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ORIGINAL PAPER

Establishing a sustainable development assessment framework for a smart city using a hybrid Z-fuzzy-based decision-making approach

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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 proposes a comprehensive sustainable assessment framework for the SD level of smart cities. First, an assessment system is proposed, which is composed of built form, urban infrastructure, environmental, social, and economic dimensions. These dimensions can be subdivided into 25 indicators. Second, a Z-fuzzy-based multiple criteria decision-making (MCDM) approach is developed to clarify the internal influence of the indicators and to determine the SD performance of smart cities. The Z-based decision-making trial and evaluation laboratory (Z-DEMATEL) technique was used to determine the mutual influence relationship among the indicators and to obtain their influence weights. Moreover, the Z-based technique for order preference by similarity to the ideal solution with the aspiration level (Z-TOPSIS-AL) approach was applied to analyze the sustainable development performance of a smart city. In this paper, we selected Xiamen city as a case study. The results demonstrate that "quality of life," "per capita gross domestic product (GDP)," and "GDP growth rate" are the top three indicators, and their influence weights are 0.05, 0.046, and 0.046, respectively. From the perspective of dimensions, "economic" is the most influential dimension in the sustainable development of Xiamen. In addition, "GDP growth rate" has the greatest room for improvement overall. 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.

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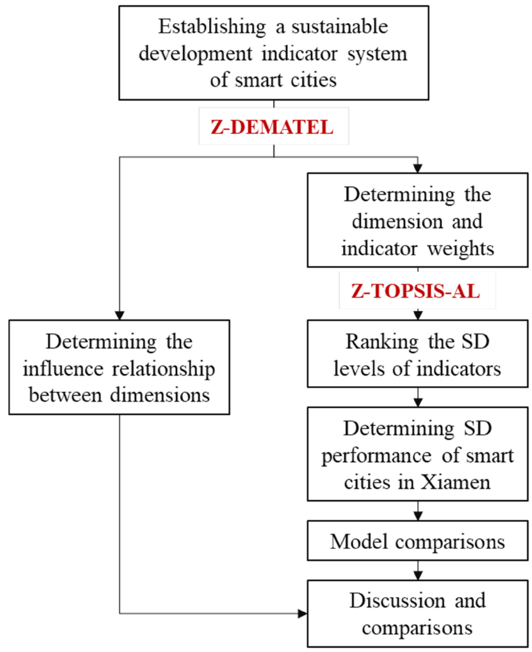
Graphical abstract



Keywords Smart city · Sustainability · Z-based decision-making trial and evaluation laboratory · Z-based technique for order preference by similarity to the ideal solution · Performance assessment

Abbreviations

AI	Artificial intelligence
DANP	DEMATEL-based analytic network process
FDM	Initial fuzzy decision matrix
GDP	Gross Domestic Product
GRA	Grey relational analysis
ICT	Information and communications technology
INRM	Impact relationship matrix
IoT	The internet of things
MCDM	Multiple criteria decision-making
NIS	Negative ideal solution
PCA	Principal component analysis
PIS	Positive ideal solution
SD	Sustainable development
SRA	Grey with sequential relationship analysis
Z-DEMATEL	Z-based decision-making trial and evaluation laboratory
Z-TOPSIS-AL	Z-based technique for order preference by similarity to the ideal solution with the aspiration level

Introduction

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 gross domestic product (GDP) (Mokarrari and Torabi 2021). Moreover, the urbanization process has been accelerating. By 2050, the urban population is expected to account for 69% (6.7 billion) of the world's total population (Benites and Simoes 2021). The increase in the number of urban residents has exacerbated the emission of greenhouse gases, and has brought challenges to urban transportation, medical care, education and other activities closely related to residents (Aydin 2014; Karakurt and Aydin 2023). In addition, the increase in urban population is accompanied by the demand for energy, resources, space, infrastructure, etc. (Wu and Chen 2021). To address this challenge, the application of artificial intelligence (AI), block chain, digital technology and other technical frameworks is an important driving force for the sustainable development (SD) of cities (Dana et al. 2022; Liu et al. 2022; Shahnewaz Siddiquee et al. 2022). With the widespread use of ICT, there are growing calls for the use of 5G, AI, the internet of things (IoT), and other technologies to manage cities; this urbanization process can lead to smart cities (Tura and Ojanen 2022). The SD of smart cities is related to the future development prospects of cities.

