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# Analysis on the Legal System of International Technology Trade Management Based on Data Mining Analysis

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## ABSTRACT

With the rapid development of computer and information technology, people can obtain and store data in a faster and cheaper way, which makes the amount of data and information grow exponentially. Based on data mining technology, this paper systematically analyzes and compares the basic situation and evolution of international trade networks and international human relations networks using the bilateral trade data and human relations data of countries and regions in the world. The research shows that the strength external entropy, strength internal entropy, and network weight entropy of the whole international trade network from 2008 to 2014 are generally lower than 0.75. The whole network still showed a downward trend from 2010 to 2015, but it began to rise steadily after 2016. The monopolistic behavior in international technology trade has a significant impact on the fundamental freedoms and rights of citizens.

## KEYWORDS

Data Mining, Data Reduction, Legal System, Model, Technology Trade

## INTRODUCTION

In today's world, the development of technology is constantly changing. A country's level of technology has become the primary indicator of its comprehensive national strength. Competition in the international economy and trade ultimately boils down to competition in technology. In the early stages of the Industrial Revolution, technological progress and international technology transfer were relatively slow, and the product life cycle was long, which put countries that led in technological innovation in a favorable competitive position globally for a long time. Generally, contract clauses that reflect restrictive business practices are called restrictive business clauses (Hammad et al., 2021). On

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a broad scale, restricting competition, whether reflected in contracts or other international economic activities, is often referred to as a restrictive business practice (Rehman et al., 2015).

With the enhancement of competition in some technical fields and the increase of technology exports in developing countries, strengthening the management of technology exports is also an essential part of technology trade management in developing countries. Technology transfer is often carried out together with technology trade. The government must take measures to control technology transfer because the government bears more important responsibilities in technology trade than traditional physical trade. As a result, all countries manage technology trade with different priorities (Jarosław & Sobkowiak, 2015). Restrictions on market access or excessive restrictions on competition through other means may negatively impact international trade, especially developing countries' international trade and economic development. Strengthening the management of technology trade is an essential component of foreign trade system reform in various countries. Developing countries focus on managing technology imports, while developed countries focus on managing technology exports. As the most technologically developed country, the United States has the most influential technology trade management system. From 2010 to 2015, the external, internal, and network weight entropy of the total international trade network were generally lower than 0.75 and showed a downward trend. However, they began to rise steadily after 2016. The above results indicate that in a complete international trade network, the heterogeneity of output intensity, input intensity, and the intensity of all trade relations is significantly greater than the heterogeneity of nodes. China's foreign technology trade management system still faces challenges, such as outdated concepts and lagging legislation. Perfecting the technology trade legislation as soon as possible is necessary for rejuvenating the country through science and technology and developing foreign trade. Data mining involves extracting implicit, unknown, nontrivial, and potentially valuable information or patterns from large databases or data warehouses. This new field has great application value in database research, which integrates the theories and technologies of databases, artificial intelligence, machine learning, statistics, and other fields. Based on data mining analysis, this paper investigates the application of technical risk under force majeure by analyzing the types of technical risk.

The impact of anti-monopoly laws on economic life is highly complex, and their formulation and implementation have different effects on various social foundations (Meng, 2020). The policy objective or theoretical basis of anti-monopoly legislation involves protecting competition or consumers' interests, which is the same as the constitution that requires the development of a socialist market economy (Zhi & Zhou, 2018). Of course, with the improvement of competition in some technology fields and the increase of technology exports from developing countries, strengthening the management of technology exports is also essential to managing technology trade in developing countries.

This article is innovative in the following ways:

1. It discusses the use of data mining technology and its application in international trade enterprises. It also analyzes the use of data mining technology to construct a legal system for international technology trade management. The research object of this data mining is the effectiveness of the Chinese stock market. The study aims to determine this effectiveness based on the relationship between internal information in the stock market and the relationship between the stock market and the macro economy, which is a business understanding.
2. It defines the definition and scope of government behavior in force majeure events, conducts typological research, analyzes the types of government behavior with force majeure factors, and draws a conclusion on whether the principle of force majeure applies to government behavior.

The network constructed in this paper is not a spatial network, and the spatial relationship between nodes in the network has yet to be further tested (Sahoo & Gupta, 2021). Therefore, future research will focus on whether the international trade network embedded in the international interpersonal network is more conductive or inhibitory to the economy.

## RELATED WORK

Since the 1960s, with the accelerated development of technological progress and the development of international technology transfer, western scholars have mainly studied the theory of international technology trade from the perspectives of motivation and mechanism. Motivation theory research primarily aims to establish a three-generation model of North–South trade and international technology transfer.

