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DYNAMIC MULTI-ATTRIBUTE EVALUATION OF DIGITAL ECONOMY DEVELOPMENT IN CHINA: A PERSPECTIVE FROM INTERACTION EFFECT

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Abstract. This study aims to reflect the grey information coverage and complex interactions effect in digital economy development. Therefore, a multi-attribute decision making method based on the grey interaction relational degree of the normal cloud matrix (GIRD-NCM) model is proposed. First, the original information coverage grey numbers are transformed into normal cloud matrixes, and then a novel Minkowski distance between normal clouds is proposed by using different information principles. Second, the GIRD-NCM model is established according to the Choquet fuzzy integral and grey relational degree. Finally, the dynamic comprehensive evaluation of digital economy development in China from 2013 to 2020 is conducted. The implementation, availability, and feasibility of the GIRD-NCM model are verified by comparative analysis with three existing evaluation models. The empirical findings reveal a stable growth trend in China's digital economy, with an annual growth rate of 7.87%, however, there are notable regional development disparities. The change in interaction degree has no effect on the rankings of provinces that are in the lead or have a moderately high level of digital economy development, but has a positive and negative impact on the rankings of these provinces with high and low levels of digital economy development, respectively.

Keywords: digital economy evaluation, grey relational degree, fuzzy integral, grey information coverage, normal cloud matrix.

JEL Classification: C02, C52, O11.

Introduction

Background and motivation

Since human society entered the information era, the rapid development and widespread adoption of digital technologies have led to the emergence of the digital economy. Different from the agricultural or industrial economy, this new form of economy is highly dependent

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on data from the modern information networks, and driven by the digital transformation of total factor productivity. The main purpose of the digital economy is to promote productivity improvement and high-quality development for the economy by using modern techniques such as artificial intelligence and 5G (Pan et al., 2022). According to "White Paper on the Development of China's Digital Economy (China Academy of Information and Communications Technology [CAICT], 2021)", the market size of China's digital economy experienced new breakthroughs in 2021, reaching 45.5 trillion CNY, more than double that of 2016, and accounting for 39.8% of GDP (as shown in Figure 1a). By contrast, the nominal growth rate was 16.2%, which was 3.4% greater than the nominal GDP growth rate for the same period. Meanwhile, China is becoming one of the main leaders in this field, and its market size of the digital economy is already ranked second worldwide behind that of the United States in 2020 (as shown in Figure 1b). At present, the digital economy in China not only maintains a rapid growth trend but also deeply integrates with every aspect of the economy and society. It plays an important role in stimulating consumption and investment, creating jobs, and promoting green development and has gradually become an important component and growth driver of the national economy.

The digital economy is the leading force driving regional economic development, and the measurement of the digital economy has developed into a crucial foundation and support for strengthening and promoting its development management. As the importance, necessity, and urgency of growing the digital economy have come to light, various regions of China have implemented relevant appropriate policies and taken the opportunity. Due to differences in digital technology, data factor endowment and digital infrastructure among different regions in China, there is a clear regional imbalance in the development of the digital economy, with the eastern region's level of development being noticeably higher than that of the central and western regions. To promote the reasonable flow of digital resources among regions, realize the coordinated development of the digital economy, provide an important reference for regional and enterprise decision-makers, and further improve digital economy development, it is necessary to scientifically evaluate and measure the development level of the digital economy in China.

In the process of evaluating economic development, the digital economy and traditional economy are similar with respect to the statistical caliber and industrial classification system (Kosimov & Ruziboyeva, 2022). Besides, the digital economy has some unique features, as it

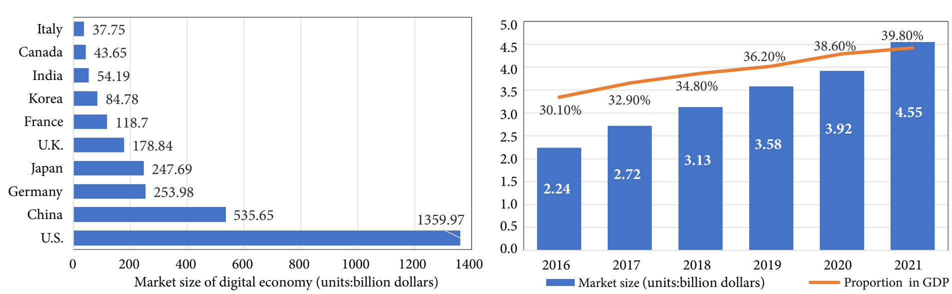

Figure 1. Description of market size and development of digital economy in China:
a – market size of digital economy; b – market size and proport

involves new fields and transcends the restrictions of industries and regions. Compared with those of the traditional economy, the quantitative metrics of the digital economy are often the information coverage grey numbers (Xiao et al., 2020a), which contain the exact number, interval number, and fuzzy language. The information coverage grey numbers can also be obtained from different channels, such as websites, questionnaires, statistical yearbooks, and communication administration bureaus, which have the characteristics of multisource heterogeneity, multiscale heterogeneity, and uncertainty. At the same time, considering many influencing factors of the digital economy, including economic growth, foreign capital dependence, industrial structure optimization, human capital and so on, there exist negative cooperation, mutual independence, and positive cooperation among evaluation attributes. Different data types and complex interaction effects exist in the digital economy, so it is difficult to accurately measure the impact of the digital economy in practice, which further restricts relevant policy formulation. Therefore, considering the above characteristics, the major goal of this study is to develop an efficient and promising digital economy evaluation method that can solve the problems of different data types, different statistical frequencies, and interactions between attributes in the digital economy. There are two main differences from existing research in digital economy evaluation:

(1) This paper considers more information types in our evaluation model, which is more suitable in real and complex metering scenarios. Most existing works are based on the information described by exact number. By building a normal cloud model, this paper integrates different information types including exact number, interval number, and fuzzy language, so as to enrich the data sources of the evaluation index system.
(2) This paper considers the interaction effect among the digital economy system. Most existing works assume that attributes are independent, which is a strong assumption and ignore the interaction between the evaluation attributes of the digital economy. Considering the complex interaction between attributes, this paper designs the dynamic interaction evaluation model to measure digital economy development.

Literature review

Considering that this paper involves data fusion techniques and digital economy evaluation, the literature in these two fields will be summarized below.

For information coverage grey numbers, data fusion is generally divided into three levels: estimation theory, uncertainty reasoning method, and the theory of intelligent computing and pattern recognition (Zhang et al., 2022c), of which uncertain reasoning methods are mainly used to solve uncertain problems of multisource heterogeneous data (Rao et al., 2022). Uncertain reasoning methods include the subjective Bayesian method (Goldstein, 2006), the DS evidence reasoning method (Dai et al., 1999), the DSm-T method (Zhao et al., 2022), and the cloud model (Li et al., 2009). However, all have their own advantages and disadvantages. For example, to produce new probability estimates using the Bayesian estimation fusion approach, access to previous data is necessary, but this is not always feasible (Muñoz et al., 2018). Li et al. (2009) put out the idea of the cloud model, which can describe the fuzziness and randomness of information. The cloud model has been widely used in the field of multisource heterogeneous information fusion, and has achieved positive results (Zhang et al., 2018, 2020). The distance measurement method between different clouds can greatly improve the rationality of the results. Researchers have conducted a number of studies on distance measurement methods, and they proposed the Hamming distance (Wang & Liu, 2012), Euclidean distance (Wang et al., 2010), and Manhattan distance (Gong et al., 2021) to define the relative distance between different normal clouds. However, Hamming distance regards the entropy and hyper entropy of normal clouds as the expected weight coefficients, which easily weakens the role of entropy and hyper entropy, resulting in overall small distance results. Euclidean distance treats the expectation, entropy, and hyper entropy equally and overemphasizes the role of hyper entropy, resulting in excessively large distance results; Although Manhattan distance comprehensively considers all the digital features of the cloud model, it will weaken the role of hyper entropy when the entropy is large.

For digital economy evaluation, most scholars have used combined or improved evaluation methods in current research, including the AHP-entropy weight method (Yang & He, 2022), improved entropy method (Wang et al., 2022), dynamic mathematical model (Horoshko et al., 2021) and so on. These evaluation methods mainly focus on the fact that the evaluation attribute is an accurate number and has the same statistical frequency. However, in the multisource information fusion system, the detection information contains much uncertainty, thus some scholars tend to adopt the grey decision method (Cui et al., 2019) and its combination method.

Grey theory mainly addresses limited and uncertain samples, and generates and extracts valuable information through the mining and development of existing information (He et al., 2023). Grey decisions, as a branch of grey theory, can effectively compare the influence between different attributes in a system (Zhang et al., 2024). At present, the classical grey decision models are the grey relational analysis (GRA) and the GM(1,N) model. Huang et al. (2020) proposed a novel dynamic GRA to evaluate the economic growth level in Taiwan. Xiao et al. (2021b) proposed an improved GM(1,N) model to evaluate the coordination degree between China's technology and economy. Moreover, many scholars have also considered the influence of the interaction between attributes in the grey decision model. For example, Ding et al. (2018) constructed IEGM(1,N) by introducing linear interaction into GM(1,N), however, this model can only measure the interaction effect between two factors. To improve this shortcoming, Xiao et al. (2021b) constructed a novel CFGM(1,N) model, which can reflect interactions among various factors. At the same time, Cao et al. (2021) proposed a novel multivariable trend interaction grey model TIGM(1,N), which can effectively reflect the impact of input variable interactions and trends on the system's behavior.

