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Enhanced Decision-Making Technique for Innovation Capability Evaluation in the Core Industries of Digital Economy under Double-Valued Neutrosophic Sets

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Abstract: The evaluation of innovation capability in the core industries of digital economy is a comprehensive analysis and assessment of the innovation capacities of industries closely related to digital technologies. The assessment typically includes aspects such as technology research and development, corporate innovation investment, talent cultivation, and market competitiveness, aiming to measure the innovation level of these industries in driving digital economic growth. Through quantitative and qualitative analysis, the evaluation helps formulate policies, optimize resource allocation, and enhance the international competitiveness and sustainable development of the core industries in the digital economy. The innovation capability evaluation in the core industries of digital economy is multi-attribute decision-making (MADM) problem. Recently, methods such as the TODIM and TOPSIS approaches have been applied to tackle these challenges. Double-Valued Neutrosophic Sets (DVNSs) are used to represent fuzzy data in the evaluation process. In this study, a Double-Valued Neutrosophic Number TODIM-TOPSIS (DVNN-TODIM-TOPSIS) approach is proposed to address MADM problems involving DVNSs. Finally, a numerical case study on the innovation capability evaluation in the core industries of digital economy is provided to demonstrate the effectiveness of the DVNN-TODIM-TOPSIS approach.

Keywords: MADM; DVNSs; TODIM approach; TOPSIS approach; innovation capability evaluation

1. Introduction

The digital economy is a series of economic forms that use data resources as key production factors, modern information networks as important carriers, and the effective use of information and communication technologies as a driving force for improving efficiency and optimizing economic structures. The purpose of evaluating the innovation capability of core industries in the digital economy is to systematically and scientifically assess and analyze the innovation potential and actual performance of industries related to the digital economy. These industries, such as artificial intelligence, big data, cloud computing, and the Internet of Things, play a key role in driving the digital transformation of the economy. By evaluating their innovation capabilities, we can identify strengths and weaknesses in areas such as technological research and development, market competitiveness, corporate innovation investment, and supply chain collaboration. The significance of this evaluation lies in providing decision-making support for governments, businesses, and research institutions. First, governments can use the results to optimize industrial policies, promote efficient resource allocation, and support the development of innovation ecosystems. Second, businesses can analyze gaps between themselves and industry leaders, formulating more targeted innovation strategies to enhance their market competitiveness. Lastly, research institutions can leverage the evaluation results to identify cutting-edge technologies and industry trends, driving forward-looking scientific research. Overall, evaluating the innovation capability of core industries in the digital economy helps promote sustainable industry development, enhances the global competitiveness of nations and regions in the digital economy, and contributes to high-quality economic growth. The innovation capability evaluation in the core industries of digital economy is MADM problem. Recently, the TODIM approach [1-5] and TOPSIS approach [6-8] have been applied to handle such problems. The TODIM-TOPSIS method combines the advantages of both TODIM and TOPSIS, offering the following three key benefits: First, it balances the decision-maker's subjective preferences with objective data analysis. TODIM, based on cumulative prospect theory, takes into account the decision-maker's psychological preferences, particularly their risk aversion when facing potential losses. On the other hand, TOPSIS objectively evaluates the relative merits of alternatives by calculating their distances from the ideal and negative-ideal solutions. By combining these methods, TODIM-TOPSIS achieves a balance between subjective and objective factors, making the decision-making process more reasonable and effective. Second, it excels in handling complex and uncertain decision-making environments. TODIM is particularly suited to addressing multi-criteria problems with high levels of uncertainty, as it accurately reflects the decision-maker's true intentions, especially in risky contexts. Meanwhile, TOPSIS, through the construction of ideal solutions, effectively resolves multi-dimensional decision problems, providing clear ranking results. This makes the TODIM-TOPSIS method highly effective in complex scenarios, applicable to decision analysis across various fields. Lastly, it is easy to implement and widely applicable. The computational process of TOPSIS is relatively simple, making it easy to understand and execute, while TODIM enhances the method's flexibility and applicability. Together, they create a method that can be employed in complex system evaluations, such as in education or technology assessments, and can be easily implemented using common computational tools, making it practical for real-world applications. Double-Valued Neutrosophic Sets (DVNSs) [9] have been employed to represent fuzzy data during the quality evaluation process. DVNSs offer significant advantages in evaluating the effectiveness of multimedia-based college English teaching. First, they handle uncertainty and ambiguity, accurately representing fuzzy data in the evaluation process. Second, DVNS simultaneously considers truth, indeterminacy, and falsity, providing more comprehensive evaluation results. Lastly, DVNS is flexible and applicable to complex evaluation scenarios, assisting decision-makers in making more rational judgments when faced with uncertainty and ambiguous information. In this study, we propose the DVNN-TODIM-TOPSIS approach to solve MADM problems with DVNSs. Finally, a numerical study on the innovation capability evaluation in the core industries of digital economy is presented to validate the effectiveness of the DVNN-TODIM-TOPSIS model.

The structure of this paper is as follows: Section 2 provides an introduction to DVNSs. In Section 3, the DVNN-TODIM-TOPSIS method is proposed within the DVNS framework. Section 4 presents a case study illustrating the innovation capability evaluation in the core industries of digital economy, accompanied by a comparative analysis. Finally, Section 5 offers concluding remarks.