Wiedmann and Lenzen (2018) extended the Krugman model and transformed it into a neoclassical dynamic equilibrium model with two elements, distinguishing between short-term and long-term equilibrium. Making a significant improvement, he argues that the rate of technology transfer in North–South trade is proportional to the gap in production costs between the two places (Wiedmann & Lenzen, 2018). Evison (2017) proposes a dynamic game model that internalizes technology innovation and transfer and simulates the North–South trade and technology transfer process as the game result of decision optimization on both sides. Ferguson and Gars (2020) argue that by playing catch-up with technology, a country's ability to learn is eventually reflected in its activities in the form of inherent fixed advantages. In the long run, these countries will achieve income convergence (Ferguson & Gars, 2020). Dalin et al. (2017) expanded their research on the internal market structure of transnational corporations, analyzed the internal technology transfer of transnational corporations, and advocated technology transfer through internal transactions of transnational corporations. Yang (2017) analyzed the limitations of Krugman's new trade theory and pointed out that the system can initiate international trade by creating comparative advantages. Tang and Zhao (2017) studied the internal influence mechanism of the system on international trade. Lou (2020) studied the relationship between asset specificity and specialization and its impact on trade integration. Zuo and Yang (2017, pp70) studied the role of institutions in trade and the economic history of Europe and America, proposing that "the development of long-distance trade in Europe is a more complex organization form of internal sustainable development."

Association rule mining finds interesting associations or related links between itemsets in a large amount of data. This critical subject in data mining has been widely studied in the industry in recent years. Cutie and Blessing E(2017) put forward the problem of mining association rules between itemsets in customer transaction databases, which is independent of the frequency set algorithm to avoid certain defects of the frequency set method and to explore a new method of mining association rules. The rest of the algorithms are primarily based on the Apriori algorithm given by Xu et al. (2017) or its variants or extensions . Susto et al. (2015) introduced pruning technology to reduce the size of the candidate set Ck, which can significantly improve the performance of algorithms for generating all frequency sets (Xu, 2019). Ghaffarian and Shahriari (2017) designed a partition-based algorithm that logically divided the database into several disjoint blocks. It considered each block separately, generating all frequency sets for it, merging the generated sets to generate all possible frequency sets, and calculating the support degree of these itemsets (Susto et al., 2015).

Based on data mining analysis, this paper investigates the application of technical risk under force majeure by analyzing the types of technical risk. Thus, using bilateral trade data and interpersonal relationship data from countries and regions worldwide, it systematically analyzes and compares the basic situation and evolution of the international trade network and the international interpersonal relationship network.

With the analysis methods and concepts of complex networks and social networks becoming increasingly in-depth in the study of economic networks, scholars at home and abroad have also gained a deeper understanding of the structural characteristics, evolutionary laws, and even dynamic mechanisms of international trade networks (Ren et al., 2021). However, existing research faces several issues. At present, no specialized economic theory can directly explain and demonstrate the impact of human networks on the structure of international trade networks (Garg et al., 2022). The existing research mainly uses trade flow data to construct international trade networks directly, ignoring the differences in relative trade intensity and failing to reflect the different impacts and roles of trade flow on two countries with trade relations (Garg et al., 2022). Therefore, this article constructs a new framework for studying international trade networks, dividing them into different levels based on the flow, proportion, and preferences of import and export trade between countries (Hamza et al., 2022).

## METHODS

### Data Mining

Data mining can be broadly defined as the process of extracting hidden, previously unknown, and potentially valuable information and knowledge from a large number of incomplete, noisy, fuzzy, and random practical application data (Ghaffarian & Shahriari, 2017). Data mining is a deep data analysis method. Simply put, it is used to extract or "mine" knowledge from a large amount of data.

The process of data mining includes business understanding, data understanding, data preparation, modeling, program evaluation, and scheme implementation (Zhu et al., 2018), as shown in Figure 1.

The process of using data mining technology for research involves several steps. First, the research object and purpose must be clarified. The research object of this data mining is the effectiveness of China's stock market. The research aims to judge the effectiveness of China's stock market through the relationship between internal stock market information and between the stock market and the macro economy. This is referred to as business understanding.

Secondly, it is necessary to analyze the studied data and clarify the practical meaning of each index and data point to mine the required information more accurately; this is known as data understanding. Figure 2 illustrates the research method of this article.

Thirdly, missing values and discretization must be carried out on the original data according to the needs of the model algorithm, which is the data preparation process. Then, according to the research purpose, we can select different algorithms, build models, and select the most appropriate model according to an evaluation of the model results, known as scheme evaluation and implementation.

