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A DATA-DRIVEN MODEL AND METHODOLOGY FOR PREDICTING THE EFFICACY OF STRATEGIC SANCTIONS

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Abstract: The scientific rigour and precision of major strategic decisions at the national level have been demonstrated to directly impact a nation's sovereignty, economic security, and diplomatic standing. In the contemporary geopolitical landscape, characterised by the proliferation of intricate international relations, the discord between established systems and emergent demands has attained a heightened degree of visibility. This has resulted in a substantial escalation in the intricacy and ambiguity of strategic conflicts among nations. Among the various measures employed, the implementation of sanction policies directed against specific countries is of particular significance in achieving political and national security objectives. However, the factors that influence sanction policies are characterised by their multi-dimensionality and strong interdependencies (highly coupled nature). Conventional research paradigms, predicated on qualitative analysis, are progressively inadequate to satisfy the decision-making demands inherent in complex scenarios. This has given rise to a pressing need for AI technologies to construct efficient and precise analytical frameworks. The present paper proposes a deep neural network-based analytical method for the evaluation of sanction policies enacted by nations (or international organizations). The efficacy of this method is demonstrated by its ability to predict the potential outcomes of such policies, thereby providing critical information and knowledge support for the scientific formulation of national sanction strategies. The core approach involves the curation of data from extensive historical records to form quantitative indicators related to sanction policies. A deep neural network is then employed to model the intrinsic relationships between these indicators and the effects of sanctions, enabling the prediction of outcomes in new contexts and offering decision support for critical policy formulation. In conclusion, the model was trained on the Global Sanctions Database (GSDB-R3), resulting in an efficient predictive model for sanction policy effectiveness. The analysis of metrics such as accuracy and recall demonstrates the feasibility and effectiveness of the proposed method in predicting the outcomes of sanction policies.
Keywords: Artificial neural network; Strategic sanctions; Predictive analysis

1 INTRODUCTION

1.1 Research Background and Motivation

National sanctions are restrictive measures imposed by sovereign states or international organizations through targeted policies against a subject country (or its domestic entities and individuals) to achieve specific political, security, or diplomatic objectives. They are, in essence, a strategic means of exerting pressure between nations. Due to their comprehensive and profound impact, sanction policies not only directly affect various sectors of the targeted country—such as its economy, society, and livelihood—thereby triggering systemic risks, but also set off a series of chain reactions for the sanctioning parties. A case in point is the multiple rounds of sanctions imposed by Western countries on Russia in 2022, which encompassed energy, finance, investment, trade, shipping, and other domains, affecting numerous entities and individuals. As a result, Russia's revenue from oil and gas exports plummeted; several major banks were excluded from the SWIFT international payment system, hindering cross-border trade settlements for Russian enterprises and restricting the use of its foreign exchange reserves; the ruble depreciated significantly. In terms of public livelihood, the sanctions caused shortages of essential goods (e.g., medicines, electronic products), driving up domestic inflation and significantly increasing the cost of living for ordinary citizens. Therefore, accurately assessing the impact of national sanction policies is crucial for decision-makers to analyze the strategic landscape.

The scientific formulation of national sanction policies constitutes a complex systematic project. It typically requires evaluating the effects of a proposed policy after its introduction, with the core task being the prediction of its impact. Accurately forecasting the effects of one's own sanction policies can assist decision-makers in assessing the rationality of policy design, thereby facilitating optimization. Conversely, accurately predicting the effects of adversarial sanction policies enables decision-makers to better gauge the situation and devise appropriate counterstrategies.

