a multidimensional framework. Cities 81: 145–160.

Yigitcanlar T, Kamruzzaman M, Foth M, Sabatini-Marques J, da Costa E, Ioppolo G (2019) Can cities become smart without being sustainable? A systematic review of the literature. Sustain. Cities Soc. 45: 348–365.

Yigitcanlar T, Kankanamge N, Vella K (2020) How Are Smart City Concepts and Technologies Perceived and Utilized? A Systematic Geo-Twitter Analysis of Smart Cities in Australia. J. Urban Technol. 28(1–2): 135–154.

Zadeh L A (2011) A note on Z-numbers. Inf. Sci. 181(14): 2923–2932.

Zhan J, Sun B, Zhang X (2020) PF-TOPSIS method based on CPFRS models: An application to unconventional emergency events. Comput. Ind. Eng. 139: 106192.

Zhang D, Pee L G, Pan S L, Cui L L (2021) Big data analytics, resource orchestration, and digital sustainability: A case study of smart city development. Gov. Inf. Q. 101626 (in press).

Zhang F, Wang Y, Ma X, Wang Y, Yang G, Zhu L (2019) Evaluation of resources and environmental carrying capacity of 36 large cities in China based on a support-pressure coupling mechanism. Sci. Total Environ. 688: 838–854.

Zhang P, Yuan H, Tian X (2019) Sustainable development in China: Trends, patterns, and determinants of the "Five Modernizations" in Chinese cities. J. Clean Prod. 214: 685–695.

Zhou Y, Yi P T, Li W W, Gong C J (2021) Assessment of city sustainability from the perspective of multi-source data-driven. Sustain. Cities Soc. 70: 102918.

Zhu S, Li D, Feng H (2019) Is smart city resilient? Evidence from China. Sustain. Cities Soc. 50: 101636.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- GraphicalAbstract.docx