Finally, when the data change, it is necessary to prepare the data again and rebuild the model. Every data mining process is a learning process. We can achieve scientific decision-making and an implementation plan through continuous learning.

**Figure 1. Data mining process**

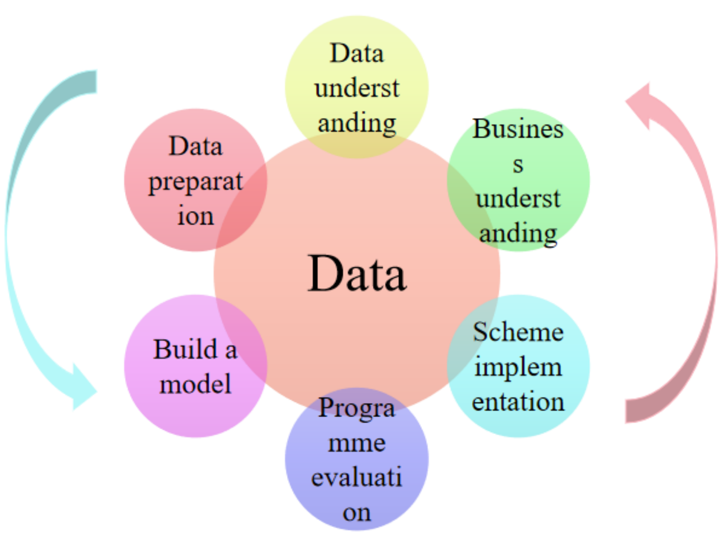
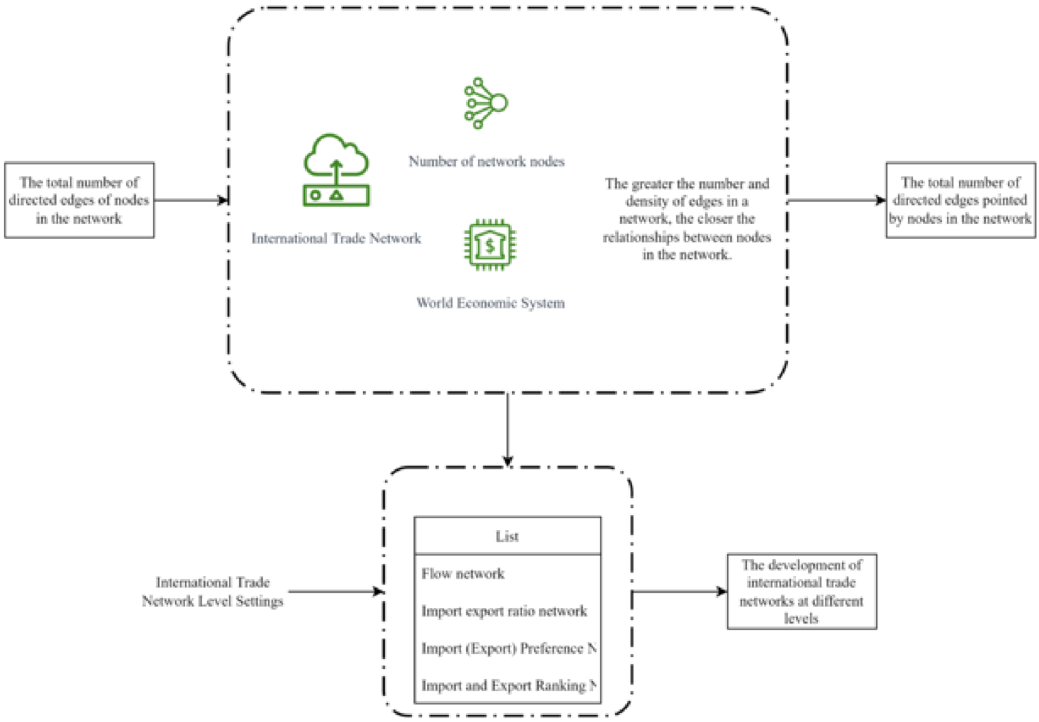


**Figure 2. Legal system of international technology trade management based on data mining technology**




## Node Number, Edge Number, and Density

The network node number N refers to the number of all nodes included in the network. The more nodes in a network, the larger the scale of the network. Therefore, if the number of nodes in a network is increasing, it means that the network is in the process of development and growth. In the international trade network, if the number of network nodes is increasing, it shows that more and more countries have become integrated into the world economic system and started to establish and develop trade relations with other countries against the backdrop of economic globalization.