2. Literature review

In the future, within the high-quality development goals that China needs to achieve in the areas of technological and economic development, it is essential to realize a high level of technological self-reliance and strength, and to move into the ranks of innovative countries. This includes building a modern economic system through the creation of a new development pattern. High-tech industries will play a crucial role in achieving these goals: they can drive economic growth, promote balanced regional development, and shift the focus of production factors from material resources and capital to the creative role of labor. Innovative technologies have broad prospects in the digitalization of high-tech industries. In 2021, China’s digital economy reached a scale of 4.55 trillion yuan, a nominal year-on-year growth of 16.2%, accounting for a staggering 39.8% of GDP. This demonstrates that the digital economy holds a very important position in the national economy, with its supportive role for various industries becoming increasingly evident. However, at present, the development of high-tech industries exhibits regional imbalances. In 2019, the main business income of high-tech industries in the eastern region reached 10.9388 trillion yuan, while the central region accounted for 2.5109 trillion yuan, and the western region for 2.1385 trillion yuan. In recent years, economic development trends have shown the emergence of a large number of high-tech services in the market, laying the foundation for innovative economic development. In countries with advanced high-tech industries, the emergence of the digital economy stimulates innovative production activities that drive national development. To achieve further development of high-tech industries and promote balanced development across all regions, improving innovation efficiency should be an inevitable choice. In the face of the new dynamics brought by the digital economy era, fully leveraging industrial digitalization can provide new momentum to improve innovation efficiency. It is clear that the digital economy and high-tech industries are closely interconnected, and the digital transformation of industries will form digital industrial clusters in China, which will be an important guarantee for building China’s core competitive advantage through the digital economy. Cheng [10] was one of the earliest researchers to explore the innovative development of the digital cultural industry. He noted that due to China's vast internet user base, the digital cultural industry had grown rapidly. Although it had already taken shape, the industry lacked unified recognition due to its strong innovation and fast-changing products and models. Later, Cui, Zheng and He [11] examined the innovative development of the media industry in the digital economy era. They emphasized that traditional research methods in media economics needed to adapt to the new paradigm of the digital economy. Yu [12] further explored the role of the global unified coding identification system in the digital economy, arguing that coding empowerment was a key tool in driving industrial innovation and digitizing product information, thus promoting the development of the digital economy. In 2020, Zhou [13] took a more systematic approach, analyzing the transformation of industrial innovation under the digital economy. She suggested that traditional innovation policies needed systemic reforms to adapt to the revolutionary changes brought by the digital economy. In 2021, Ma [14] measured the innovation efficiency of China's high-tech industries using a three-stage DEA model. She found that the level of digital economy development had a significant positive impact on innovation efficiency and recommended strengthening digital infrastructure. In the same year, Han [15] discussed the construction of an innovation ecosystem in the digital economy era, emphasizing the importance of enterprise technological innovation, industrial chain collaboration, and the deep integration of various sectors. In 2022, Jiang [16] used the entropy weight method to empirically analyze the role of the digital economy in enhancing the innovation capability of the circulation industry. He found that the digital economy significantly promoted innovation in the circulation industries, particularly in the eastern and central regions. Zhang, Guo, Sun and Jia [17] proposed an evaluation system for the innovation capability of core industries in the digital economy, highlighting the regions such as Beijing, Zhejiang, Guangdong, and Shanghai excelled in innovation. In 2023, Li and Guo [18] studied how the digital economy enhanced the innovation efficiency of high-tech industries, finding that information development made the largest contribution, followed by digital transactions. Yang [19] focused on Henan Province, exploring the innovation cluster development of the region's core industries in the digital economy. She pointed out that Henan still faced shortcomings in technological innovation and the number of leading enterprises. Zhang, Liu and Liu [20] analyzed the impact of the digital economy on the innovation performance of high-tech industries, finding that digital economy development indirectly improved innovation performance through R&D input. In 2024, Wang, Hui and Xu [21] focused on the driving effect of the digital economy on the innovation of traditional industries in China. They found that the digital economy significantly impacted innovation by promoting industrial transformation and consumer demand. Lastly, Liao [22] explored the innovative development of Hangzhou's cultural and tourism industries under the empowerment of the digital economy, systematically summarizing the practical experience of how the digital economy drives innovation in the industry.

3. Preliminaries

Kandasamy [9] put forward the DVNSs.

Definition 2 [9]. The DVNSs is put forward:

$$DA = \left\{ \left(x, DT_A(x), DIT_A(x), DIF_A(x), DF_A(x) \right) \middle| x \in X \right\} \tag{1}$$

with $DT_A(x)$ is truth-membership, $DIT_A(x)$ is listed as indeterminacy leaning for truth-membership, $DIF_A(x)$ is listed as indeterminacy leaning for falsity-membership indeterminacy-membership, $DF_A(x)$ is listed as falsity-membership, $DT_A(x), DIT_A(x), DIF_A(x), DF_A(x) \in [0,1]$, $0 \le DT_A(x) + DIT_A(x) + DIF_A(x) + DF_A(x) \le 4$.

The DVNN is listed as: $DA = (DT_A, DIT_A, DIF_A, DF_A)$, $DT_A, DIT_A, DIF_A, DF_A \in [0,1]$, $0 \le DT_A + DIT_A + DIF_A + DF_A \le 4$.

Definition 2. Let $DA = (DT_A, DIT_A, DIF_A, DF_A)$, the score value is constructed:

$$DSV(DA) = \frac{(2 + DT_A + DIT_A - DIF_A - DF_A)}{4},\ DSV(DA) \in [0,1]. \tag{2}$$

Definition 3. Let $DA = (DT_A, DIT_A, DIF_A, DF_A)$, the accuracy value is constructed:

$$DAV(DA) = \frac{(DT_A + DIT_A + DIF_A + DF_A)}{4},\ DAV(DA) \in [0,1]\ . \tag{3}$$

The order between two DVNNs is put forward.

Definition 4. Let $DA = (DT_A, DIT_A, DIF_A, DF_A)$ and $DB = (DT_B, DIT_B, DIF_B, DF_B)$, let $DSV(DA) = \frac{(2 + DT_A + DIT_A - DIF_A - DF_A)}{4}$ and $DSV(DB) = \frac{(2 + DT_B + DIT_B - DIF_B - DF_B)}{4}$, and let $DAV(DA) = \frac{(DT_A + DIT_A + DIF_A + DF_A)}{4}$ and $DAV(DB) = \frac{(DT_B + DIT_B + DIF_B + DF_B)}{4}$, then if $DSV(DA) < DSV(DB)$, $DA < DB$; if $DSV(DA) = DSV(DB)$, Then (1)if $DAV(DA) = DAV(DB)$, $DA = DB$; (2) if $DAV(DA) < DAV(DB)$, $DA < DB$.