The combined methods of GRA are commonly used in the evaluation of the digital economy with multisource heterogeneous information. To jointly solve complex decision-making problems, the main purpose of the combined methods is to take full advantage of fusing different information by using other models and selecting the optimal solution by using GRA (Chu & Xiao, 2023). The combined methods include the combination of the information coverage grey numbers and GRA (Xiao et al., 2020a), the combination of the dynamic weighting operator and GRA (Jana & Pal., 2021), the combination of linguistic 2-tuples and

GRA (Xiao et al., 2020b), and the combination of Z numbers and GRA (Li et al., 2022). Moreover, some scholars have also combined cloud models with other evaluation methods to build a comprehensive cloud model evaluation method. For example, the combination of hierarchical TOPSIS and cloud model (Liu et al., 2018), the combination of interval rough theory and cloud model (Xiao et al., 2021a), and the comprehensive cloud model evaluation method make full use of the advantages of the cloud model in dealing with the fuzziness and randomness of language evaluation value and the advantages of other evaluation methods in determining the weights of the identified dimensions and criteria.

In total, the cloud model, as a common data fusion method, can well describe the ambiguity and randomness of information. However, to improve the accuracy of the results, the measurement method for the distance between normal clouds still needs to be discussed. In addition, GRA, as a popular evaluation model in grey theory, can be used to solve decision-making problems with limited and uncertain information; however, the combination of the normal cloud model and GRA is rarely considered in the current research. To solve the above problem, this paper constructs a novel grey dynamic decision-making model for digital economy evaluation. The distance measurement method between different clouds is characterized first, and considering the uncertainty, ambiguity and imprecise information that exist in the evaluation process of the digital economy, the normal cloud model and GRA are combined. The proposed model not only addresses different data types and statistical frequencies but also considers the interaction between attributes, so it is crucial to measure China's digital economy development.

Contributions

The main contributions are as follows:

(1) A novel Minkowski distance method is proposed to measure differential information between different normal clouds. The Minkowski distance overcomes the weaknesses of Hamming distance, Euclidean distance and Manhattan distance; it not only makes full use of the three numerical characteristics of the normal cloud model but also reflects the information differences between clouds, and has good flexibility and stability.

(2) A dynamic evaluation model GIRD-NCM is established. The proposed model can deal with both randomness and fuzziness in evaluation system and measure the interaction effect of positive cooperation, negative cooperation and independence between attributes. At the same time, it also reflects the temporal and spatial dynamic development trends of the digital economy.

(3) The novel GIRD-NCM model is applied to evaluate the digital economy development in China from 2013 to 2020. The empirical example dynamically analyzes the development level of the digital economy for each province and studies the impact of the interactivity of indicators on the ranking's stability. Finally, the effectiveness of the proposed model is verified through model comparison analysis.

1. Methodology

This section will discuss the transformation of information coverage grey numbers and cloud model, and the difference information measurement between normal clouds.

1.1. Information coverage grey numbers and transformation of normal clouds

The definition and expression form of information coverage grey numbers are described in the reference of Xiao et al. (2020a).

Definition 1. Let *U* be the universe of discourse and *C* be a qualitative concept in *U*. If $x(x \in U)$ is a random instantiation of concept *C*, which satisfies $x : N(Ex, En'^2)$, $En' : N(En, He^2)$, and certainty degree of *x* with the *C* satisfies:

$$\mu(x) = \exp\left\{-\frac{(x-Ex)^2}{2(En')^2}\right\}, \tag{1}$$

then the distribution of *x* in the universe *U* is called a normal cloud.

The three numerical characters of normal cloud are denoted as $C(Ex, En, He)$, where *Ex*, *En* and *He* represent expectation, entropy and hyper entropy respectively. Since some indicators in evaluation matrix are discrete, continuous and language coverage grey numbers (Xiao et al., 2020a), these grey information coverage numbers can be transformed into normal cloud (*Ex*, *En*, *He*), as shown in the following equations.

(1) Transformation of discrete coverage grey numbers and normal cloud model

Some discrete coverage grey numbers x_i can be transformed into three numerical characters according to following steps:

$$Ex = \frac{1}{n}\sum_{i=1}^{n} x_i, \; En = \sqrt{\frac{\pi}{2}} \times \frac{1}{n}\sum_{i=1}^{n}\left|x_i - Ex\right|, \; He = \sqrt{\left|\frac{1}{n-1}\sum_{i=1}^{n}(x_i - Ex)^2 - (En)^2\right|}. \tag{2}$$

(2) Transformation of continuous coverage grey numbers and normal cloud model

For the remark of continuous coverage grey numbers $\left[C_{\min}, C_{\max}\right]$, the cloud parameter computation formula is as follows:

$$Ex = (C_{\min} + C_{\max})/2, \; En = (C_{\max} - C_{\min})/6, \; He = k. \tag{3}$$

k is a constant. It can be adjusted specifically according to its fuzzy remarks.

(3) Transformation of language coverage grey numbers and normal cloud model

For five levels of language coverage grey numbers, the corresponding cloud models are shown in Table 1.

Table 1. Transformation of Language coverage grey number and normal cloud model

Language coverage grey number	Cloud model
Excellent	C(1.0000,0.1309,0.0262)
Good	C(0.7000,0.0809,0.0162)
Medium	C(0.5000,0.0500,0.0100)
Poor	C(0.3000,0.0809,0.0162)
Very Poor	C(0.0000,0.1309,0.0262)

1.2. The difference information of normal clouds

Definition 2. Assuming C_1, C_2 is two normal clouds, F is set of the normal clouds, d is mapping: $d: F \times F \rightarrow R$, if $d(C_1, C_2)$ satisfies: (a) $d(C_1, C_2) \geq 0$, $d(C_2, C_1) \geq 0$; (b) $d(C_1, C_2) = d(C_2, C_1)$; (c) $d(C_1, C_3) \leq d(C_1, C_2) + d(C_2, C_3)$, where C_3 is any normal clouds, then $d(C_1, C_2)$ is the distance between C_1 and C_2, it is also called different information between C_1 and C_2.

Definition 3. For the clouds $C_1(Ex_1, En_1, He_1)$ and $C_2(Ex_2, En_2, He_2)$, therefore

(1) The Hamming distance between C_1 and C_2 is (Wang & Liu, 2012)

$$d_{HA}(C_1,C_2) = \left|(1 - \frac{En_1^2 + He_1^2}{En_1^2 + He_1^2 + En_2^2 + He_2^2})Ex_1 - (1 - \frac{En_2^2 + He_2^2}{En_1^2 + He_1^2 + En_2^2 + He_2^2})Ex_2\right|. \quad (4)$$

(2) The Euclidean distance between C_1 and C_2 is (Wang et al., 2010)

$$d_{EU}(C_1, C_2) = \sqrt{(Ex_2 - Ex_1)^2 + (En_2 - En_1)^2 + (He_2 - He_1)^2}. \quad (5)$$

(3) The Manhattan distance of C_1 and C_2 is (Gong et al.,2021)

$$d_{MA}(C_1,C_2) = \left|Ex_2 - Ex_1\right| + \left|En_2 - En_1\right| + \left|(\sqrt{En_2^2 + He_2^2} - En_2) - (\sqrt{En_1^2 + He_1^2} - En_1)\right|. \quad (6)$$

Hamming distance, which is a weighted combination of expectancies of two normal clouds, and is a simple method for reducing the effects of entropy and hyper entropy. As can be seen from Definition 3, the distance determined by this method is generally quite small. Additionally, distance is not defined when the entropy and hyper entropy are both 0. At the same time, Euclidean distance is the distance between different clouds, it treats hyper entropy, entropy, and expectation equally, but overemphasizes the role of hyper entropy, resulting in an excessively large estimated distance overall. Manhattan distance reflects the impact of hyper entropy through the expected curve and the standard deviation of the expected curve with entropy $\sqrt{En^2 + He^2} - En$, and comprehensively considers all the digital features of the normal cloud model. However, the role of hyper entropy is diminished when the entropy is high.

By using approximately identical transformations for standard deviation of Manhattan,

$$\sqrt{En^2 + He^2} - En = \frac{He^2}{\sqrt{En^2 + He^2} + En} = \frac{He}{\sqrt{En^2 + He^2} + En} \times He,$$

therefore

$$d_{MA}(C_1,C_2) = \left|Ex_2 - Ex_1\right| + \left|En_2 - En_1\right| + \left|\frac{He_2}{\sqrt{En_2^2 + He_2^2} + En_2} \times He_2 - \frac{He_1}{\sqrt{En_1^2 + He_1^2} + En_1} \times He_1\right|. \quad (7)$$

By comparing the above equations, it can be shown that the Hamming distance and the Manhattan distance both treat relative ratios of the combination of entropy and hyper entropy as weight coefficient, the weight coefficient is different due to distinct combination forms; Euclidean distance and Manhattan distance only take different weight coefficients for the hyper entropy. The three distance methods both reflect different processes for hyper entropy, and the introduction of hyper entropy in the normal cloud model is helpful for the representation and measurement of knowledge. In order to accurately depict the position and shape of clouds, making full use of the different effects of the three numerical characters, the Minkowski distances are given in the following.

Definition 4. For the clouds $C_1(Ex_1, En_1, He_1)$ and $C_2(Ex_2, En_2, He_2)$, the Minkowski distance between C_1 and C_2 is

$$d_{MI}(C_1,C_2)=\sqrt[p]{\left|Ex_2-Ex_1\right|^p+\left|En_2-En_1\right|^p+\left|\lambda_2 He_2-\lambda_1 He_1\right|^p}. \tag{8}$$

where $p\in\{1,2,\cdots\}$; λ_1, λ_2 are weight coefficients, and $0 \le \lambda_1, \lambda_2 \le 1$.

Based on Definition 4, it is easy to get the following results.

Theorem 1. The distance of Minkowski $d_{MI}(C_1, C_2)$ satisfies Definition 2, and

(1) If $En_1 = He_1 = En_2 = He_2 = 0$, then the normal clouds degenerate to real numbers, $d_{MI}(C_1, C_2) = |Ex_2 - Ex_1|$.

