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Risk Management of Import and Export Products Based on Big Data Analysis: Assessment Model with IndetermSoft Set

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Abstract: Risk management in the import and export sector has become increasingly complex due to globalization, technological advancements, and evolving regulatory landscapes. The integration of big data analytics into risk evaluation processes has revolutionized the ability to detect, assess, and mitigate potential threats across international trade operations. This study explores the application of multi-criteria decision-making methods methodologies for assessing risks associated with import and export products, focusing on quality compliance, supply chain vulnerabilities, cybersecurity threats, and regulatory adherence. By leveraging data analytics, businesses and regulatory bodies can enhance decision-making processes, reduce financial losses, and maintain high-quality standards in cross-border trade. We use the IndetermSoft set to deal with indeterminacy in the criteria values. Two MCDM methods are used in this study such as SWARA method to compute the criteria weights and the COPRAS method to rank the alternatives.

Keywords: Risk Management; Import and Export Products; Big Data Analysis; IndetermSoft Set.

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1. Introduction

The global trade landscape is characterized by dynamic shifts in market demands, regulatory policies, and supply chain networks, making risk management a critical component of import and export operations. Traditional risk assessment methods often struggle to keep pace with the rapid flow of international transactions, leading to increased exposure to financial, legal, and operational uncertainties. With the advancement of big data technologies, businesses can now analyze vast amounts of structured and unstructured data to improve risk identification and mitigation strategies. Big data analytics offers a systematic approach to evaluating trade risks, enabling real-time monitoring, predictive insights, and strategic decision-making to enhance product safety and regulatory compliance[1], [2].

One of the most pressing concerns in international trade is the quality assurance of imported and exported products. Variations in manufacturing standards, counterfeit goods, and discrepancies in supply chain documentation pose significant risks to businesses and consumers alike. Big data-driven risk management allows for continuous monitoring of product quality by analyzing historical trends, inspection records, and real-time sensor data. This proactive approach helps detect anomalies and irregularities, preventing the circulation of substandard or hazardous goods in the global market. Ensuring product compliance with international standards minimizes financial losses, legal disputes, and reputational damage for stakeholders[3], [4].

Supply chain transparency and cybersecurity are also integral aspects of risk evaluation in import and export operations. Global trade relies on complex networks of suppliers, distributors, and logistics providers, each presenting potential vulnerabilities. Digital threats such as data breaches, fraud, and cyber-attacks can compromise sensitive trade information, leading to financial losses and regulatory non-compliance. Through big data analytics, companies can track supply chain movements, identify weak links, and implement cybersecurity measures to safeguard trade transactions. Real-time data processing enhances the accuracy of risk assessments, allowing businesses to anticipate disruptions and strengthen supply chain resilience.

Regulatory compliance remains a significant challenge for importers and exporters due to the variations in trade policies across different countries. Non-compliance with customs regulations, environmental laws, and safety standards can result in shipment delays, financial penalties, and legal consequences. Big data analytics helps organizations stay ahead of regulatory changes by analyzing historical compliance patterns, automating document verification, and predicting potential red flags in trade documentation. By streamlining regulatory adherence, businesses can ensure smooth trade operations while reducing the likelihood of customs-related disputes[5], [6].

The integration of big data into risk management not only enhances operational efficiency but also fosters a more sustainable and secure global trade ecosystem. As artificial intelligence (AI) and machine learning continue to evolve, risk evaluation models can become more refined, enabling businesses to detect emerging threats with greater accuracy. This research underscores the importance of adopting a data-driven approach to risk assessment in import and export processes, advocating advanced analytics to mitigate risks, optimize trade efficiency, and enhance consumer trust in international markets[7], [8].

By offering an organized way for assessing and contrasting various options according to several criteria, multi-criteria approaches can aid in the resolution of selection issues. The factors taken into consideration and the Risk Management of Import and Export Products application field determine the selection[9], [10]. Due to the increasing complexity and significance of decision-making in Risk Management of Import and Export Products, research on multi-criteria selection in Risk Management of Import and Export Products situations has changed dramatically in recent years[11], [12].

The structure of the paper is as follows. Steps of MCDM methods for Risk Management of Import and Export Products are conducted in Section 2. Section 3 presents a case study of Risk Management of Import and Export Products by dealing with indeterminacy values by the IndetermSoft set. The paper is concluded in Section 4.