Definition 5[9]. $DA = (DT_A, DIT_A, DIF_A, DF_A)$, $DB = (DT_B, DIT_B, DIF_B, DF_B)$, the operations are constructed:

(1) $DA \oplus DB = \left(DT_A + DT_B - DT_A DT_B, DIT_A + DIT_B - DIT_A DIT_B, DIF_A DIF_B, DF_A DF_B \right);$

(2) $DA \otimes DB = \left(DT_A DT_B, DIT_A DIT_B, DIF_A + DIF_B - DIF_A DIF_B, DF_A + DF_B - DF_A DF_B \right);$

(3) $\lambda DA = \left(1-\left(1-DT_A\right)^{\lambda}, 1-\left(1-DIT_A\right)^{\lambda}, \left(DIF_A\right)^{\lambda}, \left(DF_A\right)^{\lambda} \right), \lambda > 0;$

(4) $\left(DA\right)^{\lambda} = \left(\left(DT_A\right)^{\lambda}, \left(DIT_A\right)^{\lambda}, 1-\left(1-DIF_A\right)^{\lambda}, 1-\left(1-DF_A\right)^{\lambda} \right), \lambda > 0.$

Definition 6[9]. Let $DA = \left(DT_A, DIT_A, DIF_A, DF_A \right)$ and $DB = \left(DT_B, DIT_B, DIF_B, DF_B \right)$, then the normalized Euclidean distance between $DA = \left(DT_A, DIT_A, DIF_A, DF_A \right)$ and $DB = \left(DT_B, DIT_B, DIF_B, DF_B \right)$ is:

$$ED\left(DA, DB\right) = \sqrt{\frac{1}{4}\left(\begin{array}{l} \left|DT_A - DT_B\right|^2 + \left|DIT_A - DIT_B\right|^2 \\ + \left|DIF_A - DIF_B\right|^2 + \left|DF_A - DF_B\right|^2 \end{array} \right)} \tag{4}$$

4. DVNN-TODIM-TOPSIS approach

4.1. DVNN-MADM issues

The DVNN-TODIM-TOPSIS approach is put forward for MADM. Let $DA = \left\{ DA_1, DA_2, \cdots, DA_m \right\}$ be alternatives and $DG = \left\{ DG_1, DG_2, \cdots, DG_n \right\}$ be attributes with weight values $d\omega$, $d\omega_j \in [0,1], \sum_{j=1}^{n} d\omega_j = 1$.

The DVNN-TODIM-TOPSIS approach is put forward for MADM.

Step 1. Put forward the DVNN-matrix $DR = \left[DR_{ij} \right]_{m \times n} = \left(DT_{ij}, DIT_{ij}, DIF_{ij} DF_{ij} \right)_{m \times n}$

$$DR = \left[DR_{ij} \right]_{m \times n} = \begin{array}{c} \\ DA_1 \\ DA_2 \\ \vdots \\ DA_m \end{array} \begin{array}{c} \begin{array}{cccc} DG_1 & DG_2 & \cdots & DG_n \end{array} \\ \left[\begin{array}{cccc} DR_{11} & DR_{12} & \cdots & DR_{1n} \\ DR_{21} & DR_{22} & \cdots & DR_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ DR_{m1} & DR_{m2} & \cdots & DR_{mn} \end{array} \right] \end{array} \tag{5}$$

Step 2. Normalize $DR = \left[DR_{ij} \right]_{m \times n}$ into $NDR = \left[NDR_{ij} \right]_{m \times n}$.

For benefit attributes:

$$\begin{array}{l} NDR_{ij} = \left(DT_{ij}^N, DIT_{ij}^N, DIF_{ij}^N, DF_{ij}^N \right) \\ = DR_{ij} = \left(DT_{ij}, DIT_{ij}, DIF_{ij} DF_{ij} \right) \end{array} \tag{6}$$

For cost attributes:

$$
\begin{aligned}
NDR_{ij} &= \left(DT_{ij}^{N}, DIT_{ij}^{N}, DIF_{ij}^{N}, DF_{ij}^{N} \right) \\
&= \left(DF_{ij}, DIF_{ij}, DIT_{ij}\, DT_{ij} \right)
\end{aligned}
\tag{7}
$$

4.2. DVNN-TODIM-TOPSIS model for MADM

The DVNN-TODIM-TOPSIS approach is put forward for MADM.

(1) Put forward relative weight:

$$rd\omega_j = d\omega_j \Big/ \max_j d\omega_j , \tag{8}$$

(2) The dominance sorting degree (DSD) $DSD_j\left(DA_i, DA_t\right)$ of DA_i over DA_t for DG_j is put forward:

$$
DSD_j\left(DA_i, DA_t\right) = \begin{cases}
\dfrac{rd\omega_j \times \left(HD\left(NDR_{ij}, NDR_{tj}\right)\right)^{\alpha}}{\sum_{j=1}^{n} rd\omega_j} & \text{if } SV\left(NDR_{ij}\right) > SV\left(NDR_{tj}\right) \\
0 & \text{if } SV\left(NDR_{ij}\right) = SV\left(NDR_{tj}\right) \\
-\dfrac{1}{\theta} \dfrac{\sum_{j=1}^{n} rd\omega_j \times \left(HD\left(NDR_{ij}, NDR_{tj}\right)\right)^{\beta}}{rd\omega_j} & \text{if } SV\left(NDR_{ij}\right) < SV\left(NDR_{tj}\right)
\end{cases}
\tag{9}
$$

The α, β is put forward in light with Ref.[23].