(2) If $p = 2, \lambda_1 = \lambda_2 = 1$, then $d_{MI}(C_1, C_2) = d_{EU}(C_1, C_2)$.

(3) If $p=1, \lambda_1 = \dfrac{He_1}{\sqrt{En_1^2+He_1^2}+En_1}, \lambda_2 = \dfrac{He_2}{\sqrt{En_2^2+He_2^2}+En_2}$, then $d_{MI}(C_1, C_2) = d_{MA}(C_1, C_2)$.

Theorem 1 demonstrates that the distance of Minkowski degenerates to the distance of real numbers when $En_1 = He_1 = En_2 = He_2 = 0$. In addition, Euclidean distance is a special case of Minkowski distance, and the role of hyper entropy can be moderated and weakened when $0 < \lambda_1, \lambda_2 < 1$. At the same time, Manhattan distance is also a special case of Minkowski distance, the role of hyper entropy has not been weakened for Minkowski distance when the entropy is large. Therefore, Minkowski distance is not only a generalized form of the distance of real numbers, Euclidean distance and Manhattan distance, but also overcomes the shortcomings of Hamming distance, Euclidean distance and Manhattan distance. On the other hand, considering different selections for parameter p, λ_1, λ_2, Minkowski distance also has good flexibility and can reflect the differences between cloud models of various categories.

Six normal clouds are chosen in this research to demonstrate the effectiveness of Minkowski distance. The numerical experiments and comparison analysis are conducted through simulation examples, the findings are displayed in Figure 2.

$C_1 = (3, 3.123, 2.05), C_2 = (2, 3, 1), C_3 = (1.585, 3.556, 1.358),$

$C_4 = (8.308, 9.172, 7.537), C_5 = (5.853, 2.858, 3.804), C_6 = (5.497, 7.572, 5.678).$

The distance of different clouds is calculated according to Definitions 3–4, it's worth notice that the Minkowski distance between different normal clouds is determined when $p=2, \lambda_1 = \dfrac{He_1}{\sqrt{En_1^2+He_1^2}+En_1}, \lambda_2 = \dfrac{He_2}{\sqrt{En_2^2+He_2^2}+En_2}$. The results are shown in Table 2.

The position and shape of the first three normal clouds C_1, C_2 and C_3 are shown in the left of Figure 2, it is found that the distance between C_1 and C_3 is the largest, followed by C_1, C_2, and C_2 and C_3 is the smallest, however, Hamming distance between C_1 and C_2 is the smallest in Table 2, which contradicts the results of Figure 2. The reason for the results is that Hamming distance regards the entropy and hyper entropy of normal clouds as the expected weight coefficients, the roles of entropy and hyper entropy is weakened. At the same time,

Table 2. The comparison of different distance methods

Distance	(C_1, C_2)	(C_1, C_3)	(C_2, C_3)	(C_4, C_5)	(C_5, C_6)	(C_4, C_6)
d_{HA}	0.0872	0.7505	0.5361	3.8931	0.1324	3.5632
d_{EU}	1.4552	1.6336	0.7807	7.7349	3.7306	5.0853
d_{MA}	1.5734	2.2102	1.0592	9.5685	5.2181	5.0776
P = 2	1.1036	1.5235	0.6994	6.8215	3.3336	4.7274
P = 3	1.0302	1.4361	0.6249	6.4395	2.9938	4.7147

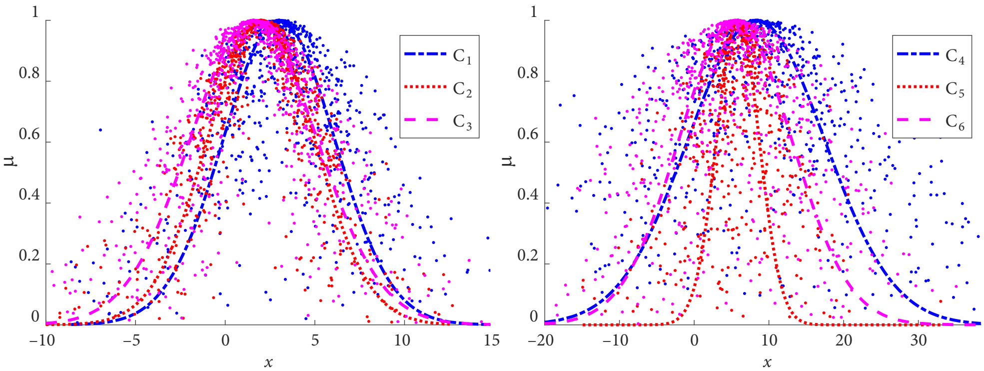

Figure 2. Six normal clouds and its expected curve with entropy

according to observing the position and shape of the C_4, C_5 and C_6, it shows that the distance between C_4 and C_5 is the largest, followed by C_4 and C_6, and C_5 and C_6 is the smallest, however, the Manhattan distance betweenC_4 and C_6 is the smallest in Table 2, which contradicts the results of Figure 2. The Euclidean distance and Minkowski distance in Table 2 all show consistent results with Figure 2, but the Minkowski distance works better, because Euclidean distance amplifies the role of hyper entropy, resulting in a larger distance between normal clouds. The results of the two Minkowski distances (p = 2, p = 3) not only make full use of the three numerical characteristics of the normal cloud model, but also reflect the differences between cloud models of various categories, so the Minkowski distance has good stability.

1.3. Dynamic decision-making method of GIRD-NCM model

In this paper, we propose a dynamic decision-making method of GIRD-NCM model based grey information coverage. In order to effectively describe the interaction between attributes, Sugeno (1974) proposed the concept of λ fuzzy measure and ϕ_s transfer function.

Definition 5. Let $U = \{1,2,\cdots,n\}$ be a finite set of attributes, $P(U)$ be a power set of U, (U, $P(U)$) be a measurable space, and $g: P(U) \to [0,1]$ be a set of functions, satisfying the following conditions:

(1) $g(\varnothing) = 0,\ g(U) = 1$;

(2) $\forall A, B \in P(U)$, if $A \subseteq B$, then $g(A) \le g(B)$;

(3) $\forall A, B \in P(U), A \cap B = \varnothing$, and $\lambda > -1$, then there is

$$g(A \cup B) = g(A) + g(B) + \lambda\, g(A) g(B). \tag{9}$$

Then g is called as λ fuzzy measure, and λ determines the interaction between the attributes. If $\lambda = 0$, means all attributes are independent of each other; If $-1 < \lambda < 0$, means there exists negative cooperation among all attributes; If $\lambda > 0$, means there exists active cooperation among all attributes.

Definition 6. Assuming $\phi_s : [0,1] \times [0,1] \to [0,1]$, $\phi_s(\xi, w)$ is called as a transfer function, where

$$\phi_s(\xi, w) = \begin{cases} 0, & \xi = 1, w = 0 \\ 1, & \xi = 0, w = 1 \\ 0, & \xi = 0, w < 1 \\ \dfrac{((1-\xi)^2 / \xi^2)^w - 1}{((1-\xi)^2 / \xi^2) - 1}, & \text{otherwise} \end{cases}. \tag{10}$$

According to Definition 6, then the λ fuzzy measure can be determined by the attribute weights w_k and ϕ_s, namely

$$g_\xi(T) = \phi_s(\xi, \sum_{k \in T} w_k), \forall T \in P(U),\ k = 1, 2, \cdots, n, \tag{11}$$

where $\xi = 1 / (\sqrt{1+\lambda} + 1)$ is the interaction degree of attribute T.

For normal cloud matrix $X_1, X_2, \ldots, X_m$, the grey interaction relational degree model of the normal cloud matrix is proposed. Let X be a grey information coverage factor set, $X_0 \in X$ be a reference factor matrix, $X_i \in X$ be a comparison factor matrix, $i = 1, 2, \ldots, m$, where X_0 and X_i are all formed by normal clouds (Gong et al.,2021). Taking the set of column vectors as $U = \{u_1, u_2, \cdots, u_q\}$. Suppose $r((Ex_{kj}^{(0)}, En_{kj}^{(0)}, He_{kj}^{(0)}), (Ex_{kj}^{(i)}, En_{kj}^{(i)}, He_{kj}^{(i)}))$ is a real number, w_k and v_j are the weights of the kth row vector and the jth column vector, respectively ,which satisfy $0 \le w_k \le 1$, $\sum_{k=1}^{p} w_k = 1$, $0 \le v_j \le 1$ and $\sum_{j=1}^{q} v_j = 1$. Inspired by the grey relational analysis (GRA), then

$$\gamma_{0i}^{(j)}(u_k) \triangleq r((Ex_{kj}^{(0)}, En_{kj}^{(0)}, He_{kj}^{(0)}), (Ex_{kj}^{(i)}, En_{kj}^{(i)}, He_{kj}^{(i)})) = \frac{\Delta_{\min} + \rho \Delta_{\max}}{\Delta_{kj}^{(0i)} + \rho \Delta_{\max}},$$

where $\Delta_{\min} = \min_i \min_k \min_j \Delta_{kj}^{(0i)}$ and $\Delta_{\max} = \max_i \max_k \max_j \Delta_{kj}^{(0i)}$ are the three-level minimum difference and three-level maximum difference, respectively, the difference information

$$\Delta_{kj}^{(0i)} = d_{MI}((Ex_{kj}^{(0)}, En_{kj}^{(0)}, He_{kj}^{(0)}), (Ex_{kj}^{(i)}, En_{kj}^{(i)}, He_{kj}^{(i)}))$$

is the Minkowski distance between $(Ex_{kj}^{(0)}, En_{kj}^{(0)}, He_{kj}^{(0)})$ and $(Ex_{kj}^{(i)}, En_{kj}^{(i)}, He_{kj}^{(i)})$; ρ is a distinguishing coefficient, and $\rho \in (0, 1)$ (Generally $\rho = 0.5$); the subscript (k) satisfies:

$$\gamma_{0i}^{(k)}(u_{(1)}) \le \gamma_{0i}^{(k)}(u_{(2)}) \le \cdots \le \gamma_{0i}^{(k)}(u_{(q)}),\ A_{(j)} = \{u_{(j)}, u_{(j+1)}, \quad , u_{(q)}\}, \gamma_{0i}(u_{(0)}) = 0.$$

Definition 7. For any ordered subset $A_{(j)}$ from the power set of U, let its λ fuzzy measure be $\mu(A_{(j)})$, where $\mu(A_{(j)}) = \phi_s\left(\xi, \sum_{u_{(\tau)} \in A_{(j)}} w(u_{(\tau)})\right)$, then the grey interaction relational degree of normal cloud matrix between X_0 and X_i can be signed as $\int \gamma_\lambda(X_0, X_i) d\mu$, where

$$\int \gamma_\lambda(X_0, X_i) d\mu = \sum_{k=1}^{p} v_k \sum_{j=1}^{q} [\gamma_{0i}^{(k)}(u_{(j)}) - \gamma_{0i}^{(k)}(u_{(j-1)})] \mu(A_{(j)}). \tag{12}$$

At the same time, The GIRD-NCM $\int \gamma_\lambda (X_0, X_i) d\mu$ satisfies four axioms of grey relation analysis, and it is easy to prove according to the reference of Xiao et al. (2020a).