The number of edges $M$ of a network is the number of all connections in the network. For a directed network, its calculation formula is:

$$M = \sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij} \tag{1}$$

in which $a_{ij}$ is the element in the corresponding unauthorized adjacency matrix of the network, $a_{ij} = 1$ indicates that there is a directed edge pointing from node $i$ to node $j$, and $a_{ij} = 10$ indicates that there is no directed edge pointing from node $i$ to node $j$.

The density of a network refers to dividing the number of edges existing in the network by the greatest number of edges that may exist in theory. For a directed network, its calculation formula is:

$$D = M / \left[ N \left( N - 1 \right) \right] \tag{2}$$

Generally, the greater the number and density of edges in a network, the closer the relationship between nodes. Therefore, if the number and density of edges in the network increase, the nodes in the network tend to make more connections, and the network of relationships between nodes will be denser.

## Grade Setting of International Trade Network

The international trade network described in this paper includes many dimensions (Wei et al., 2022), such as the flow network, import (export) proportion network, import (export) preference network, and import (export) ranking network (Xiong et al., 2021), and the strength of relations between countries and regions in the international trade network of many dimensions may be quite different (Ma et al., 2021). Therefore, this paper divides the network into different levels (Wang et al., 2020) to analyze whether differences exist in the development and evolution of international trade networks with different dimensions at different levels. In particular, it explores whether the structural characteristics and development and evolution process of strong relationship networks significantly differ from those of the whole network and lower-level networks (Yang et al., 2020).

Trade in goods with high technological content involving intellectual property rights has become another regulatory area for technology trade. Thus, in a broad sense, the technology trade management system should include two aspects: (1) the regulation of unfair trade practices of foreign imported goods infringing on US intellectual property rights (Hu et al., 2022), and (2) the protection and control of the export of technology (Ismail et al., 2022). To ensure the comparability of international trade networks in different years and different dimensions after being divided into different grades, this paper adopts the following methods to set the grades of networks: First, for the international trade networks in different dimensions, the grade threshold is set with 2019 as the standard, which makes the networks at each grade comparable in time (Yang et al., 2021). Secondly, the level thresholds of networks in other dimensions are determined based on the number of edges in different level ranking networks to ensure that the networks of the same level and different dimensions have the same or a similar number of edges, thus ensuring that the networks of different dimensions are comparable at the same level (Jaggannadha Rao, 2021). Then, the values with the weight ranking of $208 * i$ are extracted as the $i$ -th level threshold of the trade network of this dimension. Based on this, the grade thresholds of the flow network, proportion network, and preference network within the international trade network can be obtained (Gu et al., 2022).

## Output (Input) Degree and Output (Input) Intensity

In a directed network, the outgoing degree of node $i$ refers to the total number of directed edges pointed from node $i$ in the network, and the incoming degree refers to the total number of directed edges pointing to node $i$ in the network, and their calculation formulas are (Xu et al., 2017):

$$k_i^{out} = \sum_{j=1}^{N} a_{ij}, k_i^{in} = \sum_{i=1}^{N} a_{ji} \tag{3}$$

Accordingly, in weighted directed networks, the outgoing strength of node $i$ refers to the sum of the weights of all directed edges pointing out from node $i$ in the network, and the incoming strength refers to the sum of weights of directed edges pointing to node $i$ in the network, and its calculation formulas are as follows:

$$s_i^{out} = \sum_{j=1}^{N} w_{ij}, s_i^{in} = \sum_{i=1}^{N} w_{ji} \tag{4}$$

## Data Reduction

The purpose of data reduction is to reduce the size of the mined data, but this does not affect the final mining results. Existing data reduction includes (Xue et al., 2018) (1) data aggregation, (2) reducing the dimensions, (3) data compression, and (4) data block reduction, such as using clustering or parameter models to replace the original data.

Because the data used for data analysis may contain hundreds of attributes—most irrelevant to the mining task and redundant—missing related attributes or retaining irrelevant attributes increases the amount of data for harmful, irrelevant, or redundant attributes, which may slow down the mining process. Therefore, ensuring a certain degree of correlation between input and output is often a necessary preparation before data mining. Information gain can be used to examine the correlation between attributes.

Entropy is the weighted average of system information, that is, the average information of the system (Al Sobbahi & Tekli, 2022). The principle of information gain index is taken from information theory.

Let $S$ be a set of $s$ data samples. Assuming that there are $m$ different classifications, $m$ different classes $C_i = \left(1, 2, \cdots, m\right)$ are defined. Let $s_i$ be the number of samples in class $C_i$. The expected information for a given sample classification is shown in the following formula (Větrovsky et al., 2018):

$$I\left(s_1, s_2, \cdots, s_m\right) = -\sum_{i=1}^{m} p_i \log_2\left(p_i\right) \tag{5}$$

where $p_i$ is the probability that any sample belongs to $C_i$ and is estimated by $s_i / s$.