The $DSD_j\left(DA_i\right)$ for DG_j is obtained:

$$
DSD_j\left(DA_i\right) = \left[DSD_j\left(DA_i, DA_t\right) \right]_{m \times m}
= \begin{array}{c} \\ DA_1 \\ DA_2 \\ \vdots \\ DA_m \end{array}
\begin{array}{c}
\begin{array}{cccc} DA_1 & DA_2 & \cdots & DA_m \end{array} \\
\begin{bmatrix}
0 & DSD_j\left(DA_1, DA_2\right) & \cdots & DSD_j\left(DA_1, DA_m\right) \\
DSD_j\left(DA_2, DA_1\right) & 0 & \cdots & DSD_j\left(DA_2, DA_m\right) \\
\vdots & \vdots & \cdots & \vdots \\
DSD_j\left(DA_m, DA_1\right) & DSD_j\left(DA_m, DA_2\right) & \cdots & 0
\end{bmatrix}
\end{array}
$$

(3) Put forward the overall DSD of alternative DA_i over others for DG_j :

$$DSD_j\left(DA_i\right) = \sum_{t=1}^{m} DSD_j\left(DA_i, DA_t\right) \tag{10}$$

The overall DSD is obtained:

$$DSD=\left(DSD_{ij}\right)_{m\times n}=\begin{array}{cccccc} & DG_1 & DG_2 & \cdots & DG_n \\ DA_1 & \sum_{t=1}^{m} DSD_1\left(DA_1,DA_t\right) & \sum_{t=1}^{m} DSD_2\left(DA_1,DA_t\right) & \cdots & \sum_{t=1}^{m} DSD_n\left(DA_1,DA_t\right) \\ DA_2 & \sum_{t=1}^{m} DSD_1\left(DA_2,DA_t\right) & \sum_{t=1}^{m} DSD_2\left(DA_2,DA_t\right) & \cdots & \sum_{t=1}^{m} DSD_n\left(DA_2,DA_t\right) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ DA_m & \sum_{t=1}^{m} DSD_1\left(DA_m,DA_t\right) & \sum_{t=1}^{m} DSD_2\left(DA_m,DA_t\right) & \cdots & \sum_{t=1}^{m} DSD_n\left(DA_m,DA_t\right) \end{array}$$

(4) Put forward the PIS (positive ideal solution) and NIS (negative ideal solution):

$$PIS=\left(PIS_1,PIS_1,\cdots,PIS_n\right) \tag{11}$$

$$NIS=\left(NIS_1,NIS_1,\cdots,NIS_n\right) \tag{12}$$

$$PIS_j=\max_{j=1}^{n}\Pi_{ij},NIS_j=\min_{j=1}^{n}\Pi_{ij} \tag{13}$$

(5) Put forward the Euclidean distance and closeness coefficient (CC). The optimal choice has the largest CC information.

$$ED\left(DA_i,PIS\right)=\sqrt{\sum_{j=1}^{n}\left(\Pi_{ij}-PIS_j\right)^2} \tag{14}$$

$$ED\left(DA_i,NIS\right)=\sqrt{\sum_{j=1}^{n}\left(\Pi_{ij}-NIS_j\right)^2} \tag{15}$$

$$CC\left(DA_i,PIS\right)=\frac{ED\left(DA_i,NIS\right)}{ED\left(DA_i,PIS\right)+ED\left(DA_i,PIS\right)} \tag{16}$$

5. Data analysis and comparative analysis

The evaluation of innovation capability in the core industries of the digital economy is an in-depth analysis and comprehensive assessment of the innovation levels within key industries of the digital economy. These core industries include artificial intelligence, blockchain, the Internet of Things, cloud computing, and big data, which form the foundation of the digital economy and play a crucial role in the global economic transformation. By systematically evaluating the innovation capabilities of these industries, the assessment reveals their performance and potential in areas such as technological research and development, innovation output, market share, and industrial collaboration. First, the innovation capability evaluation helps identify the level of technological innovation within core industries. By analyzing indicators such as R&D investment, the number of patents, and technological breakthroughs, it is possible to gauge an industry’s position in global technology competition. In addition, the evaluation focuses on corporate innovation investments, including talent acquisition, research funding, and the application of innovative business models. These factors collectively influence the industry’s innovation dynamism. Second, the evaluation can highlight the industry's competitive position in the market. The rapid development of the digital economy has led to increasingly fierce market competition. By analyzing market share, product innovation speed, and market responsiveness, the evaluation helps understand how core industries maintain their competitive edge in the global market. Finally, the assessment examines the collaborative innovation capacity within the industry chain. Digital economy industries are often highly interconnected, and the innovation capabilities of a single enterprise or industry are insufficient to drive overall progress. Therefore, the evaluation considers the collaborative innovation ability between upstream and downstream sectors of the industry chain, as well as the efficiency of cooperation within industrial clusters. Overall, the evaluation of innovation capability in the core industries of the digital economy provides valuable reference points for policymakers, business leaders, and academic researchers. It not only helps identify bottlenecks in industry development but also offers strategic support for enhancing global competitiveness and promoting high-quality economic growth. This evaluation encourages sustained innovation in the core industries of the digital economy, ensuring their vitality and competitiveness in future development. The innovation capability evaluation in the core industries of digital economy is MADM. Five core industries of digital economy are assessed with 21 attributes as shown in Table 1.

The DVNN-TODIM-TOPSIS is utilized to solve the innovation capability evaluation in the core industries of digital economy.

Table 1. The list of criteria.

C	Criteria
C_1	Leadership Capability
C_2	Funding Availability
C_3	Innovation Output
C_4	Process Automation
C_5	Customer-Centric Innovation
C_6	Risk Management Criteria
C_7	Return on Investment (ROI)
C_8	Technological Readiness
C_9	R&D Intensity
C_{10}	Regulatory and Policy Criteria
C_{11}	Market Responsiveness
C_{12}	Culture of Innovation
C_{13}	Global Competitiveness
C_{14}	Cost Efficiency
C_{15}	Data Analytics Capability
C_{16}	Cybersecurity Preparedness
C_{17}	Environmental and Social Criteria
C_{18}	Skill Development
C_{19}	Adaptability to Change
C_{20}	Intellectual Property (IP) Management
C_{21}	Knowledge Sharing

Step 1. Construct the decision matrix as shown in Table 2.

Step 2. Normalize the decision matrix as shown in Table 3.

Step 3. Obtain the criteria weights as shown in Figure 1.

Step 4. Obtain the weighted normalized decision matrix as shown in Table 4.

Step 6. Construct PIS and NIS.

Step 7. Compute the separation measure.

Step 8. Compute the distance form each alternative and we ranked alternatives as shown in Figure 2.