Keeping an eye on the sustainability of smart cities is a topic worthy of industry and academic research.

Several studies have considered the evaluation of urban sustainability. 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). Smart cities mean that urban public transportation is smarter, urban medical care is more convenient, resource utilization is better, etc. (Gavurova et al. 2022). Macke et al. (2019) evaluated the sustainability of smart cities from the perspective of urban community residents. Sugandha et al. (2022) proposed a conceptual framework of social sustainability of smart cities. However, a large portion of the current literature is devoted to studying urban sustainability assessment or smart city assessment (Yi et al. 2021; Zhou et al. 2021), while few studies have addressed a framework and methodology for evaluating the SD of smart cities. Most of the literature focuses on the three pillars of the economic, environmental, and social aspects for evaluation of urban sustainability, but the city's architectural form and level of infrastructure construction have not been considered. To fill this gap, the objective of this study was to determine the indicators that affect the SD of smart cities, clarify the influencing relationships and the degree of importance of the indicators, and demonstrate the application value and rationality of the assessment model through a case study.

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 for 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 the 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. 2021). The prerequisite for assessing the SD effects of smart cities is to build a complete evaluation index system. The indicators included in this system should be distinguishable and multilevel, and there may be mutual influence relationships among them. 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. 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) considered smart devices as components of a smart city, and proposed a smart city assessment system based on self-organization theory. 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 of 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. 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. (2021) assessed the sustainable performance of first-tier cities in China based on GRA, and 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 AL concept 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). This model has not been proposed in other articles. The advantages and contributions of this paper are as follows:

(i) This study constructs an evaluation system for smart city development from the perspective of sustainable development and technology application. The framework comprises five components, namely built form, urban infrastructure, environmental sustainability, social sustainability, and economic sustainability.
(ii) This study takes the influencing relationships among the indicators, and visually displays them through graphics. Here, we consider that Z-numbers reflect information uncertainty and expert reliability.
(iii) This study comprehensively uses and compares the four methods of DEMATEL, fuzzy DANP, grey DEMATEL, and Z-DEMATEL to measure the weights of the indicators. This provides a practical demonstration program for the methodology of the smart city sustainability assessment system. In addition, Z-TOPSIS-AL is used to measure the current sustainable development status of cities.
(iv) This study conducted case analysis of four famous second-tier cities in China at the indicator, dimensional, and overall levels.

The remainder of this paper is organized as follows. The relevant literature on the SD of smart cities is introduced in Section "Materials". Section "Methodology" describes the methodology employed. In Section "Results", data and result analysis is conducted. A case study and discussion are presented in Section "Discussion". Section "Conclusion" presents the conclusions and directions of future research related to the model.

Materials

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).

The built form affects the sustainable development of a city. Many indicators contribute to the built form, such as the building densities, land use, block shape, public place arrangement, and smart materials (Ahmadian 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 (Shamsuzzoha et al. 2021). Urban transportation, ICT, logistics distribution networks and other technologies constitute urban infrastructure; they are the core of supporting urban "smartness." Smart city infrastructure is the city's system of connecting utilities, basic facilities, and services, ranging from smart transportation facilities to new ICT systems, from urban data management centers to smart healthcare and more. The sustainable development of smart cities emphasizes three pillars of development: economy, society, and environment (Wątróbski et al. 2022). Sugandha et al. (2022) suggested that social sustainability should include equity, social capital, quality of life, and so on. Song et al. (2022) proposed a model involving the dimensions of economy and environment to evaluate the sustainability of smart cities. However, the sustainable development of smart cities should consider not only the three pillars of environment, economy, and society, but also the use of ICT technology to improve the level of urban planning and infrastructure. Therefore, how to consider urban development from the dual perspectives of wisdom and sustainable development is an important innovation of this research.