Let attribute $A$ have $v$ different values $\left\{a_1, a_2, \cdots, a_v\right\}$ and be able to be divided into $v$ subsets $\left\{S_1, S_2, \cdots, S_v\right\}$ in which $S_j$ contains samples in $S$ with value $a_j$ on $A$. Let $s_j$ be the number of samples of class $C_i$ in subset $S_j$. The entropy divided into subsets by $A$ is as follows:

$$E\left(A\right) = \sum_{i=1}^{v} \frac{s_{1j} + \cdots + s_{mj}}{s} I\left(s_{1j} + \cdots + s_{mj}\right) \tag{6}$$

Term $\frac{s_{1j} + \cdots + s_{mj}}{s}$ acts as the weight of the $j$ th subset and is equal to the number of samples in the subset (i.e., the $A$ value is $a_j$) divided by the total number of samples in $S$. The smaller the entropy value, the higher the purity of the subset partition. For a given subset $S$:

$$I\left(s_{1j} + \cdots + s_{mj}\right) = -\sum_{i=1}^{m} p_{ij} \log_2\left(p_{ij}\right) \tag{7}$$

$p_{ij} = \frac{s_{ij}}{\left|S_j\right|}$ is the probability that the sample in $S_j$ belongs to class $C$.

The information gain obtained by entropy at node $A$ is:

$$Gain\left(A\right) = I\left(s_1, s_2, \cdots, s_m\right) \text{-} E\left(A\right) \tag{8}$$

In the correlation analysis method, we can calculate the information gain of each attribute that defines the sample in $S$. Let the attribute correlation threshold for identifying a weak correlation be $a_0$. If the information gain of an attribute is less than this threshold, it is considered a weak correlation and should be deleted.

## Mining Association Rules

Let $I = \left\{I_1, I_2, \cdots, I_m\right\}$ be the set of all items where $I_k = \left(k = 1, 2, \cdots, m\right)$ is called an item. The collection of items is called an itemset, and the itemset containing $k$ items is called $k-$ itemset.

A transaction is an itemset, which is a subset of $I$, and each transaction is associated with a unique identifier $\mathrm{Tid}$. Different transactions together constitute transaction set $D$, which constitutes the transaction database of association rule discovery. If itemset $X \subseteq T$, it is said that transaction $T$ supports itemset $X$ and that transaction $T$ contains itemset $X$. The association rule is an implication of the form $X \Rightarrow Y$, where $X \subset I, Y \subset I$ and $X \cap Y \neq \varnothing$.

The four parameters describing the attributes of association rules are as follows:

1. Support degree

Mathematically defined, the support degree of itemset $X$ in $D$ represents the probability that any transaction from $D$ contains $X$, which is defined as:

$$\mathrm{support}\left(\mathrm{X}\right) = \frac{\left|\left\{T \middle| T \in DandX \subseteq T\right\}\right|}{\left|D\right|} \tag{9}$$

The support degree of association rule $X \Rightarrow Y$ is defined as:

$$\mathrm{support}\left(\mathrm{X} \Rightarrow \mathrm{Y}\right) = \mathrm{support}\left(\mathrm{X} \cup \mathrm{Y}\right) = \frac{\left|\left\{T \middle| T \in DandX \subseteq T\right\}\right|}{\left|D\right|} \tag{10}$$

where “$\left| \ \right|$” represents the number of elements in the set.

2. Credibility

The reliability of association rule $X \Rightarrow Y$ can be expressed by the following formula:

$$X \Rightarrow Y \ confidence\left(X \Rightarrow Y\right) = \frac{\left|\left\{\left|T\right| \in Dand\left(X \cup Y\right) \subseteq T\right\}\right|}{\left|\left\{T \middle| T \in DandX \subseteq T\right\}\right|} = \frac{\mathrm{support}\left(\mathrm{X} \cup \mathrm{Y}\right)}{\mathrm{supportX}} \tag{11}$$

3. Expected credibility

The expected reliability of association rule $X \Rightarrow Y$ can be expressed as:

$$\text{expected confidence}\left(\mathrm{X} \Rightarrow \mathrm{Y}\right) = \frac{\left|\left\{T \middle| T \in D and Y \subseteq T\right\}\right|}{\left|D\right|} \tag{12}$$

4. Action degree

The effect of association rule $X \Rightarrow Y$ can be expressed as:

$$lift\left(X \Rightarrow Y\right) = \frac{confidence\left(X \Rightarrow Y\right)}{\text{expectedconfidence}\left(X \Rightarrow Y\right)} \tag{13}$$

For the association rule $X \Rightarrow Y$, $P\left(X\right)$ represents the probability of occurrence of itemset $X$ in transactions, and $P\left(Y \middle| X\right)$ represents the probability of occurrence of itemset $Y$ in transactions with itemset $X$.