For a long time, academic research on macro-level decision-making problems such as predicting the effects of national sanctions has relied on traditional social science methods. The core approaches include qualitative analysis and rule-based quantitative research. Qualitative analysis primarily involves historical case studies, policy document interpretation, and expert interviews—for instance, identifying key factors influencing sanctions by examining historical cases. Rule-based quantitative research, on the other hand, typically relies on domain knowledge combined with basic applied statistical models (such as logistic regression or event history analysis) to construct specific mathematical models that capture correlations between a limited set of indicators and the achievement of sanction objectives. However, these methods have significant drawbacks: Firstly, they fail to fully exploit the knowledge embedded in massive datasets, making it difficult to integrate and analyze unstructured data such as policy documents and news announcements comprehensively. Secondly, traditional statistical analysis methods struggle to capture the intrinsic relationships among multidimensional variables within complex systems, often leading to "spurious correlations." Thirdly, they lack generalizable predictive capability; both qualitative analysis dependent on expert experience and rule-based quantitative analysis require tailor-made models and rules for specific problems, hindering their transferability to other contexts.

1.2 Research Status

In the field of economic sanction policy analysis, traditional research mainly relies on qualitative methods, such as case analysis, expert opinion integration, and policy text interpretation. For example, Ozgur discussed the types of sanctions, the relationship between the sanction - imposing party and the target party[1], and analyzed the impact of structural factors on the consequences of sanctions by studying cases of economic sanction consequences. Kerim took the 2014 Ukrainian crisis and the sanctions on Russia as examples to raise questions about the effectiveness of trade sanctions [2]. Katharina adopted the Qualitative Comparative Analysis (QCA) method and combined data from the Targeted Sanctions Consortium to study the negative externalities of UN sanctions [3].

Such research can provide a macro - level understanding of sanction policies. However, against the backdrop of today's highly integrated global economy, the combined application of sanction measures, and the multi - dimensional and complex interaction of factors influencing sanctions, their limitations have become increasingly prominent. Traditional research is unable to quantify many implicit influencing factors, such as the mediating effect of international public opinion trends and the game between domestic political forces in the target country on the impact of sanctions. Moreover, it cannot handle massive unstructured data (such as the attitude of the public towards sanctions on social networks), resulting in insufficient accuracy and forward - looking of research conclusions, which makes it difficult to adapt to the current complex and changing international political and economic situation.

In terms of AI - assisted strategic decision - making, a large number of relevant studies and application explorations have emerged. In the field of intelligent assistants, enterprises have developed decision - support tools using AI technology, which can provide managers with industry - assisted predictions, risk early warnings, and other information based on big data, greatly improving the efficiency and scientificity of enterprise strategic decision - making. Meng Xiaoyu and others studied the specific application and development direction of medical AI in the medical field by analyzing existing medical AI application cases and combining clinical data and AI technology [4]. Wang Jundong proposed a distribution network fault - assisted decision - making method based on knowledge graphs [5]. By constructing a fault dispatching knowledge graph and applying AI technology, it realizes fast, intelligent, and accurate fault handling decision - support. Chen Yao proposed an intelligent highway maintenance decision - support system that integrates new - generation information technologies such as BIM [6], big data, and AI to assist decision - makers in scientifically formulating maintenance strategies.

AI-based industry application models have been deployed in more fields, and by integrating multi-source information such as massive data, policy change updates, and user demands, they have demonstrated stronger predictive capabilities than traditional econometric models in areas including comprehensive forecasting for the electric power, energy, and medical industries, as well as assessment of industry development prospects. However, focusing on the specific topic of national sanction policies, no systematic research literature that deeply integrates AI has been retrieved so far. The existing research system on sanction policies is in urgent need of introducing the innovative analytical paradigm and powerful data processing capabilities brought by AI technology.

This study conforms to this development trend and attempts to introduce AI technology into the analysis of inter - national sanction policies. It aims to leverage the capabilities of AI technology in in - depth mining of multi - source heterogeneous data and modeling of complex relationships to make up for the shortcomings of traditional research, construct a more accurate and efficient analytical framework for sanction policies, and provide scientific support for relevant strategic decisions.

1.3 Main Contributions of This Study

The overall idea of this study is as follows: Based on the analysis of information related to inter - national and inter - organizational sanction policies formed by sorting out historical case information, the relevant information is quantified to develop characteristic indicators that can describe the sanction actions, sanction types, and sanction time. These characteristic indicators are used as inputs, and the effect of sanction policies is used as the network output to establish a multi - layer perceptron model. Through the training of the model, the accurate and efficient judgment of the effect and evolution trend of sanction policies is realized.