2. MCDM Methods

The three main steps of this study are organized as follows:

1. The SWARA method is used to compute the criteria weights.
2. The COPRAS method is used to rank the alternatives.
3. The IndetermSoft Set is used to deal with different values in the main criteria.

Step 1. Computing the criteria weights.

This step we show the steps of the SWARA methodology to compute the criteria weights to rank the alternatives.

Initial sorting the criteria

First, the criteria are sorted based on the relative importance by the opinions of experts and decision makers.

Determine the coefficient of the criteria

$$K_j = \begin{cases} 1 \;\; if\ j = 1 \\ X_j + 1 \;\; if\ j > 1 \end{cases}; j = 1,2,3, \dots, n \tag{1}$$

Determine the initial weight of the criteria as:

$$q_j = \begin{cases} 1 \;\; if\ j = 1 \\ \frac{q_j}{K_j} \;\; if\ j > 1 \end{cases}; j = 1,2,3, \dots, n \tag{2}$$

Determine the relative weight

$$w_j = q_j / \sum_{j=1}^{n} q_j \tag{3}$$

Step 2. Sorting the alternatives.

Then, in this step we apply the steps of the COPRAS method to rank the alternatives[13], [14].

Create the decision matrix.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}_{mn}; i = 1, \dots, m; j = 1, \dots, n \tag{3}$$

Determine the normalized decision matrix.

$$d_{ij} = x_{ij} \sum_{i=1}^{m} x_{ij} \, ; j = 1, \ldots, n \tag{4}$$

Determine the weighted normalized matrix.

$$y_{ij} = w_j d_{ij} \tag{5}$$

Determine max and min indexes for positive and cost criteria

$$R_{+i} = \sum_{j=1}^{g} y_{ij}; i = 1, \ldots, m \tag{6}$$

$$R_{-i} = \sum_{j=g+1}^{n} y_{ij}; i = 1, \ldots, m \tag{7}$$

Determine the significance of value of each alternative

$$S_i = R_{+i} + \frac{\sum_{i=1}^{m} R_{-i}}{R_{-i} \sum_{i=1}^{m} \frac{1}{R_{-i}}} \tag{8}$$

Step 3. IndetermSoft Set

Let U be a universe of discourse and H be non-empty subset of U, and the powerset is a P(H). Let set of criteria such as c and C is the set of criteria values[15], [16].

A function F: $C \rightarrow P(H)$ is called IndetermSoft set if:

The set C and P(H) have some indeterminacy or at least one criterion has an indeterminacy.

3. Case Study

This section shows the case study of the MCDM method. We can show the validation of the proposed approach by computing the criteria weights and ranking the alternatives. This study has 12 main criteria and seven alternatives. The criteria of this study are organized as follows:

- Product Compliance with International Standards (High compliance, Moderate compliance, Low compliance)
- Supply Chain Transparency (Fully transparent)
- Manufacturing Quality Control (Moderate quality control)
- Logistics and Transportation Risks (Low transportation risk)
- Product Safety and Consumer Protection (Highly safe with certifications)
- Regulatory and Customs Compliance (Fully compliant)
- Market Reputation and Consumer Feedback (Excellent market reputation)
- Cybersecurity and Data Protection in Trade (Strong Cybersecurity Measures)
- Environmental and Sustainability Impact (Sustainable and eco-friendly)

- Counterfeit and Fraud Risks (Low risk of counterfeiting)
- Big Data Predictive Analytics Accuracy (Highly accurate predictions)
- Crisis Management and Risk Response (Proactive and well-prepared)

The alternatives of this study are:

- Chemical and Industrial Materials
- Medical Equipment and Devices
- Textile and Apparel
- Automobile Components and Machinery
- Pharmaceutical Products
- Electronics and Consumer Goods
- Food and Agricultural Products

From the previous criteria, we have indeterminacy in one criterion. So, we use the IndetermSoft set to deal with this indeterminacy.

Step 1. Computing the criteria weights.

Initial sorting the criteria.

Eq. (1) is used to determine the coefficient of the criteria.

Eq. (2) is used to determine the initial weight of the criteria.

Eq. (3) is used to determine the relative weight as shown in Fig 1.