If the association considered by the rule is the presence or absence of an item, it is a Boolean association rule. For example, the shopping mode of purchasing financial software as well as computers can be expressed by the following rules:

$$computer \Rightarrow financial\_management\_software \tag{14}$$

$$\left[\text{support} = 2\%, \text{confidence} = 60\%\right] \tag{15}$$

Association rule mining can be extended to other data mining application fields, such as classification learning or correlation analysis (i.e., the identification and analysis of related attributes can be performed through the appearance or absence of related data items; Wei et al., 2019).

Many algorithms exist for mining association rules, among which the Apriori algorithm proposed by Agrawal and others is considered a milestone (Gupta et al., 2020). The Apriori algorithm is the most famous association rule mining algorithm and has been used by most commercial products; thus, this paper takes this algorithm as an example to explain the basic mining algorithm (Mahmud et al., 2020).

The basic idea of the Apriori algorithm is that it starts from $k = 1$, scans the database $D$, finds all itemsets whose support degree is greater than the minimum support degree (called the "frequent set") and generates a set $L1$ of frequent $1-$ itemsets. Then, a set $C2$ of candidate $2-$ itemsets containing two items is generated from $L1$, a set $L2$ of frequent $2-$ itemsets is generated from $C2$, and so on until $C_k$ is empty, and the algorithm ends.

In order to generate all frequent itemsets, the Apriori algorithm uses the recursive method. The pseudo-code of the algorithm can be expressed as:

$L1$ : A collection of all frequent itemsets
$C_k$ : A set of all candidate $k-$ itemsets
$L_k$ : A collection of all frequent $k-$ itemsets
$for\left(k = 2; L_{k-1} \neq \varnothing; k++\right) do\ begin$
Use $L_{k-1}$ to make $C_k$ ;
$C_k$ is filtered according to support and confidence

$for$ all transactions (records) $t \in D$ $do$ $begin$

Traverse all candidate items in the candidate set $C_k$ contained in the record item $t$;

$end$

All candidate sets with support greater than the minimum support in $L_k = C_k$

$end$

$\text{Result} = \mathrm{U}_{\mathrm{k}} L_k$

## ANALYSIS AND DISCUSSION OF RESULTS

Taking the data from China's international technical trade management legal system as the original data set, the association mining analysis is carried out, the support degree is 3%, and the confidence degree is 10%. The results of rule mining in the data set are shown in Table 1.

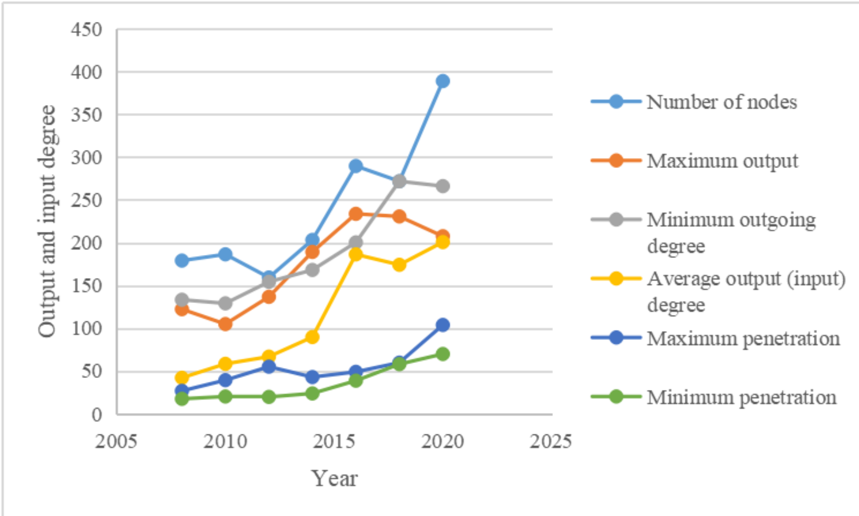
As seen in Table 1, rule $Hs\ Id = 6003200,\ org\ Id = 340 \Rightarrow Qty >= 5478$ is not a strong rule in the data set.