Based on the above review, a large body of literature examines the development performance of sustainable cities from only three dimensions, namely environmental, social, and economic sustainability. We believe that the sustainable development of smart cities should not only consider these three pillars, but should also take into account the use of advanced ICT technology to complete urban infrastructure and urban planning. This idea is supported by many studies (Macke et al. 2018; Zhang et al. 2019; Song et al. 2020; Chen and Zhang 2020; Gavurova et al. 2022). In summary, we believe that measuring the SD of smart cities involves five dimensions, namely urban built forms, urban infrastructure construction, environmental sustainability, social sustainability, and economic sustainability. In addition, there has not been any research that combines the Z-DEMATEL and Z-TOPSIS-AL techniques to discuss the smart city sustainable development issues. This study not only takes into account the uncertainty of the information, but also assesses the confidence in the expert assessment. On the other hand, we identify the mutual influence among the indicators and use a more effective way to determine the SD development performance of Xiamen City. Table 1 shows the smart city sustainability assessment system formed by these five dimensions and their corresponding indicators.

Methodology

We describe the proposed methodology in this section. First, we introduce the concept and calculation program of Z-numbers. We then develop complete assessment scales for Z-DEMATEL and Z-TOPSIS-AL. The operating process of the improved Z-DEMATEL and Z-TOPSIS-AL techniques is then introduced.

Table 1 The assessment system for the sustainability of smart cities

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), Macke et al. (2018)
	Land use patterns (C_{12})	Types of urban land, such as the distribution of cultivated land, garden land, and forestland	Gavurova et al. (2022)
	Block sizes and shapes (C_{13})	The sizes, styles, and spatial layouts of urban blocks	Huovila et al. (2019)
	Public space arrangement (C_{14})	Outdoor and indoor spaces publicly used by citizens in daily life and social life	Chen and Zhang (2020), Zhang et al. (2019)
	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 and Gangele (2020), Sadowski and Maalsen (2020), Zhu et al. (2019)
Urban Infrastructure (D_2)	Smart transportation (C_{21})	The collection of traffic information through high-tech means and the provision of traffic information services using real-time traffic data	Sharma et al. (2020), Gavurova et al. (2022)
	ICT systems (C_{22})	The infrastructure and components that realize modern computing	Akande et al. (2019), Sharma et al. (2020)
	Distribution networks (C_{23})	Interconnected nodes distributed in different locations and with multiple terminals	Makhdoom et al. (2020), Sharma et al. (2020)
	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), Sharma et al. (2020)
	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)
	Medical and health systems (C_{26})	The building of a network system for hospitals and the establishment of an enterprise-level application system based on it so as to realize the smooth circulation and high sharing of various kinds of information such as information on people, finances, and things	Sharma et al. (2020), Sadoughi et al. (2020)

Table 1 (continued)

Dimensions	Indicators	Descriptions	References
Environmental sustainability (D_3)	Wastewater treatment (C_{31})	The use of physical, chemical, and biological methods to treat and purify wastewater and decrease pollution so as to achieve wastewater recycling and reuse and to make full use of water resources	Prasad and Alizadeh (2020), Akande et al. (2019), Zhu et al. (2019)
	Air pollution control (C_{32})	Pollutant emission control technologies and policies adopted to handle city air pollutants	Feizi et al. (2020), Akande et al. (2019), Gavurova et al. (2022)
	Solid waste treatment (C_{33})	The concentration of various wastes in the city and the combination of 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), Sharma et al. (2020)
	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	Zhu et al. (2019), Macke et al. (2018)
	Energy efficiency (C_{35})	The level of urban energy consumption and utilization effect	Akande et al. (2019), Zhu et al. (2019), Sharma et al. (2020)
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), Gavurova et al. (2022)
	Quality of life (C_{42})	Comparison of the higher living standards of citizens and the satisfaction of social and spiritual needs	Feizi et al. (2020), Macke et al. (2018)
	Equality and social inclusion (C_{43})	The attention paid to the rights and interests of more different groups of citizens and the importance attached 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), Gavurova et al. (2022)
Economy Sustainability (D_5)	E-commerce development (C_{51})	The degree of development of urban e-commerce and related industries	Chen and Zhang (2020), 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. (2021), 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. (2021),
	Tertiary industry per GDP (C_{54})	Per capita GDP of the tertiary industry	Chen and Zhang (2020), Yi et al. (2021),
	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	Khurana et al. (2019), Marco et al. (2019)

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 has been proposed that Z-numbers and MCDM can be integrated to evaluate alternatives (Hsu et al. 2021). To further illustrate this concept, this study reveals the principles of converting fuzzy numbers into Z-numbers. The specific implementation details are as follows.