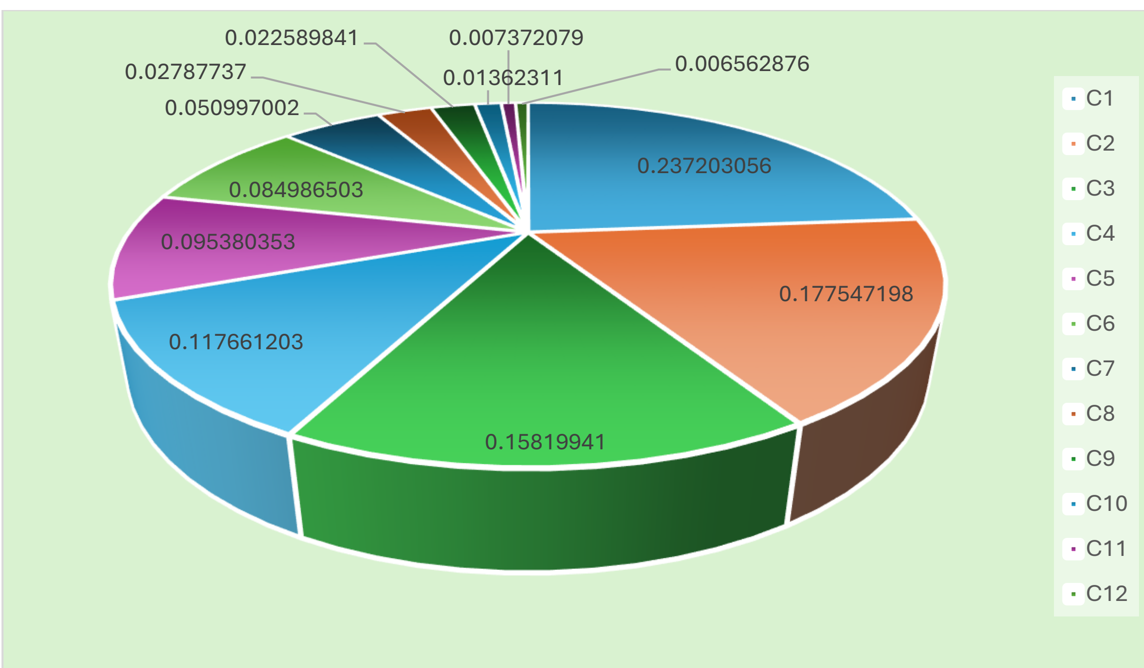

Fig 1. The criteria weights.

Step 2. Sorting the alternatives.

Then we apply the COPRAS method to deal with indeterminacy in the first criterion. So, we apply the COPRAS method seven cases in each time we obtain the rank of the alternatives. These values (High compliance, Moderate compliance, Low compliance) are used seven times.

First Case

Eq. (3) is used to create the decision matrix. Three experts evaluate 12 criteria and 7 alternatives by crisp values.

Eq. (4) is used to determine the normalized decision matrix as shown in Table 1.

Eq. (5) is used to determine the weighted normalized matrix as shown in Table 2.

Eq. (6 and 7) is used to determine max and min indexes for positive and cost criteria

Then we determine the significance of value of each alternative using Eq. (8). Then we ranked the alternatives.

Table 1. Normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.161073	0.129953	0.185611	0.146509	0.12788	0.120073	0.128902
C_2	0.203544	0.163455	0.127091	0.1023	0.140788	0.140526	0.122296
C_3	0.098326	0.177664	0.107934	0.190211	0.130089	0.187842	0.107934
C_4	0.150631	0.131078	0.141559	0.133701	0.170395	0.131078	0.141559
C_5	0.130567	0.151871	0.153435	0.142877	0.153435	0.121817	0.145998
C_6	0.14774	0.160826	0.132992	0.107109	0.191741	0.169951	0.089642
C_7	0.184986	0.107779	0.126501	0.14178	0.139929	0.152836	0.146189
C_8	0.061719	0.146608	0.126146	0.164679	0.239152	0.1911	0.070597
C_9	0.143138	0.13599	0.169147	0.105081	0.15839	0.143312	0.144943
C_{10}	0.187926	0.191708	0.153958	0.160798	0.106027	0.091281	0.108302
C_{11}	0.120195	0.144841	0.1204	0.18099	0.195707	0.153122	0.084744
C_{12}	0.142495	0.168782	0.127265	0.137902	0.127672	0.168782	0.127102