Above all, the operation steps about dynamic decision-making method of the GIRD-NCM model are shown as follows, and the flow chart is shown in Figure 3.

Step 1. Establish the decision index system.

Step 2. Normalize the coefficient matrix by using function transformation methods of grey generation in Xiao and Mao (2013), and obtain the standard values of q evaluation criteria in p years for the m schemes.

Step 3. The normalized matrix is converted to a cloud matrix $X_i = (Ex_{kj}^{(i)}, En_{kj}^{(i)}, He_{kj}^{(i)})_{p\times q}$ according to Equations (2) and (3), and Table 1.

Step 4. For the normal cloud matrix $X_1, X_2, \ldots, X_m$, a positive ideal matrix X^+ and negative ideal matrix X^- are determined by the method from Xiao et al. (2020b).

Step 5. Regard the positive ideal matrix X^+ and negative ideal matrix X^- as the reference factor matrix, and cloud matrix $X_i = [(Ex_{kj}^{(i)}, En_{kj}^{(i)}, He_{kj}^{(i)})]_{p\times q}$, $i = 1, 2, ..., m$, as the comparison factor matrix, and then use Equation (12) to calculate GIRD-NCM $\int \gamma_\lambda (X^+, X_i) d\mu$ and $\int \gamma_\lambda (X^-, X_i) d\mu$.

Step 6. The optimization model of subordination degree is established. Suppose that scheme X_i is subordinate to the positive ideal matrix X^+ with the degree of affiliation $t_i(\lambda)$, then X_i is subordinate to the negative ideal matrix X^- with degree of affiliation $1 - t_i(\lambda)$. In order to determine the optimal degree of affiliation $t_i(\lambda)$, the following objective function is established, where

$$t_i(\lambda) = \frac{\int \gamma_\lambda (X^+, X_i) d\mu}{\int \gamma_\lambda (X^+, X_i) d\mu + \int \gamma_\lambda (X^-, X_i) d\mu}. \tag{13}$$

Step 7. Rank the m schemes based on the value of for $t_i(\lambda)$, $i = 1, 2, ..., m$. The greater the value of t_i, the better the scheme is.

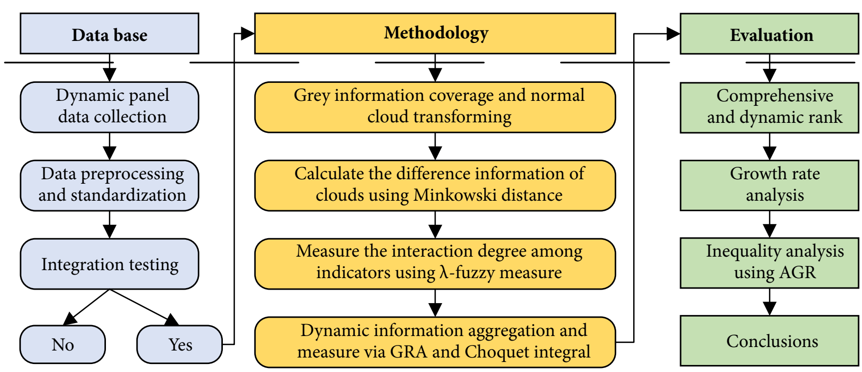

Figure 3. Flow chart of the proposed model

2. Data collection and preprocessing

2.1. Digital economic index

Based on existing literature, there are two types of methods to measure the digital economy index. The one is the index system method, which generally uses digital infrastructure, digital economy application, digital industrialization and industrial digitization to construct the index system, then calculate the digital economy index (Zhang et al., 2022a). The other one is the assessment report index method, including the digital inclusive finance index (Lian et al., 2023) and the digital economy index (Zhu et al., 2022), this method is mainly released by research institutions. This paper comprehensively considers the above two types of methods and integrates the digital inclusive finance index into the index system. Therefore, the digital economy index constructed in this paper consists of four dimensions: infrastructure, digital industrialization, industrial digitalization, and applications. We select 9 secondary indicators and 25 sub-indicators to build a comprehensive digital economy development level evaluation system after extensive literary research. Specific indicators are selected and explained as shown in Figure 4.

(1) Infrastructure: Infrastructure is a prerequisite for digital economy growth. This includes spending money on the Internet, mobile communication, and other network infrastructure. It also encourages the development of test cities for the fusion of three networks (Internet, telecoms network and cable television network), with the goal of creating a secure and intelligent network infrastructure system for the digital economy. Infrastructure includes three indicators: communication infrastructure, communication service, and Internet development. In the aspects of communication infrastructure, the construction level of network infrastructure such as Internet and mobile communication network is mainly considered, the better the construction of u_1 and u_2, the higher the development level of communication infrastructure in the region. Communication services reflect the need for mobile infrastructure. The faster digital technology develops, the higher the need for u_3 and u_4. Communication development reflects the coverage of digital infrastructure construction. The more the number of u_5 and u_6, the wider the coverage of digital technology development.

(2) Digital industrialization: The term "digital industrialization" refers to the enhancement of the information industry brought about by digital technology, involving digital production and innovation. It includes two indicators: innovation ability and value of quality. In the aspects of innovation ability, digital technology's fundamental research and development capabilities are focused, the growth of u_7, u_8, and u_9 can encourage industrial upgrading and innovation-driven. Quality value reflects the efficiency gains and value added by the digital economy to various industries, including the total value of technology contracts (u_{10}), as well as the growth in scale and profits of the core industries of the digital economy, such as software, information services and communications (u_{11},u_{12},u_{13}).

(3) Industrial digitalization: In terms of industrial digitization, the emergence of digital economy optimizes production process of traditional industries by using digital information technology, promoting digital development of different industries (Matthess &

Kunkel, 2020). It includes two indicators: input and output. In the aspects of input of industrial digitalization, it focuses on the investment in core industries of the digital economy, u_{14},u_{15} and u_{16} will gradually rise as the digital economy develops more favorably. In the aspect of the output of industrial digitalization, the impact of the emergence of the digital economy on industrial digital development is mainly considered, and the construction effect of industrial digital development is scientifically evaluated through u_{17} and u_{18} indicators.

(4) Applications: Digital application mainly includes the application scenarios of digital technology in digital life services, such as digital payment, digital health, digital community, etc. It includes two indicators: digital inclusive finance and e-commerce. In the aspects of digital finance, different dimensions of digital finance development are mainly considered. Therefore, the status of digital finance is investigated from u_{19}, u_{20},u_{21} and u_{22}, which can better measure the degree of digitalization and universality of financial development. In the aspect of E-commerce, the development status of the E-commerce industry is mainly considered (Chen et al., 2023), and the development level of e-commerce activities is measured through u_{23},u_{24},and u_{25}.

In this paper, 31 provinces in China are used as research objects for the period of 2013 to 2020 (excluding Hong Kong, Macao and Taiwan due to missing data). Data can come in from many different sources and take on many different forms, while $u_1 - u_6$, $u_{10} - u_{12}$, u_{14} and $u_{23} - u_{25}$ are collected from the China Statistical Yearbook; $u_7 - u_9$ and $u_{15} - u_{16}$ are obtained from the China Statistical Yearbook on Science and Technology; u_{13} is taken from China City Statistical Yearbook; u_{17} is derive from the Informatization development report for each province; $u_{19} - u_{22}$ are compiled by the Digital Finance Research Center of Peking University and Ant Financial Services Group. In addition, u_{18} is obtained from a questionnaire for residents in each province. The missing values are supplemented by interpolation. These 25 indicators include discrete coverage grey numbers, continuous coverage grey numbers and language coverage grey numbers, so the original multisource heterogeneous data decision matrix is constructed, of which the u_{17} is a continuous coverage grey number, u_{18} is a language coverage grey number, and others are discrete coverage grey numbers. At the same time, all indicators are benefit-type criteria, i.e., the higher the criteria value is, the better the development level of the digital economy. Chinese mainland can be divided into the following four regions, namely, Eastern, Central, Western, and Northeast, the detailed geographical distribution of these four major regions is shown in the reference of Meng and Qu (2022).

2.2. Weighting and interaction test of the digital economic index

We should first determine the weight vector of the year and the evaluation index. In this paper, the weight vector of these 8 years is denoted as $V = (v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8)$, which satisfies $v_1 < v_2 < v_3 < v_4 < v_5 < v_6 < v_7 < v_8$ according to the principle of new information priority, thus we define $V = \frac{1}{36}(1,2,3,4,5,6,7,8)$. Then, the weights of 24 evaluation indicators can be determined by using entropy weight method, and the detailed results are shown in Figure 4.