Assume there is a Z-number,$Z = \left(\tilde{F}, \tilde{R}\right)$, where $\tilde{F}$ is the assessment score and $\tilde{R}$ is the reliability degree of $\tilde{F}$. $\tilde{F} = \left(f, \mu_{\tilde{F}}\right)|x \in [0, 1]$ and $\tilde{R} = \left(x, \mu_{\tilde{R}}\right)|x \in [0, 1]$ 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 in 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 $c_i = \left\{c_1, c_2, \ldots, c_n\right\}$. 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 into the corresponding membership function (fuzzy number). The assessment scale and membership function 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)

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)

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.

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:

$$Z = [(1, 2, 3), (0.3, 0.5, 0.7)].$$

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 $\tilde{F} = M$:

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

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.

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

Table 4 Z-DEMATEL semantic variables and membership functions

Reliability	Impact assessment				
	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)

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)

its corresponding membership function. The results are shown in Table 6.

Improved Z-DEMATEL model

Applying the 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 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 using crisp scores. Several fuzzy theoretical approaches have been mixed with DEMATEL to reflect uncertainties (Gul 2019). Unfortunately, there is a slight degree of confidence in the estimates of decision makers applying these methods. 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. This study proposes an improved Z-DEMATEL method which is able to generate a set of indicators' influential weights as 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:

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

$$s.t.\begin{cases} \min_k \; l_{ij}^k \le l_{ij} \le \max_k \; l_{ij}^k, \\ \min_k \; m_{ij}^k \le m_{ij} \le \max_k \; m_{ij}^k, \\ \min_k \; u_{ij}^k \le u_{ij} \le \max_k \; u_{ij}^k, \\ l_{ij} \le m_{ij} \le u_{ij}. \end{cases} \quad (3)$$

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

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

Reliability	Performance assessment				
	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)

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

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

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 Eqs. (3–6), as shown in Eq. (7):

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

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 1: 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 $\otimes y_{ij} = \left(y_{ij}^{L}, y_{ij}^{M}, y_{ij}^{U}\right)$.

$$\varepsilon = \min\left\{\frac{1}{\max_i \sum_{j=1}^{n} a_{ij}^{U}}, \frac{1}{\max_j \sum_{i=1}^{n} a_{ij}^{U}}\right\} \tag{9}$$

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

The normalized direct relation matrix can be calculated according to Eqs. (10–12); the specific calculation process can be seen in 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 $\otimes t_{ij} = \left(t_{ij}^{L}, t_{ij}^{M}, t_{ij}^{U}\right)$.

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

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

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.

Equations (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):

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

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

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

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

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 defuzzify 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 defuzzifying program of Eq. (17). The matrix $\otimes \boldsymbol{T}$ is used to recognize the influence between each indicator and to draw arrows (indicating the direction of influence) to get an INRM.

Step 6 Generate the impact weight of the 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),$w_i = \left\{w_1, w_2, \dots, w_n\right\}$. Here, the sum of weights is required to be 1:

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

Z-TOPSIS-AL approach

The TOPSIS model is one of the 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. The TOPSIS approach is meant to comprehend and operate performance integration and has been used in miscellaneous decision-making issues (Zhan et al. 2020). In this paper, TOPSIS is combined with fuzzy theory to reflect the uncertainty of the practical assessment environment, and the AL replaces a relatively good solution. The detailed TOPSIS procedure is described as follows.

Step 1: Define symbols.

Suppose there are m projects $A_i = \left\{A_1, A_2, \dots, A_m\right\}$ and n indicators $c_j = \left\{c_1, c_2, \dots, c_n\right\}$, and the weight of the indicators is defined as $w_j = \left\{w_1, w_2, \dots, w_n\right\}$. Each decision-maker D_k ($k = 1, 2, \dots, p$) 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 5. 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 $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$; 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 $k = 1, 2, \dots, p$.