Table 2. The decision matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	(0.62, 0.23,0.64, 0.33)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.32, 0.79,0.56, 0.87)	(0.44, 0.52,0.62, 0.94)	(0.52, 0.14,0.26, 0.76)
C_2	(0.52, 0.14,0.26, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.44, 0.52,0.62, 0.94)	(0.32, 0.79,0.56, 0.87)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)	(0.62, 0.23,0.64, 0.33)
C_3	(0.44, 0.52,0.62, 0.94)	(0.12, 0.55,0.23, 0.76)	(0.52, 0.14,0.26, 0.76)	(0.21, 0.54,0.60, 0.75)	(0.12, 0.55,0.23, 0.76)	(0.44, 0.52,0.62, 0.94)	(0.12, 0.55,0.23, 0.76)
C_4	(0.32, 0.79,0.56, 0.87)	(0.62, 0.23,0.64, 0.33)	(0.62, 0.23,0.64, 0.33)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.13, 0.46,0.76, 0.81)
C_5	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.21, 0.54,0.60, 0.75)
C_6	(0.13, 0.46,0.76, 0.81)	(0.44, 0.52,0.62, 0.94)	(0.13, 0.46,0.76, 0.81)	(0.62, 0.23,0.64, 0.33)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.32, 0.79,0.56, 0.87)
C_7	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.12, 0.55,0.23, 0.76)	(0.44, 0.52,0.62, 0.94)
C_8	(0.62, 0.23,0.64, 0.33)	(0.21, 0.54,0.60, 0.75)	(0.32, 0.79,0.56, 0.87)	(0.44, 0.52,0.62, 0.94)	(0.44, 0.52,0.62, 0.94)	(0.32, 0.79,0.56, 0.87)	(0.52, 0.14,0.26, 0.76)
C_9	(0.52, 0.14,0.26, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.44, 0.52,0.62, 0.94)	(0.32, 0.79,0.56, 0.87)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.62, 0.23,0.64, 0.33)
C_{10}	(0.44, 0.52,0.62, 0.94)	(0.12, 0.55,0.23, 0.76)	(0.52, 0.14,0.26, 0.76)	(0.21, 0.54,0.60, 0.75)	(0.62, 0.23,0.64, 0.33)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)
C_{11}	(0.32, 0.79,0.56, 0.87)	(0.62, 0.23,0.64, 0.33)	(0.62, 0.23,0.64, 0.33)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)
C_{12}	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)
C_{13}	(0.13, 0.46,0.76, 0.81)	(0.44, 0.52,0.62, 0.94)	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.62, 0.23,0.64, 0.33)	(0.44, 0.52,0.62, 0.94)
C_{14}	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.13, 0.46,0.76, 0.81)	(0.62, 0.23,0.64, 0.33)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.52, 0.14,0.26, 0.76)
C_{15}	(0.12, 0.55,0.23, 0.76)	(0.21, 0.54,0.60, 0.75)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.44, 0.52,0.62, 0.94)	(0.62, 0.23,0.64, 0.33)
C_{16}	(0.62, 0.23,0.64, 0.33)	(0.13, 0.46,0.76, 0.81)	(0.32, 0.79,0.56, 0.87)	(0.44, 0.52,0.62, 0.94)	(0.44, 0.52,0.62, 0.94)	(0.32, 0.79,0.56, 0.87)	(0.12, 0.55,0.23, 0.76)
C_{17}	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.44, 0.52,0.62, 0.94)	(0.32, 0.79,0.56, 0.87)	(0.52, 0.14,0.26, 0.76)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)
C_{18}	(0.52, 0.14,0.26, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)	(0.21, 0.54,0.60, 0.75)	(0.62, 0.23,0.64, 0.33)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)
C_{19}	(0.44, 0.52,0.62, 0.94)	(0.52, 0.14,0.26, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)
C_{20}	(0.32, 0.79,0.56, 0.87)	(0.44, 0.52,0.62, 0.94)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)
C_{21}	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)	(0.44, 0.52,0.62, 0.94)	(0.32, 0.79,0.56, 0.87)
	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.44, 0.52,0.62, 0.94)	(0.52, 0.14,0.26, 0.76)
C_2	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.62, 0.23,0.64, 0.33)
C_3	(0.44, 0.52,0.62, 0.94)	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)
C_4	(0.32, 0.79,0.56, 0.87)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.13, 0.46,0.76, 0.81)
C_5	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)
C_6	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.32, 0.79,0.56, 0.87)
C_7	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.12, 0.55,0.23, 0.76)	(0.44, 0.52,0.62, 0.94)
C_8	(0.62, 0.23,0.64, 0.33)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.52, 0.14,0.26, 0.76)
C_9	(0.52, 0.14,0.26, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)
C_{10}	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)
C_{11}	(0.32, 0.79,0.56, 0.87)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)
C_{12}	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)
C_{13}	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.62, 0.23,0.64, 0.33)	(0.44, 0.52,0.62, 0.94)
C_{14}	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)
C_{15}	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.62, 0.23,0.64, 0.33)
C_{16}	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.32, 0.79,0.56, 0.87)	(0.12, 0.55,0.23, 0.76)
C_{17}	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.13, 0.46,0.76, 0.81)
C_{18}	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)
C_{19}	(0.44, 0.52,0.62, 0.94)	(0.52, 0.14,0.26, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)
C_{20}	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)
C_{21}	(0.21, 0.54,0.60, 0.75)	(0.12, 0.55,0.23, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.32, 0.79,0.56, 0.87)
	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.44, 0.52,0.62, 0.94)	(0.21, 0.54,0.60, 0.75)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)
C_2	(0.13, 0.46,0.76, 0.81)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)
C_3	(0.12, 0.55,0.23, 0.76)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)
C_4	(0.62, 0.23,0.64, 0.33)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.62, 0.23,0.64, 0.33)
C_5	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)
C_6	(0.44, 0.52,0.62, 0.94)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.52, 0.14,0.26, 0.76)	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)
C_7	(0.52, 0.14,0.26, 0.76)	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.32, 0.79,0.56, 0.87)	(0.44, 0.52,0.62, 0.94)
C_8	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.44, 0.52,0.62, 0.94)	(0.21, 0.54,0.60, 0.75)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)
C_9	(0.13, 0.46,0.76, 0.81)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)
C_{10}	(0.12, 0.55,0.23, 0.76)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)
C_{11}	(0.62, 0.23,0.64, 0.33)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.62, 0.23,0.64, 0.33)
C_{12}	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)
C_{13}	(0.44, 0.52,0.62, 0.94)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.52, 0.14,0.26, 0.76)	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)
C_{14}	(0.52, 0.14,0.26, 0.76)	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.32, 0.79,0.56, 0.87)	(0.44, 0.52,0.62, 0.94)
C_{15}	(0.21, 0.54,0.60, 0.75)	(0.52, 0.14,0.26, 0.76)	(0.44, 0.52,0.62, 0.94)	(0.21, 0.54,0.60, 0.75)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)
C_{16}	(0.13, 0.46,0.76, 0.81)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)
C_{17}	(0.12, 0.55,0.23, 0.76)	(0.21, 0.54,0.60, 0.75)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)
C_{18}	(0.62, 0.23,0.64, 0.33)	(0.13, 0.46,0.76, 0.81)	(0.12, 0.55,0.23, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.12, 0.55,0.23, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.62, 0.23,0.64, 0.33)
C_{19}	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)	(0.62, 0.23,0.64, 0.33)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)
C_{20}	(0.44, 0.52,0.62, 0.94)	(0.62, 0.23,0.64, 0.33)	(0.52, 0.14,0.26, 0.76)	(0.32, 0.79,0.56, 0.87)	(0.52, 0.14,0.26, 0.76)	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)
C_{21}	(0.52, 0.14,0.26, 0.76)	(0.52, 0.14,0.26, 0.76)	(0.12, 0.55,0.23, 0.76)	(0.13, 0.46,0.76, 0.81)	(0.21, 0.54,0.60, 0.75)	(0.32, 0.79,0.56, 0.87)	(0.44, 0.52,0.62, 0.94)