With the deepening of the international division of labor, countries and regions have continuously established and developed their own commodity import and export trade relations to achieve mutual economic benefits and win-win situations, leading to an increasing number of trading partners among countries and regions. Figure 3 shows that the complete international trade network's average export (import) degree increased from 58.32 in 2010 to 186.31 in 2016. Of course, since the trading partners in some of the world's major economies have already involved all countries and regions worldwide,

**Table 1. Rule mining results**

| Credibility | Support Degree | Rule |
|---|---|---|
| 0.603 | 0.667 | $Hs\ Id = 6001200,\ org\ Id = 143 \Rightarrow Qty >= 5571$ |
| 0.882 | 0.625 | $Hs\ Id = 6003200,\ org\ Id = 340 \Rightarrow Qty >= 5478$ |
| 0.819 | 0.537 | |
| 0.746 | 0.527 | $Hs\ Id = 6004300,\ org\ Id = 440 \Rightarrow Qty >= 5488$<br>$Hs\ Id = 6002300,\ org\ Id = 240 \Rightarrow Qty >= 88$ |
| 0.902 | 0.682 | $Hs\ Id = 6002800,\ org\ Id = 140 \Rightarrow Qty >= 5368$ |
| 0.832 | 0.549 | $Hs\ Id = 6003900,\ org\ Id = 540 \Rightarrow Qty >= 6379$ |
| 0.896 | 0.674 | $Hs\ Id = 6002580,\ org\ Id = 115 \Rightarrow Qty >= 99$ |
| 0.825 | 0.713 | $Hs\ Id = 6003380,\ org\ Id = 121 \Rightarrow Qty > 79$ |
| 0.733 | 0.774 | $Hs\ Id = 6005390,\ org\ Id = 101 \Rightarrow Qty > 85$ |
| 0.741 | 0.691 | $Hs\ Id = 6001350,\ org\ Id = 114 \Rightarrow Qty > 80$ |
| 0.749 | 0.655 | $Hs\ Id = 6002500,\ org\ Id = 116 \Rightarrow Qty > 90$ |

**Figure 3. General situation of nodes out and in of international trade complete network**

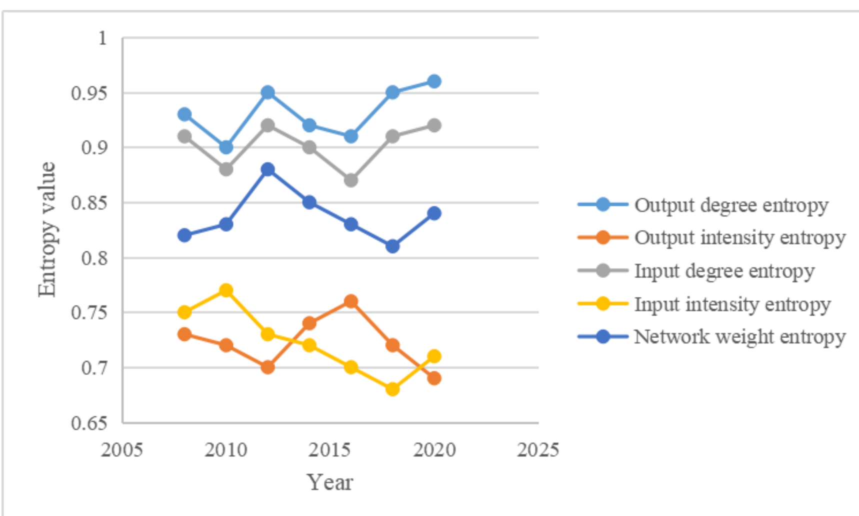



the deepening and development of the complete international trade network in the future will be further promoted mainly by developing economies.

However, the similarity of the output and input of each node in the complete international trade network mainly reflects the enhancement of interaction practices among countries. Still, it does not mean that the resources controlled by countries tend to be equal. On the contrary, enhancing interaction practices will likely allow some countries to control more resources in the network, making the network more heterogeneous.

According to the evolution of the network in Figure 4, the out-intensity, in-intensity, and network weight entropy of the complete international trade network were generally lower than 0.75 from 2008 to 2014. They follow a downward trend from 2010 to 2015, only starting to rise steadily after

**Figure 4. The evolution of network structure of international trade complete network**



2016. The above situation shows that the heterogeneity of the output intensity, input intensity, and intensity of all trade relations in the complete international trade network is larger than that of the nodes. A few countries in the network control a large part of the trade flows, while most countries only control a small part of the trade flows in the network (Prathiba et al., 2021). Developed countries regard technology exports as an essential means of expanding and occupying the world market. On the one hand, this involves appropriately exporting technology, creating an international market, and expanding the market share of its high-tech products. On the other hand, it means strictly controlling the flow of its key technologies, core technologies, and competitive high-tech to other countries, especially developing countries (Lv et al., 2022).

This research also validates the effectiveness of data mining techniques. The test results are scored based on the standard responses in the evaluation corpus. Table 2 compares the results of the final evaluation.