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. (2):

$\otimes d_{ij}^* = \frac{\otimes d_{ij}}{\max_j \left\{\otimes d_{ij}\right\}}$.(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:

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

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

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 defuzzified 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. The approximation coefficient is calculated using Eq. (27):

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

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.

Results

Xiamen city, which is located on the southeast coast of China, is a sub-provincial city with a population of 5.28 million. Xiamen is an internationally renowned garden city and a civilized city. 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 Xiamen as a smart city. Accelerating the construction of Xiamen as a smart city is of great practical significance for enhancing the city's comprehensive competitiveness and for creating a beautiful city. 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 "Materials", the assessment system of smart cities involves the five dimensions of the urban built form, urban infrastructure, environmental sustainability, social sustainability, and economic sustainability, with 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 was introduced in Section "Improved Z-DEMATEL model", 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 were invited to conduct the analysis. The group of decision-makers comprised six senior managers engaged in the smart city industry and six professors from the Urban Research Institute of a university in China. The six senior managers come from three 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 six professors have more than 15 years of experience in urban research and SD. Among these professors, two are mainly engaged in sustainable city research, one is engaged in smart environment research, one is engaged in green building research, and two are engaged in research in the field of smart cities. For this study we designed a questionnaire to generate the degree of influence between any two indicators according to Table 3. The decision-makers were invited to respond by making 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 influencing relationships and influencing 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 the 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 was transformed into a matrix similar to Table 7. The diagonal elements of

Table 7 The direct relation matrix of decision-maker 1

	C_{11}	C_{12}	C_{13}	C_{14}	$\cdots$	C_{55}
C_{11}	0	(AI,VH)	(AI,H)	(AI,VH)	$\cdots$	(EI,VH)
C_{12}	(AI,VH)	0	(AI,VH)	(AI,H)	$\cdots$	(EI,VH)
C_{13}	(AI,VH)	(AI,VH)	0	(AI,VH)	$\cdots$	(EI,VH)
C_{14}	(AI,H)	(AI,VH)	(AI,VH)	0	$\cdots$	(EI,VH)
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	(EI,VH)
C_{55}	(FI,VH)	(FI,VH)	(FI,VH)	(FI,VH)	$\cdots$	0

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 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.

According to the Z-DEMATEL step of Section "Improved Z-DEMATEL model", the influence weights of all indicators can be generated, as shown in Table 8. The larger the weight of the indicator, the greater the influence it 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.

The INRM can be drawn using the total impact relationship matrix. The mutual influence between the five dimensions can be seen in Fig. 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.

Determine the performance of the assessed project

This study focuses on the SD performance of smart cities in Xiamen. In this section, we present eight decision-makers assessing Xiamen's performance according to 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 had assessed Xiamen's performance on 25 indicators from C_{11} to C_{55}, Table 9 is 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