Table 3. The normalized decision matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.366236	0.32341	0.302736	0.363283	0.36919	0.310119	0.363283
C_2	0.345342	0.261112	0.314458	0.287785	0.364996	0.364996	0.379034
C_3	0.316577	0.358788	0.32713	0.358788	0.373863	0.352758	0.379893
C_4	0.358384	0.344832	0.394523	0.32375	0.373442	0.379465	0.23039
C_5	0.323514	0.360487	0.337379	0.388217	0.331217	0.360487	0.345082
C_6	0.242832	0.355519	0.295207	0.39361	0.390436	0.344409	0.399958
C_7	0.347107	0.319397	0.326689	0.376276	0.364608	0.367525	0.306271
C_8	0.404289	0.321138	0.313969	0.321138	0.352678	0.358413	0.352678
C_9	0.318658	0.208353	0.324105	0.356788	0.318658	0.340446	0.370406
C_{10}	0.350542	0.372451	0.317679	0.369321	0.425658	0.347412	0.239433
C_{11}	0.36177	0.34809	0.398251	0.326809	0.37697	0.282728	0.319209
C_{12}	0.321788	0.358564	0.335579	0.335579	0.32945	0.380016	0.386146

C_{13}	0.285586	0.343932	0.343932	0.333184	0.336254	0.432985	0.340861
C_{14}	0.371189	0.350567	0.273972	0.385918	0.344675	0.362351	0.365297
C_{15}	0.336669	0.289988	0.336669	0.347986	0.350815	0.316865	0.398911
C_{16}	0.386646	0.291406	0.291406	0.335472	0.35253	0.355373	0.358216
C_{17}	0.378774	0.366457	0.315645	0.366457	0.397251	0.363377	0.235579
C_{18}	0.373577	0.376614	0.329537	0.340167	0.410023	0.329537	0.318907
C_{19}	0.309061	0.316419	0.400307	0.38559	0.36793	0.370873	0.225173
C_{20}	0.372018	0.330683	0.330683	0.299681	0.323301	0.38678	0.369065
C_{21}	0.299379	0.265165	0.359255	0.367809	0.350702	0.319338	0.359255

Table 4. The weighted normalized decision matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.017487	0.015442	0.014455	0.017346	0.017628	0.014808	0.017346
C_2	0.016763	0.012675	0.015264	0.01397	0.017718	0.017718	0.018399
C_3	0.015237	0.017268	0.015745	0.017268	0.017994	0.016978	0.018284
C_4	0.016828	0.016191	0.018524	0.015201	0.017535	0.017817	0.010818
C_5	0.015105	0.016831	0.015752	0.018126	0.015464	0.016831	0.016112
C_6	0.010895	0.015951	0.013245	0.01766	0.017517	0.015452	0.017945
C_7	0.016849	0.015504	0.015858	0.018265	0.017699	0.01784	0.014867
C_8	0.0201	0.015966	0.01561	0.015966	0.017534	0.017819	0.017534
C_9	0.015393	0.010065	0.015656	0.017235	0.015393	0.016446	0.017893
C_{10}	0.015954	0.016951	0.014459	0.016809	0.019373	0.015812	0.010897
C_{11}	0.016891	0.016252	0.018594	0.015259	0.017601	0.0132	0.014904
C_{12}	0.015109	0.016836	0.015757	0.015757	0.015469	0.017843	0.018131
C_{13}	0.013216	0.015916	0.015916	0.015419	0.015561	0.020038	0.015774
C_{14}	0.018182	0.017172	0.01342	0.018903	0.016883	0.017749	0.017893
C_{15}	0.016639	0.014332	0.016639	0.017199	0.017339	0.015661	0.019716
C_{16}	0.018962	0.014291	0.014291	0.016452	0.017289	0.017428	0.017567
C_{17}	0.017529	0.016959	0.014607	0.016959	0.018384	0.016816	0.010902
C_{18}	0.017925	0.018071	0.015812	0.016322	0.019674	0.015812	0.015302
C_{19}	0.014666	0.015015	0.018996	0.018298	0.01746	0.017599	0.010685
C_{20}	0.017872	0.015887	0.015887	0.014397	0.015532	0.018582	0.017731
C_{21}	0.01433	0.012692	0.017196	0.017605	0.016786	0.015285	0.017196