Table 2. Weighted normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.038207	0.030825	0.044028	0.034752	0.030334	0.028482	0.030576
C_2	0.036139	0.029021	0.022565	0.018163	0.024997	0.02495	0.021713
C_3	0.015555	0.028106	0.017075	0.030091	0.02058	0.029717	0.017075
C_4	0.017723	0.015423	0.016656	0.015731	0.020049	0.015423	0.016656
C_5	0.012454	0.014486	0.014635	0.013628	0.014635	0.011619	0.013925
C_6	0.012556	0.013668	0.011303	0.009103	0.016295	0.014444	0.007618
C_7	0.009434	0.005496	0.006451	0.00723	0.007136	0.007794	0.007455
C_8	0.001721	0.004087	0.003517	0.004591	0.006667	0.005327	0.001968

C_9	0.003233	0.003072	0.003821	0.002374	0.003578	0.003237	0.003274
C_{10}	0.00256	0.002612	0.002097	0.002191	0.001444	0.001244	0.001475
C_{11}	0.000886	0.001068	0.000888	0.001334	0.001443	0.001129	0.000625
C_{12}	0.000935	0.001108	0.000835	0.000905	0.000838	0.001108	0.000834

Second Case

Eq. (3) is used to create the decision matrix. Three experts evaluate 12 criteria and 7 alternatives by crisp values.

Eq. (4) is used to determine the normalized decision matrix as shown in Table 3.

Eq. (5) is used to determine the weighted normalized matrix as shown in Table 4.

Eq. (6 and 7) is used to determine max and min indexes for positive and cost criteria

Then we determine the significance of value of each alternative using Eq. (8). Then we ranked the alternatives.

Table 3. Normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.099764	0.036889	0.090552	0.15674	0.210402	0.229901	0.175751
C_2	0.203544	0.163455	0.127091	0.1023	0.140788	0.140526	0.122296
C_3	0.098326	0.177664	0.107934	0.190211	0.130089	0.187842	0.107934
C_4	0.150631	0.131078	0.141559	0.133701	0.170395	0.131078	0.141559
C_5	0.130567	0.151871	0.153435	0.142877	0.153435	0.121817	0.145998
C_6	0.14774	0.160826	0.132992	0.107109	0.191741	0.169951	0.089642
C_7	0.184986	0.107779	0.126501	0.14178	0.139929	0.152836	0.146189
C_8	0.061719	0.146608	0.126146	0.164679	0.239152	0.1911	0.070597
C_9	0.143138	0.13599	0.169147	0.105081	0.15839	0.143312	0.144943
C_{10}	0.187926	0.191708	0.153958	0.160798	0.106027	0.091281	0.108302
C_{11}	0.120195	0.144841	0.1204	0.18099	0.195707	0.153122	0.084744
C_{12}	0.142495	0.168782	0.127265	0.137902	0.127672	0.168782	0.127102

Table 4. Weighted normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.023664	0.00875	0.021479	0.037179	0.049908	0.054533	0.041689
C_2	0.036139	0.029021	0.022565	0.018163	0.024997	0.02495	0.021713
C_3	0.015555	0.028106	0.017075	0.030091	0.02058	0.029717	0.017075
C_4	0.017723	0.015423	0.016656	0.015731	0.020049	0.015423	0.016656
C_5	0.012454	0.014486	0.014635	0.013628	0.014635	0.011619	0.013925
C_6	0.012556	0.013668	0.011303	0.009103	0.016295	0.014444	0.007618
C_7	0.009434	0.005496	0.006451	0.00723	0.007136	0.007794	0.007455
C_8	0.001721	0.004087	0.003517	0.004591	0.006667	0.005327	0.001968

C_9	0.003233	0.003072	0.003821	0.002374	0.003578	0.003237	0.003274
C_{10}	0.00256	0.002612	0.002097	0.002191	0.001444	0.001244	0.001475
C_{11}	0.000886	0.001068	0.000888	0.001334	0.001443	0.001129	0.000625
C_{12}	0.000935	0.001108	0.000835	0.000905	0.000838	0.001108	0.000834

Third Case

Eq. (3) is used to create the decision matrix. Three experts evaluate 12 criteria and 7 alternatives by crisp values.

Eq. (4) is used to determine the normalized decision matrix as shown in Table 5.

Eq. (5) is used to determine the weighted normalized matrix as shown in Table 6.