The strategy proposed in this work achieves close to the optimal results for all results involved in the analysis.

According to the differences in the importance of trade relations, analyzing the mechanism of network construction can allow us to grasp the order and regularity of network organization more effectively. This paper divides the international trade network into different dimensions and levels. From different perspectives, the differences in the importance of trade relations are considered in order to analyze the organization and construction rules of the international trade network.

Figure 5 compares the error trends of “Enlightenment of American hospital management related legal system on foreign-funded hospital management in China” (Meng, Y, 2022) and “Enlightenment of American hospital management related legal system on foreign-funded hospital management in China” (Ma, X, et al., 2021), and the method in this paper. The comparison shows that the training times of the ref[18] algorithm are significantly reduced. This is because when the error propagates backward, the momentum factor increases and the adaptive learning rate accelerates the convergence, reducing the total number of iterations. The total time consumption is also significantly reduced.

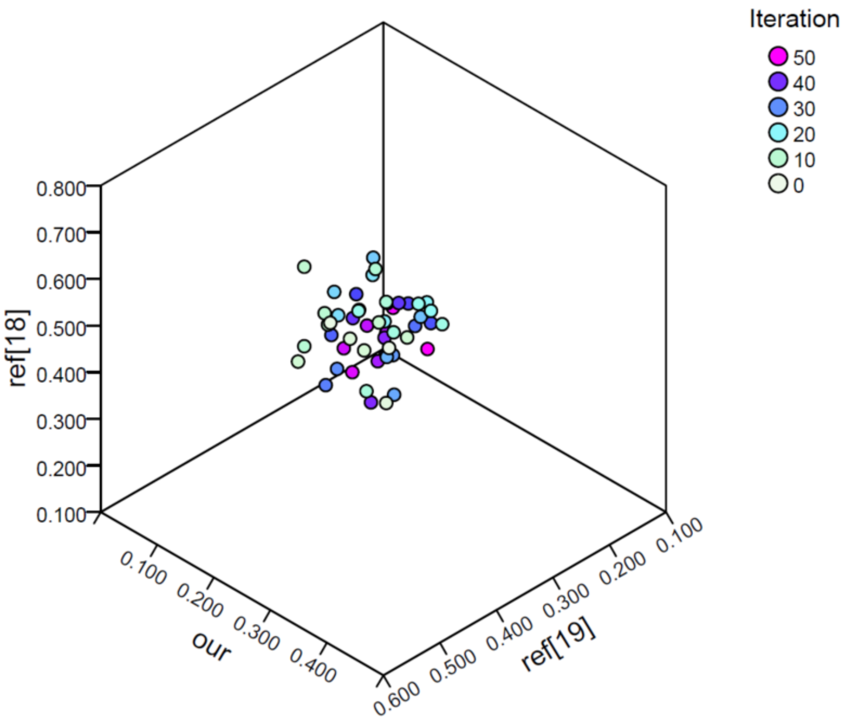
## CONCLUSION

When multinational companies constantly use restrictive business practices to create intellectual property barriers in international technology transfer, it is imperative to take the anti-monopoly law as the core and improve the legal supervision system of restrictive business practices. This paper systematically analyzes and compares the basic situation and evolution of the international trade network and the international interpersonal network by combining data mining analysis technology and the social network analysis concept, using bilateral trade data and national and regional interpersonal data. In 2008–2014, the external, internal, and network weight entropy of the international trade integrity network were generally lower than 0.75, and the overall trend still pointed downward in 2010–2015, only starting to rise steadily after 2016. In the international trade network, the heterogeneity of all trade relations’ output intensity, input intensity, and intensity was greater than that of the nodes.

**Table 2. Extraction results of legal phrases**

| Result Sequence | Macro-Average | | | Micro-Average | | |
|---|---|---|---|---|---|---|
| | Accuracy (%) | Recall (%) | F (%) | Accuracy (%) | Recall (%) | F (%) |
| DM | 8.145 | 7.752 | 7.977 | 10.004 | 7.955 | 9.024 |
| Average | 5.541 | 5.068 | 4.625 | 7.619 | 6.317 | 6.211 |
| Best | 8.155 | 10.022 | 8.714 | 11.751 | 10.124 | 10.264 |

**Figure 5. Error comparison of different algorithms**




This paper systematically constructs and describes the legal system of international technology trade management mathematically. However, many shortcomings remain that need to be further improved. In particular, the network constructed in this paper is not a spatial network, and the spatial relationship between nodes in the network has yet to be further tested. Therefore, the question of whether the international trade network embedded in the international human relations network is more economically conductive or inhibitory cannot be answered.

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