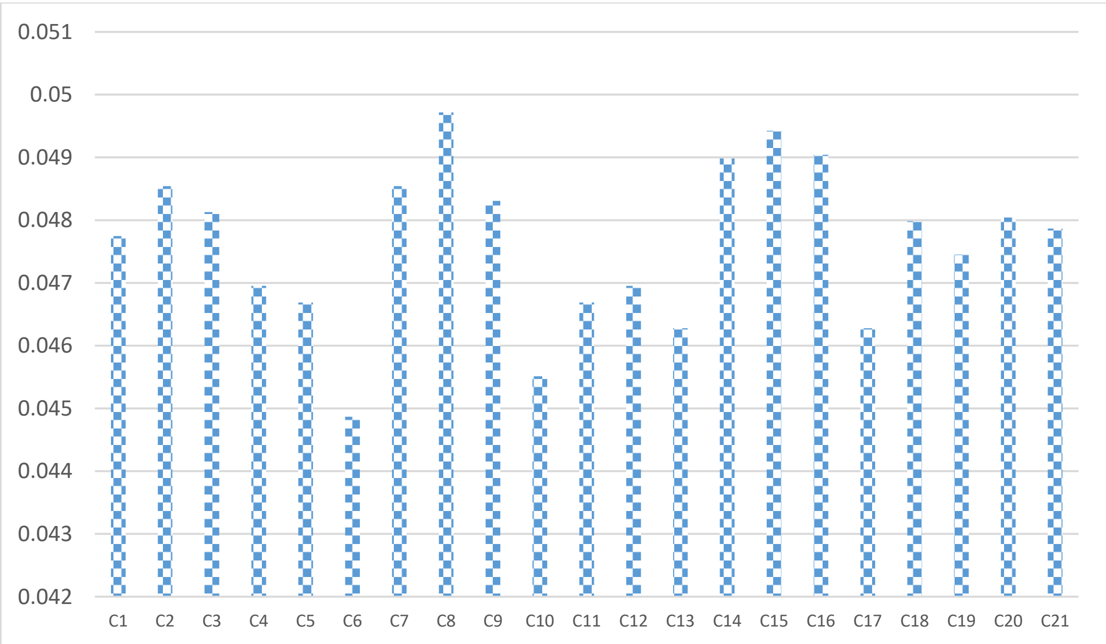

Figure 1. The criteria weights.

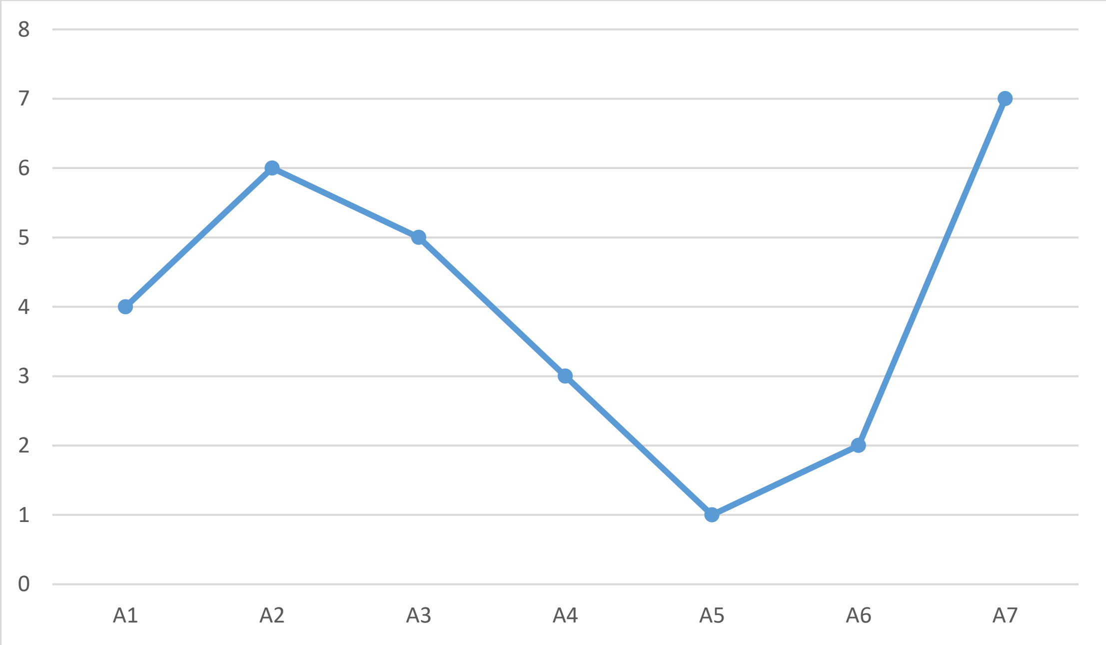

Figure 2. The rank of alternatives.

Sensitivity analysis

This section, we change the criteria weights to show the different rank of alternatives under sensitivity analysis. Figure 3 shows the different weights of criteria. Then we applied the proposed method under different criteria weights as shown in Figure 4. We show the rank of alternatives is stable. We show the alternative 7 is the best and alternative 3 is the worst.