Eq. (6 and 7) is used to determine max and min indexes for positive and cost criteria

Then we determine the significance of value of each alternative using Eq. (8). Then we ranked the alternatives.

Table 5. Normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.033682	0.151512	0.033682	0.151512	0.205904	0.263239	0.160469
C_2	0.203544	0.163455	0.127091	0.1023	0.140788	0.140526	0.122296
C_3	0.098326	0.177664	0.107934	0.190211	0.130089	0.187842	0.107934
C_4	0.150631	0.131078	0.141559	0.133701	0.170395	0.131078	0.141559
C_5	0.130567	0.151871	0.153435	0.142877	0.153435	0.121817	0.145998
C_6	0.14774	0.160826	0.132992	0.107109	0.191741	0.169951	0.089642
C_7	0.184986	0.107779	0.126501	0.14178	0.139929	0.152836	0.146189
C_8	0.061719	0.146608	0.126146	0.164679	0.239152	0.1911	0.070597
C_9	0.143138	0.13599	0.169147	0.105081	0.15839	0.143312	0.144943
C_{10}	0.187926	0.191708	0.153958	0.160798	0.106027	0.091281	0.108302
C_{11}	0.120195	0.144841	0.1204	0.18099	0.195707	0.153122	0.084744
C_{12}	0.142495	0.168782	0.127265	0.137902	0.127672	0.168782	0.127102

Table 6. Weighted normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.007989	0.035939	0.007989	0.035939	0.048841	0.062441	0.038064
C_2	0.036139	0.029021	0.022565	0.018163	0.024997	0.02495	0.021713
C_3	0.015555	0.028106	0.017075	0.030091	0.02058	0.029717	0.017075
C_4	0.017723	0.015423	0.016656	0.015731	0.020049	0.015423	0.016656
C_5	0.012454	0.014486	0.014635	0.013628	0.014635	0.011619	0.013925
C_6	0.012556	0.013668	0.011303	0.009103	0.016295	0.014444	0.007618
C_7	0.009434	0.005496	0.006451	0.00723	0.007136	0.007794	0.007455
C_8	0.001721	0.004087	0.003517	0.004591	0.006667	0.005327	0.001968

C_9	0.003233	0.003072	0.003821	0.002374	0.003578	0.003237	0.003274
C_{10}	0.00256	0.002612	0.002097	0.002191	0.001444	0.001244	0.001475
C_{11}	0.000886	0.001068	0.000888	0.001334	0.001443	0.001129	0.000625
C_{12}	0.000935	0.001108	0.000835	0.000905	0.000838	0.001108	0.000834

Fourth Case

Eq. (3) is used to create the decision matrix. Three experts evaluate 12 criteria and 7 alternatives by crisp values.

Eq. (4) is used to determine the normalized decision matrix as shown in Table 7.

Eq. (5) is used to determine the weighted normalized matrix as shown in Table 8.

Eq. (6 and 7) is used to determine max and min indexes for positive and cost criteria

Then we determine the significance of value of each alternative using Eq. (8). Then we ranked the alternatives.

Table 7. Normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.16369	0.134863	0.149277	0.134863	0.154086	0.13565	0.12757
C_2	0.203544	0.163455	0.127091	0.1023	0.140788	0.140526	0.122296
C_3	0.098326	0.177664	0.107934	0.190211	0.130089	0.187842	0.107934
C_4	0.150631	0.131078	0.141559	0.133701	0.170395	0.131078	0.141559
C_5	0.130567	0.151871	0.153435	0.142877	0.153435	0.121817	0.145998
C_6	0.14774	0.160826	0.132992	0.107109	0.191741	0.169951	0.089642
C_7	0.184986	0.107779	0.126501	0.14178	0.139929	0.152836	0.146189
C_8	0.061719	0.146608	0.126146	0.164679	0.239152	0.1911	0.070597
C_9	0.143138	0.13599	0.169147	0.105081	0.15839	0.143312	0.144943
C_{10}	0.187926	0.191708	0.153958	0.160798	0.106027	0.091281	0.108302
C_{11}	0.120195	0.144841	0.1204	0.18099	0.195707	0.153122	0.084744
C_{12}	0.142495	0.168782	0.127265	0.137902	0.127672	0.168782	0.127102