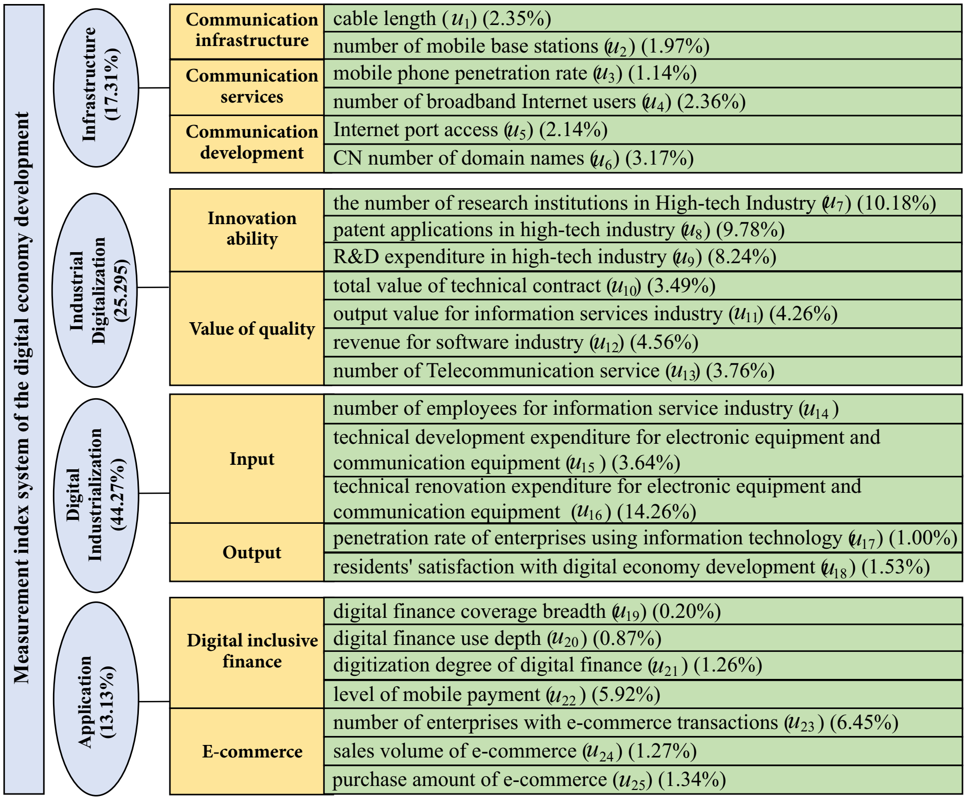

Figure 4. Measurement index system of the digital economy development

The findings indicate that the four dimensions have the following weights: digital industrialization (44.27%), industrial digitalization (25.29%), applications (17.31%), and infrastructure (13.13%). This means that digital economy growth is largely dependent on the benefits that digital technology brings to the industry and the degree of integration between digitalization and other sectors. In addition, the principle of entropy states that the index with more information will be given more weight. Figure 4 shows that the proportion of the technical renovation expenditure for electronic equipment and communication equipment (u_{16}) is the largest, 14.26%, which means that this index has the greatest impact for digital economy. Industrialization techniques encourage product development in businesses with the aid of electronic information technology, so u_{16} plays the important role in the transformation and upgrading of the traditional industries.

Meanwhile, to objectively verify the interaction between indicators, this paper conducts a two-way analysis of variance. We build a sample data matrix, in which rows represent 31 provinces and columns represent 24 indexes. The results in Table 3 show that the P value of the interaction effect is less than 0.05. Therefore, there is an obvious interaction between indicators.

Table 3. Interaction test for the index system

Source	SS	df	MS	F value	p value
Variables	193.8369	24	8.076535	366.0503	0
Provinces	37.90783	30	1.263594	57.26949	2.40×10^{-296}
Interaction effect	33.3354	720	0.046299	2.098402	4.94×10^{-48}
Error	119.6972	5425	0.022064		
Sum	384.7773	6199			

3. Analysis and results of empirical research

3.1. Dynamic comparison analysis of digital economy development

Focus on the period from 2013 to 2020, China has a surge in the digital economy (Jiang & Murmann, 2022), and the strong interaction among evaluation attributes is also proved in Table 4. Thus, this paper sets the interaction degree as ξ close to 0, namely, the value of λ approximated to 2500. The proposed method is used to calculate the GIRD-NMC matrix, and the obtained scores and annual growth rate (AGR) are displayed in Figure 5 and the left of Figure 6 respectively. If the obtained scores and AGR both are divided into three levels, namely, the rankings from 1st to 10th are defined as high level, the rankings from 11th to 20th are defined as medium level, and the rankings from 21st to 31st are defined as low level, then the 31 provinces in China can be divided into nine categories according to the above classification. The results are presented in the right of Figure 6. Based on Figures 5 and 6, we find some interesting results as follows.

First, the national AGR of the digital economy is 7.87%, showing a steady growth trend. The provinces with high AGR are Sichuan, Anhui, Hebei, Jiangxi, and Henan, most of which are in the central regions. In contrast, the provinces with a low AGR are Hainan, Xinjiang, Gansu, Jilin, and Neimenggu, most of which are in the western and northeastern regions. In addition, Guangdong has the highest AGR (12.9%), while Tianjin has the lowest AGR (4.5%).

Second, the ranked distribution of the digital economy development level and AGR for each province are relatively balanced and stable, but the regional differences are significant. From the perspective of ranked distribution, the quantity distributions of high, medium, and low levels are essentially uniform for the development level of the digital economy and AGR, in which the number of provinces keeps 10, 10, and 11 from 2013 to 2020, respectively. Meanwhile, Guangdong, Jiangsu, Beijing, and Zhejiang consistently rank as the top four provinces in digital economy development, whereas Tibet, Ningxia, Qinghai, and Gansu consistently rank as the bottom four, showing that there is a significant difference between the eastern regions and the western regions.

Thirdly, the development level of the digital economy shows a synchronous positive correlation with the AGR, and the "Double Low" phenomenon of a low AGR and low development level of the digital economy is pervasive. The right of Figure 6 shows that 31 provinces' distribution areas for the digital economy development and AGR are primarily concentrated in five areas. The provinces with higher development levels of the digital economy have a

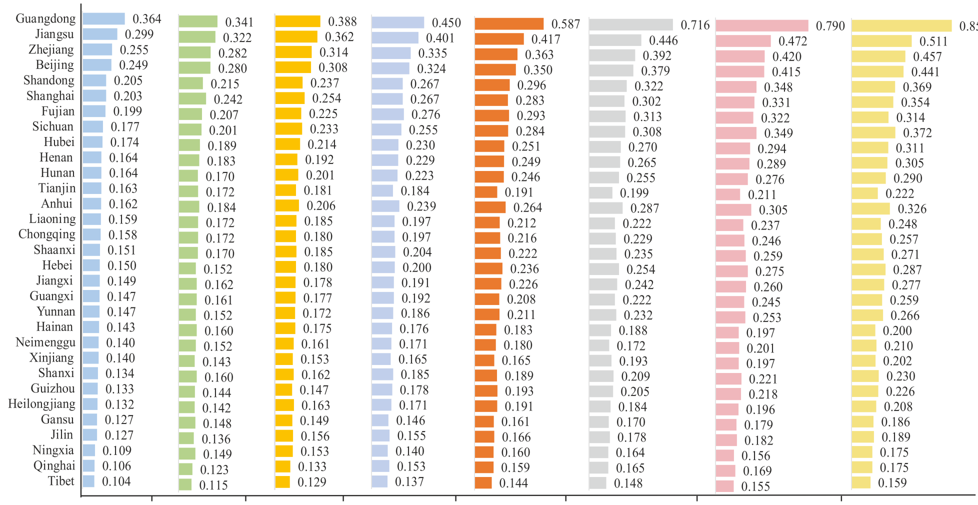

Figure 5. Comprehensive performance in provincial regions in China (2013–2020)

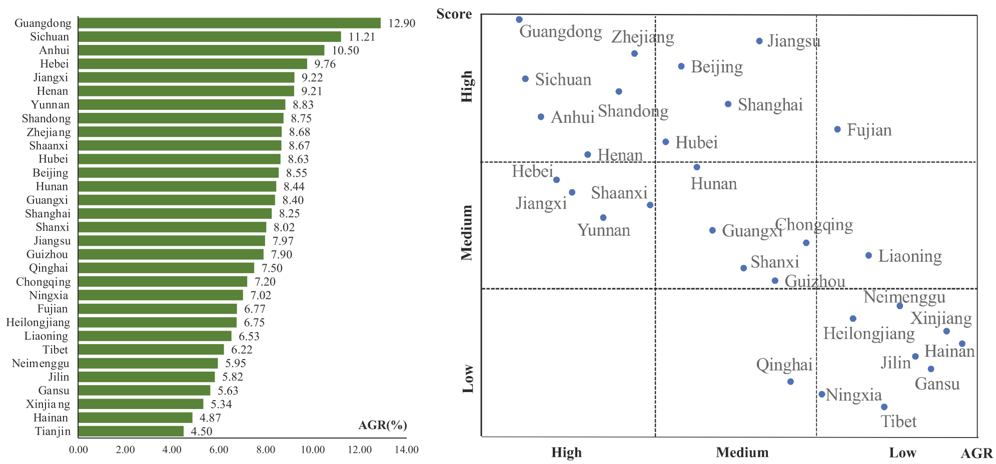

Figure 6. Classification of obtained scores and AGR

higher AGR, whereas those with lower development levels of the digital economy have a lower AGR ("Double Low" phenomenon), demonstrating a synchronous positive correlation. In addition, over one-third of all provinces experience the "Double Low" phenomenon, which are mainly prevalent in western and northeastern regions including Jilin and Gansu. Due to their comparatively underdeveloped infrastructure, low level of science and technology, and underutilized human resources, they should receive priority attention during the process of digital economy development in China.