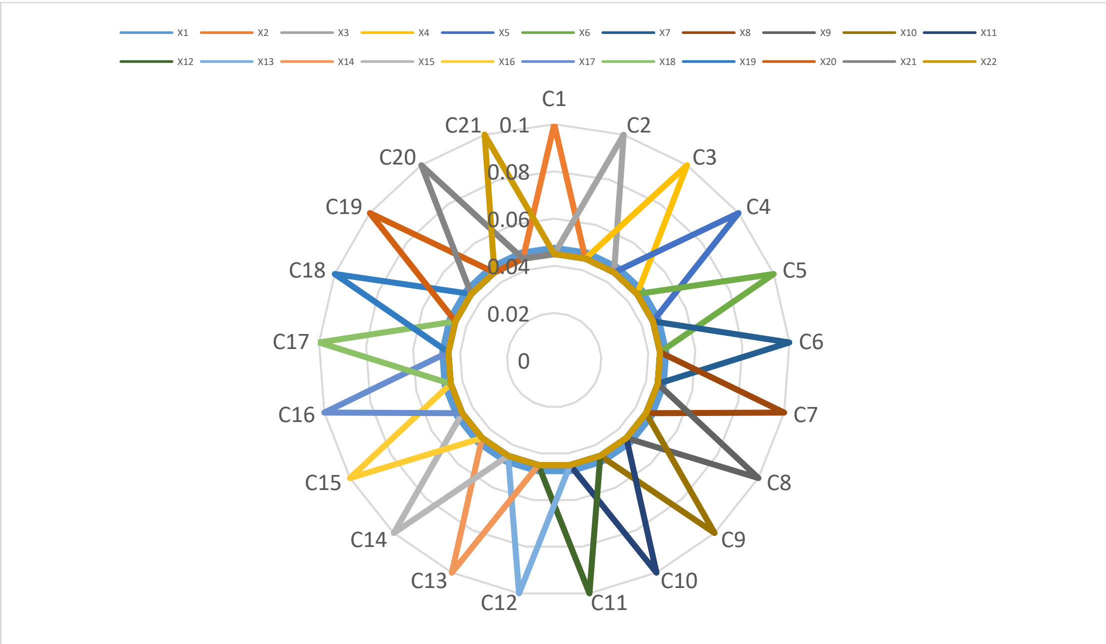

Figure 3. Different criteria weights.

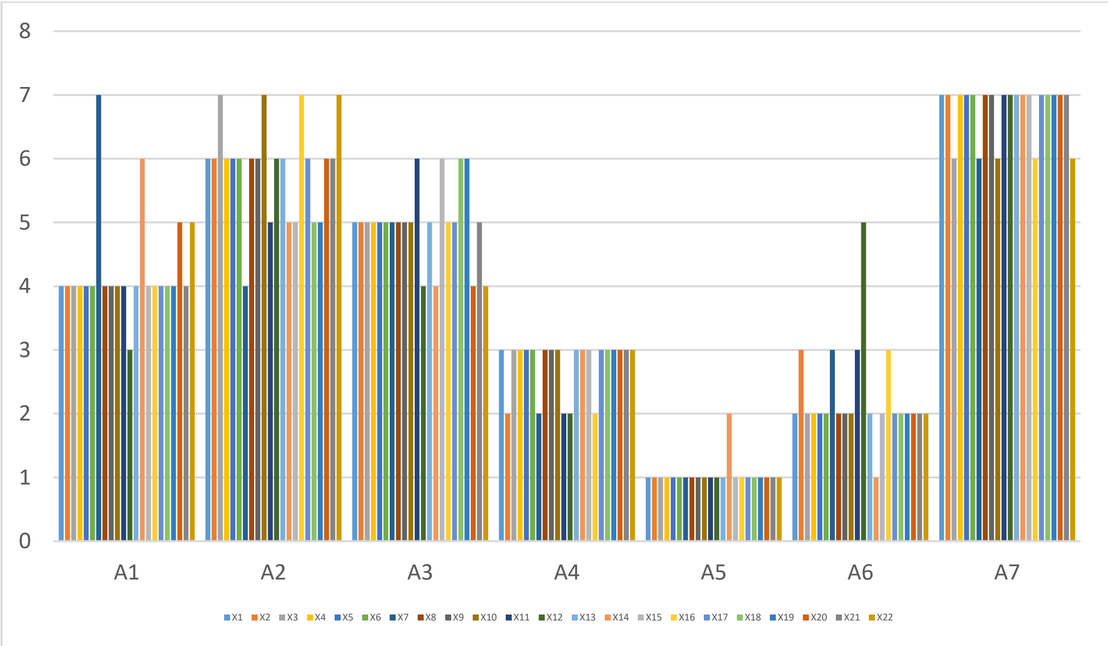

Figure 4. Different rank of alternatives.

5. Conclusion

The evaluation of innovation capability in the core industries of the digital economy is primarily used to assess the performance of industries closely related to digital technologies in terms of innovation. This evaluation system typically covers multiple dimensions, including R&D investment, the number and quality of patents, market performance, and collaborative capabilities within the industrial chain. These indicators reflect the ability of companies and industries in technological innovation, market competitiveness, and overall collaboration. Through the evaluation, the strengths and weaknesses in innovation can be identified, helping companies optimize their innovation strategies while providing a basis for governments to formulate industrial policies. The innovation capability of core industries in the digital economy directly impacts their global competitiveness and serves as a key driving force for promoting digital economic transformation and high-quality development. The innovation capability evaluation in the core industries of digital economy is MADM. Recently, the TODIM-TOPSIS approach has been applied to address MADM problems. DVNSs are used as an effective tool for representing fuzzy data in the innovation capability evaluation in the core industries of digital economy. In this study, the DVNN-TODIM-TOPSIS approach is proposed to handle MADM under DVNSs. Finally, a numerical study on the innovation capability evaluation in the core industries of digital economy is conducted to validate the DVNN-TODIM-TOPSIS model.

Based on the findings of this study, future research could explore the following three directions:

- **Expanding the application areas of the decision model**: While the DVNN-TODIM-TOPSIS method has demonstrated strong performance in evaluating innovation capabilities in core digital economy industries, its potential applications could be broadened. Future studies could apply this model to diverse domains such as teaching quality assessments, corporate management decision-making, healthcare system optimization, and more. This would allow for a thorough validation of its applicability across different contexts, providing richer data to support its use in a variety of fields.
- **Incorporating advanced uncertainty-handling techniques**: Although DVNSs are proficient in managing fuzzy information, more complex decision environments may present greater levels of uncertainty or ambiguity. Future research could integrate additional uncertainty-handling methods, such as interval numbers, grey system theory, or stochastic fuzzy sets. These approaches would strengthen the model's capacity to deal with more intricate and

dynamic information, thus enhancing its robustness when faced with uncertain or rapidly changing environments.

- **Improving computational efficiency and algorithm performance**: As decision problems grow in scale and complexity, optimizing computational efficiency becomes increasingly important. Future studies could focus on refining the algorithmic design of the DVNN-TODIM-TOPSIS method, reducing computational complexity, and improving its ability to process large datasets. Additionally, incorporating machine learning and artificial intelligence techniques for developing intelligent optimization algorithms could further enhance the method's efficiency and decision-making speed.

By exploring these research directions, the DVNN-TODIM-TOPSIS method could be expanded in terms of both its applicability and decision-support capabilities, providing more comprehensive and efficient solutions for handling complex decision-making problems.

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