Table 8. Weighted normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.038828	0.03199	0.035409	0.03199	0.03655	0.032177	0.03026
C_2	0.036139	0.029021	0.022565	0.018163	0.024997	0.02495	0.021713
C_3	0.015555	0.028106	0.017075	0.030091	0.02058	0.029717	0.017075
C_4	0.017723	0.015423	0.016656	0.015731	0.020049	0.015423	0.016656
C_5	0.012454	0.014486	0.014635	0.013628	0.014635	0.011619	0.013925
C_6	0.012556	0.013668	0.011303	0.009103	0.016295	0.014444	0.007618
C_7	0.009434	0.005496	0.006451	0.00723	0.007136	0.007794	0.007455
C_8	0.001721	0.004087	0.003517	0.004591	0.006667	0.005327	0.001968

C_9	0.003233	0.003072	0.003821	0.002374	0.003578	0.003237	0.003274
C_{10}	0.00256	0.002612	0.002097	0.002191	0.001444	0.001244	0.001475
C_{11}	0.000886	0.001068	0.000888	0.001334	0.001443	0.001129	0.000625
C_{12}	0.000935	0.001108	0.000835	0.000905	0.000838	0.001108	0.000834

Fifth Case

Eq. (3) is used to create the decision matrix. Three experts evaluate 12 criteria and 7 alternatives by crisp values.

Eq. (4) is used to determine the normalized decision matrix as shown in Table 9.

Eq. (5) is used to determine the weighted normalized matrix as shown in Table 10.

Eq. (6 and 7) is used to determine max and min indexes for positive and cost criteria

Then we determine the significance of value of each alternative using Eq. (8). Then we ranked the alternatives.

Table 9. Normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.168801	0.080826	0.184527	0.092006	0.080826	0.203531	0.189482
C_2	0.203544	0.163455	0.127091	0.1023	0.140788	0.140526	0.122296
C_3	0.098326	0.177664	0.107934	0.190211	0.130089	0.187842	0.107934
C_4	0.150631	0.131078	0.141559	0.133701	0.170395	0.131078	0.141559
C_5	0.130567	0.151871	0.153435	0.142877	0.153435	0.121817	0.145998
C_6	0.14774	0.160826	0.132992	0.107109	0.191741	0.169951	0.089642
C_7	0.184986	0.107779	0.126501	0.14178	0.139929	0.152836	0.146189
C_8	0.061719	0.146608	0.126146	0.164679	0.239152	0.1911	0.070597
C_9	0.143138	0.13599	0.169147	0.105081	0.15839	0.143312	0.144943
C_{10}	0.187926	0.191708	0.153958	0.160798	0.106027	0.091281	0.108302
C_{11}	0.120195	0.144841	0.1204	0.18099	0.195707	0.153122	0.084744
C_{12}	0.142495	0.168782	0.127265	0.137902	0.127672	0.168782	0.127102

Table 10. Weighted normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.04004	0.019172	0.04377	0.021824	0.019172	0.048278	0.044946
C_2	0.036139	0.029021	0.022565	0.018163	0.024997	0.02495	0.021713
C_3	0.015555	0.028106	0.017075	0.030091	0.02058	0.029717	0.017075
C_4	0.017723	0.015423	0.016656	0.015731	0.020049	0.015423	0.016656
C_5	0.012454	0.014486	0.014635	0.013628	0.014635	0.011619	0.013925
C_6	0.012556	0.013668	0.011303	0.009103	0.016295	0.014444	0.007618
C_7	0.009434	0.005496	0.006451	0.00723	0.007136	0.007794	0.007455
C_8	0.001721	0.004087	0.003517	0.004591	0.006667	0.005327	0.001968

C_9	0.003233	0.003072	0.003821	0.002374	0.003578	0.003237	0.003274
C_{10}	0.00256	0.002612	0.002097	0.002191	0.001444	0.001244	0.001475
C_{11}	0.000886	0.001068	0.000888	0.001334	0.001443	0.001129	0.000625
C_{12}	0.000935	0.001108	0.000835	0.000905	0.000838	0.001108	0.000834

Sixth Case

Eq. (3) is used to create the decision matrix. Three experts evaluate 12 criteria and 7 alternatives by crisp values.

Eq. (4) is used to determine the normalized decision matrix as shown in Table 11.

Eq. (5) is used to determine the weighted normalized matrix as shown in Table 12.

Eq. (6 and 7) is used to determine max and min indexes for positive and cost criteria

Then we determine the significance of value of each alternative using Eq. (8). Then we ranked the alternatives.