Fig. 1 INRM of the dimensions

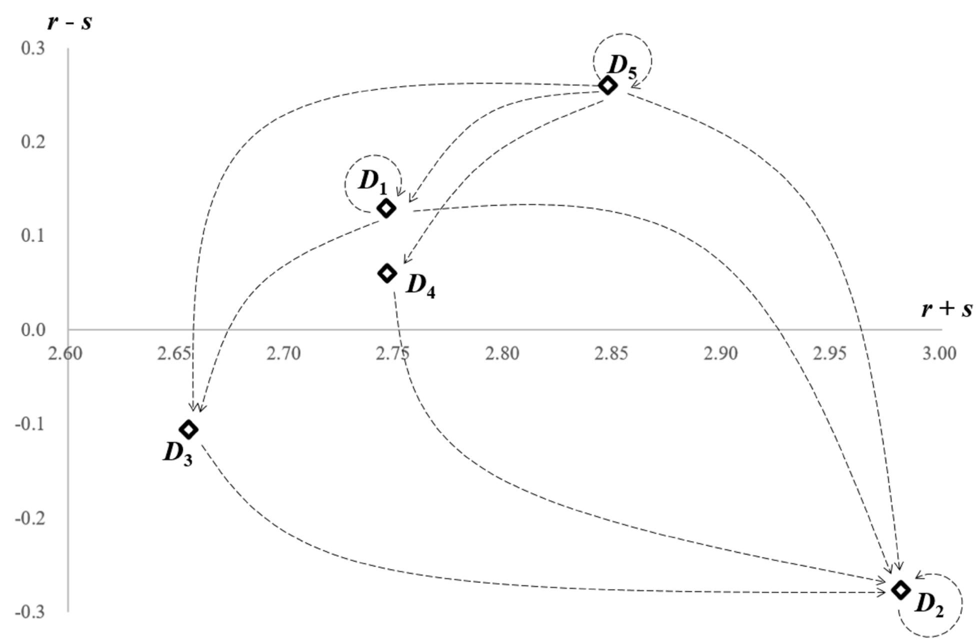


Table 9 Xiamen city's SD performance for each indicator

	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

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 either the desired level or the worst level.

Figure 2 shows the performance of Xiamen city's (blue) smart SD in each indicator. The orange bars in Fig. 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; 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 "Discussion".

Discussion

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.

As shown in Table 7, 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.

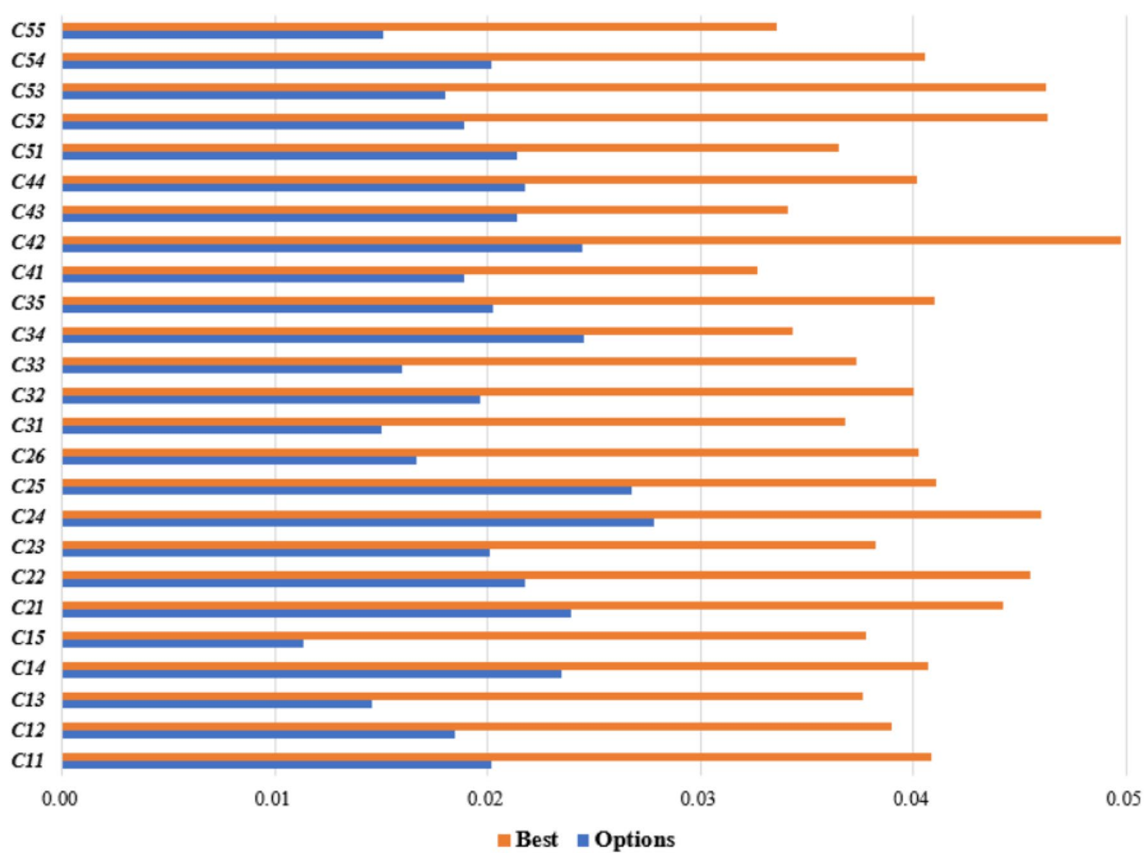


Fig. 2 Gap analysis

Table 11 The gaps and rankings that Xiamen city needs to improve for 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