There is an interesting phenomenon that Fujian's ranking for digital economy development is relatively stable and high, it has always been in the top ten, but its AGR lags behind, ranking at 22nd. It is easy to explain that Fujian has developed a series of policies to support the development of the 5G industry, which demonstrates the potential of the industry (Hong

& Chang, 2020). However, there are few application scenarios for the digital economy in Fujian at present, digital technology and real economy cannot be deeply integrated, and the industrial digital transformation is faced with great difficulties. Therefore, development speed is relatively slow. On the contrary, Qinghai's rankings for digital economy development are always below 29th, but its AGR is in the middle. The reason is that the foundation for the development of high-tech industry in Qinghai is insufficient, and this province is lack of scientific research and educational resources, therefore the digital economy development is considerably behind other provinces. However, in order to promote integrated development of industrialization and information technology, Qinghai has launched some big data projects, such as China Mobile (Qinghai) Plateau Big Data Center (Zhang et al., 2022b).

This paper uses ArcGIS software to create maps for visual display to compare the development level of the digital economy more easily in the four regions. Figure 7 shows the changes in the GIRD-NCM in each province in China. Overall, the darker the color is, the higher the digital economic development. Figure 7 shows that the GIRD-NCM of each province is gradually increasing, and the coastal economic provinces from the eastern regions have experienced the fastest growth in the digital economy; Meanwhile, the development level of the digital economy in Hebei has been significantly improved. The color of the central regions in 2020 is darker than that in 2013, indicating that the development level of the digital economy in the central regions has improved. In addition, the development of some provinces has significantly improved in the western regions, such as Sichuan, Yunnan, and Shaanxi, whereas other provinces have seen little change. In the northeast regions, all provinces showed little change as a whole.

3.2. Analysis of the impact of the interaction effect on digital economy development

The proposed method is used to evaluate the impact of the interaction value on the development of the digital economy in 31 provinces. We select 7 interaction values (λ),calculate the fuzzy measure and grey interaction relational degree of the normal cloud matrix, and then

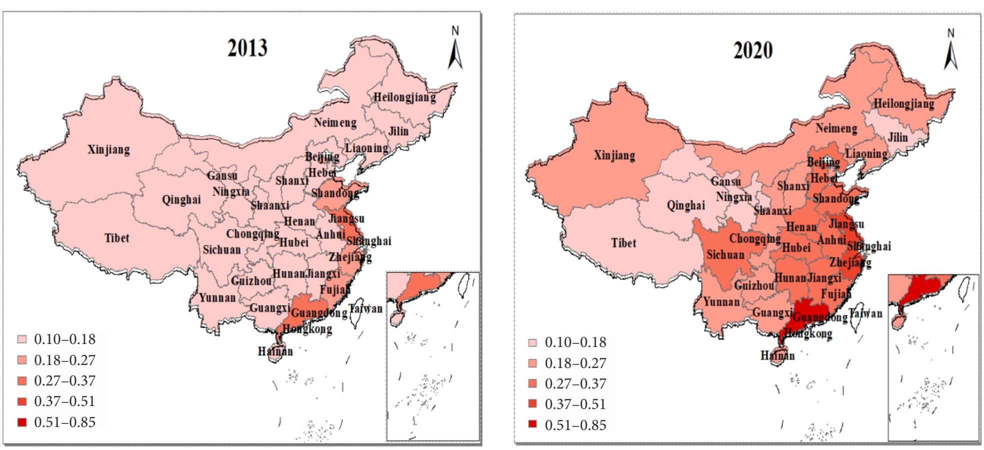

Figure 7. Spatial distribution of China's development level of digital economy

obtain the rankings (signed from M1 to M7), average rankings (signed as M8) and weighted rankings [signed M9, which is based on the uniform distribution assumption in ξ, namely, $\xi \sim U(0,1)$, seeing Equation (11)] for each province. The results are shown in Table 4, and we can get some interesting findings.

Table 4. Rankings for digital economy development based on the proposed method

Provinces	Abbr.	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Beijing	BJ	4	4	4	4	4	4	4	4	4	6	3	2
Tianjin	TJ	20	20	21	22	22	21	21	21	20	17	18	21
Hebei	HeB	13	13	13	13	13	13	13	13	13	16	13	13
Shanxi	SX	21	21	20	20	20	20	20	20	21	21	21	20
Neimenggu	NMG	25	24	24	24	24	24	25	24	25	25	23	25
Liaoning	LN	16	16	16	16	16	17	18	16	17	18	17	19
Jilin	JL	27	27	26	26	27	27	27	27	27	24	27	27
Heilongjiang	HLJ	23	23	23	23	23	23	24	23	24	22	24	24
Shanghai	SH	7	8	8	8	8	7	6	7	7	8	6	6
Jiangsu	JS	2	2	2	2	2	2	2	2	2	2	2	3
Zhejiang	ZJ	3	3	3	3	3	3	3	3	3	3	4	4
Anhui	AH	10	10	10	9	9	9	9	9	9	9	10	9
Fujian	FJ	8	7	7	7	7	8	8	7	8	4	7	8
Jiangxi	JX	15	15	15	15	15	15	15	15	15	13	15	15
Shandong	SD	5	5	5	5	5	5	5	5	5	5	5	5
Henan	Hn	11	11	11	11	11	11	11	11	10	12	11	11
Hubei	HuB	9	9	9	10	10	10	10	10	11	10	9	10
Hunan	HuN	12	12	12	12	12	12	12	12	12	11	12	12
Guangdong	GD	1	1	1	1	1	1	1	1	1	1	1	1
Guangxi	GX	19	19	19	19	19	19	19	19	19	23	20	17
Hainan	HeN	24	26	27	27	26	25	23	25	23	27	24	23
Chongqing	CQ	17	17	17	17	17	16	16	17	16	15	16	18
Sichuan	SC	6	6	6	6	6	6	7	6	6	7	8	7
Guizhou	GZ	22	22	22	21	21	22	22	22	22	19	22	22
Yunnan	YN	18	18	18	18	18	18	17	18	18	20	19	16
Qinghai	QH	29	30	30	30	30	30	29	30	29	31	30	29
Shaanxi	ShX	14	14	14	14	14	14	14	14	14	14	14	14
Gansu	GS	28	28	28	28	28	28	28	28	28	26	28	28
Tibet	XZ	31	31	31	31	31	31	31	31	31	30	31	31
Ningxia	NX	30	29	29	29	29	29	30	29	30	29	29	30
Xinjiang	XJ	26	25	25	25	25	26	26	25	26	28	26	26

Note: M1 means $\lambda = -0.9$, M2 means $\lambda = -0.5$, M3 means $\lambda = 0$, M4 means $\lambda = 10$, M5 means $\lambda = 100$, M6 means $\lambda = 500$, M7 means 2500, M8 means average rankings, M9 means weighted rankings, M10 means TOPSIS-IN, M11 means EWM-NC, M12 means MH-GRA-NC.

First, the rankings of these provinces, which are in the lead or have a moderately high development level of digital economy, are relatively stable, and are not affected by changing λ. The changes of λ have little influence on the provinces of Guangdong, Jiangsu, Beijing, Zhejiang, and Shandong, which rank consistently from 1^{st} to 5^{th}. In fact, these five provinces are the most developed regions in China, both infrastructure and related policies are relatively complete, therefore the interaction between evaluation indicators has become coordinated and stabled after the run-in period, and there is no effect of varying interaction degrees on rankings. While the provinces of Henan, Hunan, Hebei, Shaanxi, and Jiangxi rank consistently from 11^{st} to 15^{th}, the digital economy development is moderately high. These provinces have modest digital infrastructure and resources in comparison to leading provinces, and relevant policies still need to be strengthened. However, these provinces have maximized their full use of limited resources to coordinate the interaction effect between indicators, so the changes of λ also have no impact on their ranking.

Second, the changes of λ have a direct impact on the ranks of these provinces with high-, and low-level digital economy development. The former is typically positive fluctuation and the latter is typically negative fluctuation. For Sichuan, Shanghai, Fujian, Hubei, and Anhui, which are placed between 6^{th} and 10^{th}, the value of λ has a positive correlation effect on their rankings. The provinces with a high level of digital economy development have relatively ideal digital resources and infrastructure. If these provinces want to further raise the development level of the digital economy, they only need to fully utilize the coordination effect between indicators, and rationally allocate each indication based on the actual situation. And for Tianjin, Shanxi, Guizhou, Heilongjiang, Neimenggu, Xinjiang, Jilin, Gansu, Qinghai, and Ningxia, which develop slowly in the digital economy and their ranks fluctuate from 16 to 25, the value of λ has a negative correlation effect on their rankings. In fact, these provinces are located in the western and northeast regions, and their digital resources and infrastructure construction are lagging behind, so if they want to further raise the development level of the digital economy, it is not enough to only consider the interaction degree between indicators and pay more attention to coordinated development across multiple sectors, including resources, the environment, technology, human resources, and policies. Therefore, these provinces need to balance the coordination effect between indicators, gather resources for the digital economy, improve governance for digital development, and encourage technological upgrading for industrialization.