Table 11. Normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.099031	0.171705	0.144303	0.210251	0.127152	0.119389	0.128168
C_2	0.203544	0.163455	0.127091	0.1023	0.140788	0.140526	0.122296
C_3	0.098326	0.177664	0.107934	0.190211	0.130089	0.187842	0.107934
C_4	0.150631	0.131078	0.141559	0.133701	0.170395	0.131078	0.141559
C_5	0.130567	0.151871	0.153435	0.142877	0.153435	0.121817	0.145998
C_6	0.14774	0.160826	0.132992	0.107109	0.191741	0.169951	0.089642
C_7	0.184986	0.107779	0.126501	0.14178	0.139929	0.152836	0.146189
C_8	0.061719	0.146608	0.126146	0.164679	0.239152	0.1911	0.070597
C_9	0.143138	0.13599	0.169147	0.105081	0.15839	0.143312	0.144943
C_{10}	0.187926	0.191708	0.153958	0.160798	0.106027	0.091281	0.108302
C_{11}	0.120195	0.144841	0.1204	0.18099	0.195707	0.153122	0.084744
C_{12}	0.142495	0.168782	0.127265	0.137902	0.127672	0.168782	0.127102

Table 12. Weighted normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.023491	0.040729	0.034229	0.049872	0.030161	0.028319	0.030402
C_2	0.036139	0.029021	0.022565	0.018163	0.024997	0.02495	0.021713
C_3	0.015555	0.028106	0.017075	0.030091	0.02058	0.029717	0.017075
C_4	0.017723	0.015423	0.016656	0.015731	0.020049	0.015423	0.016656
C_5	0.012454	0.014486	0.014635	0.013628	0.014635	0.011619	0.013925
C_6	0.012556	0.013668	0.011303	0.009103	0.016295	0.014444	0.007618
C_7	0.009434	0.005496	0.006451	0.00723	0.007136	0.007794	0.007455
C_8	0.001721	0.004087	0.003517	0.004591	0.006667	0.005327	0.001968

C_9	0.003233	0.003072	0.003821	0.002374	0.003578	0.003237	0.003274
C_{10}	0.00256	0.002612	0.002097	0.002191	0.001444	0.001244	0.001475
C_{11}	0.000886	0.001068	0.000888	0.001334	0.001443	0.001129	0.000625
C_{12}	0.000935	0.001108	0.000835	0.000905	0.000838	0.001108	0.000834

Seventh Case

Eq. (3) is used to create the decision matrix. Three experts evaluate 12 criteria and 7 alternatives by crisp values.

Eq. (4) is used to determine the normalized decision matrix as shown in Table 13.

Eq. (5) is used to determine the weighted normalized matrix as shown in Table 14.

Eq. (6 and 7) is used to determine max and min indexes for positive and cost criteria

Then we determine the significance of value of each alternative using Eq. (8). Then we ranked the alternatives.

Table 13. Normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.151058	0.179099	0.152737	0.172929	0.116792	0.109661	0.117725
C_2	0.203544	0.163455	0.127091	0.1023	0.140788	0.140526	0.122296
C_3	0.098326	0.177664	0.107934	0.190211	0.130089	0.187842	0.107934
C_4	0.150631	0.131078	0.141559	0.133701	0.170395	0.131078	0.141559
C_5	0.130567	0.151871	0.153435	0.142877	0.153435	0.121817	0.145998
C_6	0.14774	0.160826	0.132992	0.107109	0.191741	0.169951	0.089642
C_7	0.184986	0.107779	0.126501	0.14178	0.139929	0.152836	0.146189
C_8	0.061719	0.146608	0.126146	0.164679	0.239152	0.1911	0.070597
C_9	0.143138	0.13599	0.169147	0.105081	0.15839	0.143312	0.144943
C_{10}	0.187926	0.191708	0.153958	0.160798	0.106027	0.091281	0.108302
C_{11}	0.120195	0.144841	0.1204	0.18099	0.195707	0.153122	0.084744
C_{12}	0.142495	0.168782	0.127265	0.137902	0.127672	0.168782	0.127102