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 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 city's fiscal revenue level. Therefore, the per capita GDP and GDP growth rate rank second and third, respectively, in importance for evaluating the sustainability of smart cities, which has important management implications. Data sharing/openness is considered indispensable for the development of smart cities (Mak and 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. We believe that the application of data sharing systems in transportation, medical, business,

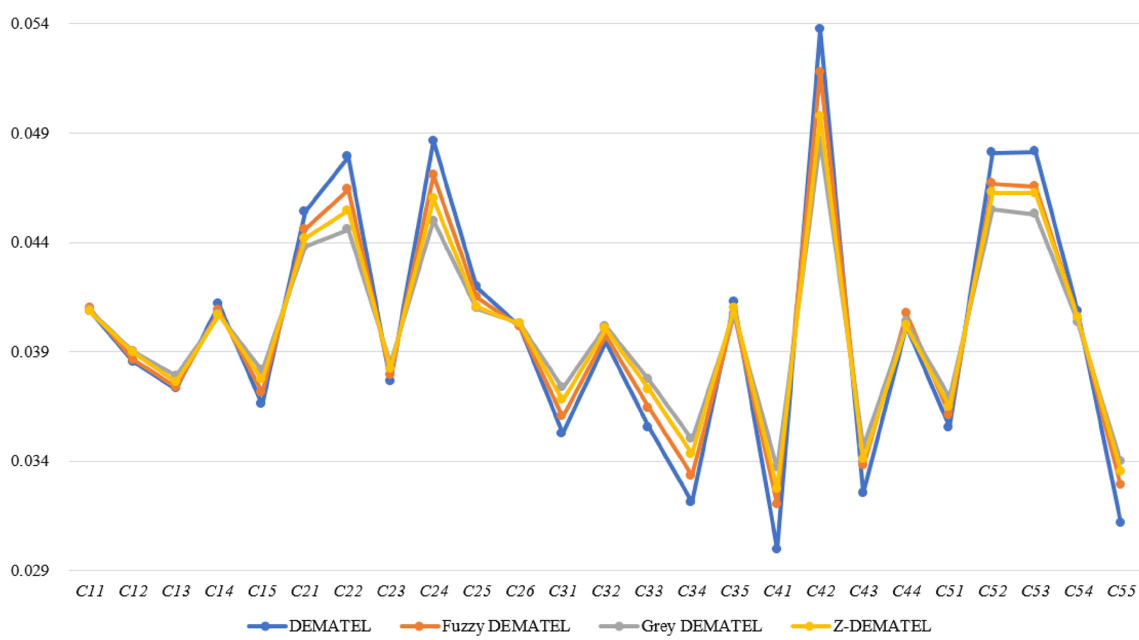


Fig. 3 The indicator weights generated by the four DEMATEL methods

and other fields will generate strong commercial value. 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, while 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 expend 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, had 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 8, 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 and Valipour 2020). It is necessary to accelerate the use of smart materials in the manufacturing industry and construction industry and to 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 of 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 five dimensions and 25 indicators, as shown in Table 1, was established in this paper. Building a smart city SD assessment system and employing an integrated Z-DEMATEL and Z-TOPSIS-AL model are the two contributions of this study.

This study has some limitations that can provide opportunities for further research. First, this paper provides an in-depth discussion only of the assessment indicators of smart cities. In future, more specific key performance indicators (KPIs) can be formulated to measure and improve Xiamen City. Second, we conducted a case analysis for only the city of Xiamen; we can sort and compare the degree of smartness and SD of multiple cities in our follow-up research. Finally, this study has not yet explored the issue of integrating the opinions of multiple experts, so the rough number method can be introduced in further work.

Author contributions Q-GS: Investigation, Writing—Original draft preparation. C-CJ: Investigation. H-WL: Conceptualization, Writing—Original draft preparation. JJHL: Writing—Review & Editing.

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Data availability The participants of this study did not give written consent for their data to be shared publicly, so due to the sensitive nature of the research supporting data is not available.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical approval This article does not contain any studies with humans or animals performed by any of the authors.

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