Thirdly, these provinces can be ranked by averaging the rankings and averaging the rankings (M8) and weighted rankings (M9) under different values of λ. The results of M8 are basically consistent with those of M9, which means these 7 values of λ are representative. According to M8 and M9, the results show that Guangdong has the best development level of the digital economy, followed by Beijing, Jiangsu, Zhejiang, Shanghai and some coastal cities. The primary explanation is that Guangdong has special geographic characteristics and that many Internet goliaths are based there. Beijing, which serves as the country's political hub, benefits from policies and advanced infrastructure, and the city's rapid growth has drawn in more educated and intelligent talent. Therefore, it encourages the growth of the digital economy. Jiangsu, Zhejiang, and Shanghai are located in a special geographic region, and there are numerous local and foreign firm headquarters as well as frequent economic and trade operations there. As a result, its economy is remarkably advanced, and the digital economy is growing quickly. While central regions like Hunan, Hubei, Jiangxi, and Henan have certain advantages in manufacturing, which is why the rankings are higher. However, western cities like Guizhou, Gansu, and Shaanxi, as well as northeastern cities like Heilongjiang and Jilin, rank relatively backward, and the infrastructure is relatively insufficient, which may influence the digital economy development. As a result, regional and local economic play an important role in China's digital economy development.

3.3. Model comparison analysis of digital economy development

We select three existing models to verify effectiveness of the proposed model, namely, which are the TOPSIS method with interval numbers (TOPSIS-IN, signed as M10) (Yue, 2011), the multi-hierarchy grey relative analysis method (MH-GRA-NC, signed as M11) (Zhu et al., 2015) and the entropy weight method for normal clouds (EWM-NC signed M12). The results are shown in Figure 8.

As shown in Figure 8, these ranks are generally close under different methods, which shows these methods are basically consistent with the common sense of the public in regional development. Under these methods, Guangdong, Jiangsu, Zhejiang and Beijing always occupy the top four places, and Qinghai, Ningxia and Xizang always stay at the tail. Meanwhile, these tiny differences in ranking indicate the characteristics of these methods and the superiority of our method (GIRD-NCM).

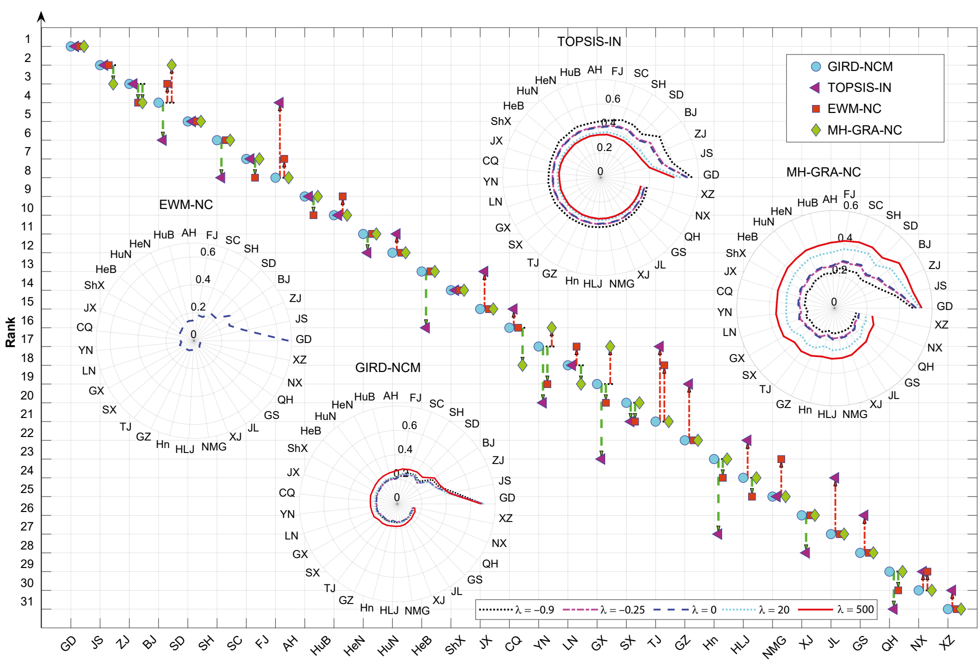

Figure 8. Measurement results and rankings comparison of four evaluation methods

From the results, the ranking distributions of our method almost keep in the consistence with those of other three methods. Therefore, these methods can be used to evaluate the digital economy development in China, demonstrating the rationality and effectiveness of the proposed method. However, from the perspective of the detailed ranking results, the ranking preference order differs slightly. As an example of a province with significant ranking disparities, such as Fujian, when using the M10, M11, and M12, Fujian ranks 4^{th}, 7^{th} and 8^{th}, respectively. In fact, Table 4 shows that in our proposed model, the ranking of Fujian is subject to some variation depending on the interaction degree, and this fluctuation ranges from seventh to eighth. This suggests that the novel method is more reasonable and flexible. In addition, Beijing's rankings in the M10, M11, and M12, which are 2^{nd}, 3^{rd}, and 6^{th}, respectively, show significant differences. Beijing is ranked fourth in proposed model, which is more reasonable and represents the median value of the first three methods.

According to the measurement results shown in Figure 8, the measurement of M10 is primarily concentrated between 0.3 and 0.6, and the measurement range of M12 is primarily concentrated between 0.2 and 0.5. The overall measurement range is more concentrated, therefore, the differences in the measurement range between provinces are not obvious. However, the measurement range of the novel method is primarily concentrated between 0.1 and 0.6, and the measurement range of the M11 is primarily concentrated between 0.04 and 0.6. The discreteness of the calculated results is better than that of the previous two methods, of which M11 is the best. However, M11 cannot distinguish the ranking of provinces with similar development levels, such as Hainan and Heilongjiang, as their measurement values are totally or almost equivalent. Therefore, the proposed method is simple to use to evaluate the development level of the digital economy due to a large amount of scattered data, and has high reliability.

Different processing techniques of information coverage grey numbers for the four evaluation methods could be the cause of the ranking disagreement. In fact, in M10, all information coverage grey numbers are transformed into interval numbers. At the same time, M11 and M12 do not transform the information coverage grey numbers, and only use their own distance formula for measurement. As a result, these data processing methods ignore the fuzziness and random correlation of variables, and it is easy to cause information loss and distortion. However, in the proposed model, all decision indicators are expressed by the cloud model, which can avoid this problem. Moreover, the novel method also considers the interaction between attributes, so it is effective and credible.

Conclusions and insights

Conclusions

Considering the fuzziness and randomness of different data types, and interaction effects between attributes in the digital economy evaluation problem, this paper develops a novel GIRD-NCM model that integrates the cloud model, Choquet fuzzy integral and GRA to evaluate the development level of the digital economy in 31 provinces of China from 2013 to 2020. Compared with the three existing evaluation methods, the proposed model is effective and reliable. Accordingly, we highlight the following conclusions. (1) China's national AGR of the digital economy is 7.87%, showing a steady growth trend, of which development level of Eastern China is the fastest, followed by the central regions, while those of the western and northeastern regions are relatively modest. (2) The ranked distribution of the digital economy development level and AGR for each province are relatively balanced and stable, but the regional differences are significant. (3) The development level of the digital economy shows a synchronous positive correlation with the AGR, and the "Double Low" phenomenon of a low AGR and low development level of the digital economy is pervasive. (4) The rankings of these provinces which are in the lead or have a moderately high level of digital economy development are relatively stable and are not affected by the change in interaction degree. (5) The changes in interaction degree have a direct impact on the ranks of these provinces with high-, and low-level digital economy development. The former is typically positive fluctuation and the latter is typically negative fluctuation. If the provinces with high development levels want to further improve, they only need to fully utilize the coordination effect between indicators. However, provinces with low development levels need to balance the coordination effect among indicators as well as gather resources for the digital economy, improve governance for digital development, and encourage technological upgrading for industrialization.

Policy insights

Based on regional difference and the influence of different interaction degrees on rankings, we recommend implementing differentiated policies and measures, to ensure the overall improvement of the digital economy. The eastern regions will continue to lead by innovation and application, with a focus on technology and human resources, take innovation as the primary driving force for development, and foster self-reliance and self-improvement in science and technology. The central region should emphasize integrated development and collaborative efficiency, support the integration of digital technologies, application scenarios and business models, and create a new mechanism for digital economy development in which all economic and social entities participate in multiple ways and work in synergy. The "Double Low" phenomenon mainly occurs in the western and northern regions of the country, which accounts for nearly one-third of the total. In terms of R&D, manufacturing, business, and management digitalization, these provinces differ significantly from other regions due to a lack of digital talent and a relatively lagging informatization development level. As a result, to support the further development of digital economy, it is essential to adopt relevant policies and allocate funds to the "Double Low" provinces, as well as to strengthen the construction of digital infrastructure, fully utilize their inherent advantages and resources, and promote technological upgrading for industrialization.

Besides, this study might have some limitations. First, we can consider more indicators when building the index system for digital economy development, such as education level and the number of digital rural demonstrations. Second, there are limitations in data selection due to the shorter development process of the digital economy in China, so it is difficult to reveal the dynamic evolution of digital economy development. More countries and regions can be considered in future studies.

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References

Cao, Y., Yin, K., Li, X., & Zhai, C. (2021). Forecasting CO_2 emissions from Chinese marine fleets using multivariable trend interaction grey model. *Applied Soft Computing*, *104*, Article 107220. https://doi.org/10.1016/j.asoc.2021.107220

Chen, L., Dong, T., Peng, J., & Dan, R. (2022). Uncertainty analysis and optimization modelling with application to supply chain management: A systematic review. *Mathematics*, 11(11), Article 2530. https://doi.org/10.3390/math11112530

China Academy of Information and Communications Technology. (2021). *White paper on China's Digital Economy*. Retrieved July 20, 2022 from https://www.100ec.cn/detail--6591053.html

Chu, J., & Xiao, X. (2023). Benefits evaluation of the Northeast Passage based on grey relational degree of discrete Z-numbers. *Information Sciences*, *626*, 607–625. https://doi.org/10.1016/j.ins.2023.02.085

Cui, L., Chan, H. K., Zhou, Y., Dai, J., & Lim, J. J. (2019). Exploring critical factors of green business failure based on Grey-Decision Making Trial and Evaluation Laboratory (DEMATEL). *Journal of Business Research*, *98*, 450–461. https://doi.org/10.1016/j.jbusres.2018.03.031

Dai, G. Z., Pan, Q., Zhang, S. Y., & Zhang, H. C. (1999). The developments and problems in evidence reasoning. *Control Theory and Applications*, *16*(4), 465–469.