Table 14. Weighted normalization matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.035831	0.042483	0.03623	0.041019	0.027703	0.026012	0.027925
C_2	0.036139	0.029021	0.022565	0.018163	0.024997	0.02495	0.021713
C_3	0.015555	0.028106	0.017075	0.030091	0.02058	0.029717	0.017075
C_4	0.017723	0.015423	0.016656	0.015731	0.020049	0.015423	0.016656
C_5	0.012454	0.014486	0.014635	0.013628	0.014635	0.011619	0.013925
C_6	0.012556	0.013668	0.011303	0.009103	0.016295	0.014444	0.007618
C_7	0.009434	0.005496	0.006451	0.00723	0.007136	0.007794	0.007455
C_8	0.001721	0.004087	0.003517	0.004591	0.006667	0.005327	0.001968

C_9	0.003233	0.003072	0.003821	0.002374	0.003578	0.003237	0.003274
C_{10}	0.00256	0.002612	0.002097	0.002191	0.001444	0.001244	0.001475
C_{11}	0.000886	0.001068	0.000888	0.001334	0.001443	0.001129	0.000625
C_{12}	0.000935	0.001108	0.000835	0.000905	0.000838	0.001108	0.000834

Then we obtained the final rank of the alternatives as shown in Fig 2. We show the alternative 5 is the best and alternative 2 is the worst.

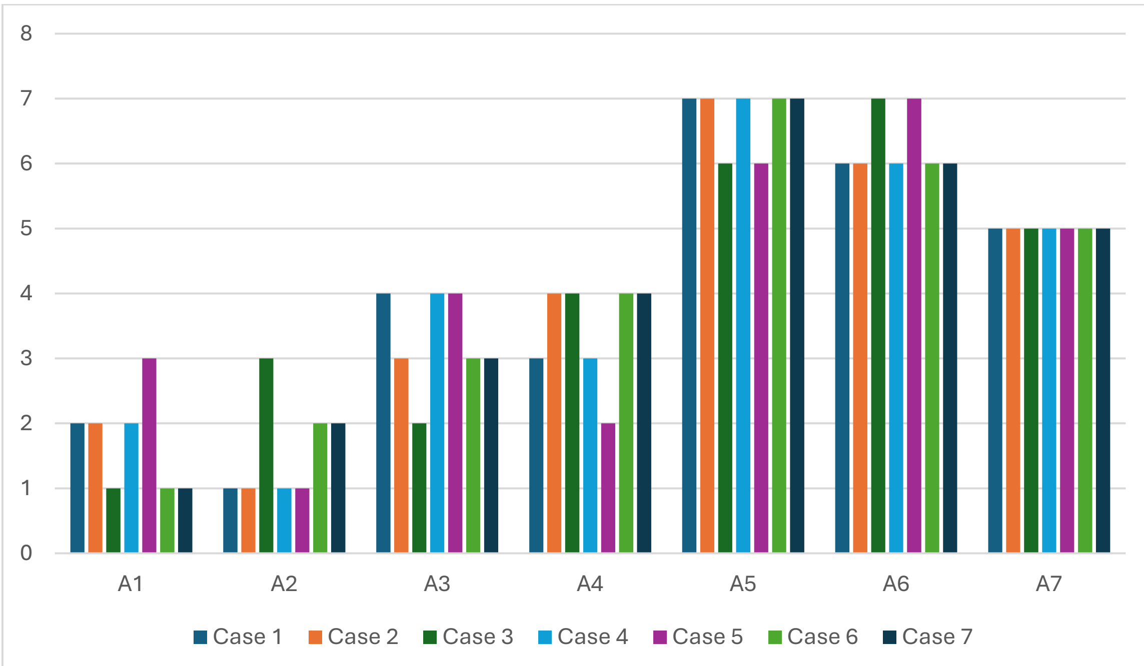

Fig 2. Final rank of alternatives.

4. Conclusions

Risk management in the import and export trade has been significantly improved by the adoption of big data analytics, allowing businesses to identify, assess, and respond to potential threats in real time. The ability to monitor product quality, enhance supply chain transparency, mitigate cybersecurity risks, and ensure regulatory compliance makes big data an invaluable tool for global trade. As trade networks continue to expand, data-driven methodologies will play a crucial role in minimizing uncertainties and safeguarding trade transactions. We used the IndetermSoft set to deal with the indeterminacy values of criteria. We had the one indeterminacy in the first criterion. So, we applied the COPRAS method into seven cases to deal with this indeterminacy. The results show alternative 5 is the best and alternative 2 is the worst.

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