Ding, S., Dang, Y. G., Ning, X., & Wang, J. J. (2018). Multivariable grey forecasting model based on interaction effect and its application. *Journal of Systems Engineering and Electronics*, *40*(3), 595–602.

Goldstein, M. (2006). Subjective Bayesian analysis: Principles and practice. *Bayesian Analysis*, *1*(3), 403–420. https://doi.org/10.1214/06-BA116

Gong, Y. B., Xu, X. K., & Liu, G. F. (2021). Research on linguistic multi-attribute decision marking method based on normal cloud expectation and variance distance. *Statistics* & *Information Forum*, *36*(10), 12–19.

Hong, Y. Z., & Chang, H. H. (2020). Does digitalization affect the objective and subjective wellbeing of forestry farm households? Empirical evidence in Fujian Province of China. *Forest Policy and Economics*, *118*, Article 102236. https://doi.org/10.1016/j.forpol.2020.102236

He, J., Mao, S., & Kang, Y. (2023). Augmented fractional accumulation grey model and its application: Class ratio and restore error perspectives. *Mathematics and Computers in Simulation*, *209*, 220–247. https://doi.org/10.1016/j.matcom.2023.02.008

Horoshko, O. I., Horoshko, A., Bilyuga, S., & Horoshko, V. (2021). Theoretical and methodological bases of the study of the impact of digital economy on world policy in 21 century. *Technological Forecasting and Social Change*, *166*, Article 120640. https://doi.org/10.1016/j.techfore.2021.120640

Huang, C. Y., Hsu, C. C., Chiou, M. L., & Chen, C. I. (2020). The main factors affecting Taiwan's economic growth rate via dynamic grey relational analysis. *PLoS ONE*, *15*(10), Article e0240065. https://doi.org/10.1371/journal.pone.0240065

Jana, C., & Pal, M. (2021). A dynamical hybrid method to design decision making process based on GRA approach for multiple attributes problem. *Engineering Applications of Artificial Intelligence*, *100*, Article 104203. https://doi.org/10.1016/j.engappai.2021.104203

Jiang, H., & Murmann, J. P. (2022). The rise of China's digital economy: An overview. *Management and Organization Review*, *18*(4), 790–802. https://doi.org/10.1017/mor.2022.32

Kosimov, J., & Ruziboyeva, G. (2022). The role of the digital economy in the world. *Scientific Progress*, *3*(2), 435–441.

Li, D., Liu, C., & Gan, W. (2009). A new cognitive model: Cloud model. *International Journal of Intelligent Systems*, *24*(3), 357–375. https://doi.org/10.1002/int.20340

Li, Y., Rao, C., Goh, M., & Xiao, X. (2022). Novel multi-attribute decision-making method based on Z-number grey relational degree. *Soft Computing*, *26*, 13333–13347. https://doi.org/10.1007/s00500-022-07487-w

Lian, X., Mu, Y., & Zhang, W. (2023). Digital inclusive financial services and rural income: Evidence from China's major grain-producing regions. *Finance Research Letters*, *53*, Article 103622. https://doi.org/10.1016/j.frl.2022.103622

Liu, H. C., Wang, L. E., Li, Z., & Hu, Y. P. (2018). Improving risk evaluation in FMEA with cloud model and hierarchical TOPSIS method. *IEEE Transactions on Fuzzy Systems*, *27*(1), 84–95. https://doi.org/10.1109/TFUZZ.2018.2861719

Meng, M., & Qu, D. (2022). Understanding the green energy efficiencies of provinces in China: A Super-SBM and GML analysis. *Energy*, *239*, Article 121912. https://doi.org/10.1016/j.energy.2021.121912

Matthess, M., & Kunkel, S. (2020). Structural change and digitalization in developing countries: Conceptually linking the two transformations. *Technology in Society*, *63*, Article 101428. https://doi.org/10.1016/j.techsoc.2020.101428

Muñoz, J., Molero-Castillo, G., Benítez-Guerrero, E., & Barcenas, E. (2018). Data fusion as source for the generation of useful knowledge in context-aware systems. *Journal of Intelligent* & *Fuzzy Systems*, *34*(5), 3165–3176. https://doi.org/10.3233/JIFS-169500

Pan, W., Xie, T., Wang, Z., & Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *Journal of Business Research*, *139*, 303–311. https://doi.org/10.1016/j.jbusres.2021.09.061

Rao, C., Gao, M., Wen, J., & Goh, M. (2022). Multi-attribute group decision making method with dual comprehensive clouds under information environment of dual uncertain Z-numbers. *Information Sciences*, *602*, 106–127. https://doi.org/10.1016/j.ins.2022.04.031

Sugeno, M. (1974). *Theory of fuzzy integral and its applications*. Tokyo Institute of Technology.

Wang, J., Dong, K., Dong, X., & Taghizadeh-Hesary, F. (2022). Assessing the digital economy and its carbon-mitigation effects: The case of China. *Energy Economics*, *113*, Article 106198. https://doi.org/10.1016/j.eneco.2022.106198

Wang, J. Q., & Liu, T. (2012). Uncertain linguistic multi-criteria group decision-making approach based on integrated cloud. *Control and Decision*, *27*(8), 1185–1190.

Wang, X. S., Wen, X, Q., Liu, D., & Wang, W. J. (2010). Trust model based on cloud theory in pervasive environment. *Computer Engineering*, *36*(7), 282–286.

Xiao, L., Huang, G., & Zhang, G. (2021a). Improved assessment model for candidate design schemes with an interval rough integrated cloud model under uncertain group environment. *Engineering Applications of Artificial Intelligence*, *104*, Article 104352. https://doi.org/10.1016/j.engappai.2021.104352

Xiao, Q., Shan, M., Gao, M., Xiao, X., & Guo, H. (2021b). Evaluation of the coordination between China's technology and economy using a grey multivariate coupling model. *Technological and Economic Development of Economy*, *27*(1), 24–44. https://doi.org/10.3846/tede.2020.13742

Xiao, Q., Shan, M., Gao, M., & Xiao, X. (2020a). Grey information coverage interaction relational decision making and its application. *Journal of Systems Engineering and Electronics*, *31*(2), 359–369. https://doi.org/10.23919/JSEE.2020.000013

Xiao, Q., Shan, M., Xiao, X., & Rao, C. (2020b). Evaluation model of industrial operation quality under multi-source heterogeneous data information. *International Journal of Fuzzy Systems*, *22*(2), 522–547. https://doi.org/10.1007/s40815-019-00776-x

Xiao, X. P., & Mao, S. H. (2013). *Grey prediction and decision making method*. Science Press.

Yang, S., & He, J. (2022). Analysis of digital economy development based on AHP-entropy weight method. *Journal of Sensors*, *2022*, Article 7642682. https://doi.org/10.1155/2022/7642682

Yue, Z. L. (2011). An extended TOPSIS for determining weights of decision makers with interval numbers. *Knowledge-Based Systems*, *24*(1), 146–153. https://doi.org/10.1016/j.knosys.2010.07.014

Zhang, J., Lyu, Y., Li, Y., & Geng, Y. (2022a). Digital economy: An innovation driving factor for low-carbon development. *Environmental Impact Assessment Review*, *96*, Article 106821. https://doi.org/10.1016/j.eiar.2022.106821

Zhang, T., Yan, L., & Yang, Y. (2018). Trust evaluation method for clustered wireless sensor networks based on cloud model. *Wireless Networks*, *24*(3), 777–797. https://doi.org/10.1007/s11276-016-1368-y

Zhang, S., Xiang, M., Xu, Z., Wang, L., & Zhang, C. (2020). Evaluation of water cycle health status based on a cloud model. *Journal of Cleaner Production*, *245*, Article 118850. https://doi.org/10.1016/j.jclepro.2019.118850

Zhang, X., Rao, C., Xiao, X., Hu, F., & Goh, M. (2024). Prediction of demand for staple food and feed grain by a novel hybrid fractional discrete multivariate grey model. 125, 85-107. https://doi.org/10.1016/j.apm.2023.09.026

Zhang, X, Y., Li, S. S., & Hu, Y. (2022b). Analysis on the ecosystem service protection effect of national nature reserve in Qinghai-Tibetan Plateau from weight perspective. *Ecological Indicators*, *142*, Article 109225. https://doi.org/10.1016/j.ecolind.2022.109225

Zhang, Y., Jiang, C., Yue, B., Wan, J., & Guizani, M. (2022c). Information fusion for edge intelligence: A survey. *Information Fusion*, *81*, 171–186. https://doi.org/10.1016/j.inffus.2021.11.018

Zhao, H., Mi, J., & Liang, M. (2022). A multi-granularity information fusion method based on logistic regression model and Dempster-Shafer evidence theory and its application. *International Journal of Machine Learning and Cybernetics*, *13*, 3131–3142. https://doi.org/10.1007/s13042-022-01584-w

Zhu, W., Duan, L., Zhang, J., Shi, Y., & Qiao, Y. (2015). Constructing a competitiveness evaluation system of listed Chinese medicine enterprises based on grey correlation. *The Journal of Grey System*, *27*(4), 40–52.

Zhu, W., Huang, J., & Cai, N. (2022). Comparing the digital economy urban network: Study based on the human resource needs in the Yangtze River Delta, China. *Journal of Urban Planning and Development*, *148*(4), Article 05022033. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000886