The main contributions of this paper are as follows:

(1) Innovatively applying intelligent computing technology to empower research on issues in the field of social sciences, and proposing a data - driven methodological framework for studying strategic issues.

(2) Innovatively designing an artificial neural network model and algorithm for predicting the effect of sanctions between countries or organizations, which can effectively avoid the risk of "empirical decision - making" and improve the accuracy and forward - looking of decision - making.

2 PROBLEM ANALYSIS AND DATA PREPARATION

2.1 Problem Description

At present, the global geopolitical pattern is undergoing in - depth restructuring. Inter - national sanction policies exhibit the characteristics of "multi - domain linkage" (such as combined energy and financial sanctions), "coupling of influencing factors" (interaction between economic dependence and international alliance support), and "complexity of effect evaluation" (interweaving of short - term economic shocks and long - term industrial supply chain transformation). Moreover, reliance on small-sample structured data (official statistical reports); simple analytical methods without dynamic interaction between them; and the lack of quantifiable prediction models in these methods.
Currently, research conditions include global public sanction databases, basic data processing capabilities, and algorithm frameworks. However, a full - process analytical system encompassing "data quantification - feature extraction - model prediction" has not yet been formed. The core scientific problem to be solved in this study is: How to construct a quantitative analytical framework integrating decision - support technologies based on the known characteristics of sanction policies and by utilizing existing multi - source historical data and basic technical conditions, and ultimately achieve three target effects. Firstly, the quantitative conversion rate of unstructured sanction information is effectively improved. Secondly, the constructed prediction model ensures the prediction accuracy of sanction impact indicators. Thirdly, it provides traceable and verifiable quantitative verification decision - making bases to avoid the risks of traditional empirical decision - making.

2.2 Problem Difficulties and Assumptions

Compared with general system prediction problems, the strategic sanction prediction problem has the following characteristics. The sources of sanction policy information are usually scattered across official bulletins of various countries, media news, academic research, etc., and the types of media include text, images, audio, and other forms. Data retrieval is cumbersome, acquisition is difficult, and the process of processing, integration, and analysis is complex. In addition, from the perspective of hierarchical attributes, the analysis of sanction policies belongs to the macro - strategic level, which requires an overall perspective to coordinate core goals. However, the factors affecting the final effect often involve multiple levels and have concealment. Due to the limitations of hierarchical positioning, it is difficult to conduct a comprehensive analysis of all influencing factors. How to extract effective content and key factors from the complex information to obtain evidence for the impact effect of sanctions, and thus support strategic - level macro - decision - making based on decision robots, is the direction that this study needs to explore.

2.3 Data Preparation

A wealth of information sources containing sanction policy information can be found in news media, official bulletins, and academic resources. For example, the Office of Foreign Assets Control (OFAC) of the U.S. Department of the Treasury, which is responsible for implementing sanctions, and the Council of the European Union mainly provide policy and legal texts as well as government announcements. Specialized analysis and statistical data can be obtained from global sanction data tracking websites (such as castellum.ai) and research reports released by think tanks like the Peterson Institute for International Economics. In addition, news media and social network platforms of various countries also report on the attitudes of the people in the sanction - imposing and target countries towards the sanctions.
From this data, we can obtain some useful sanction information, such as the identity of the sanction - imposing party, the type of sanctions, the industries affected by the sanctions, and the duration of the sanction policies. Among these, the key initial attributes that affect the sanction decision - making process, sanction results, and effects include the duration of the sanctions, the number of countries or organizations participating in the sanctions, the type of sanction measures, the purpose of the sanctions, the entities or individuals targeted by the sanctions, the subject matter of the sanctions, and the exemption conditions for the sanctions.
The attribute values of some information are listed as follows. For the name of the sanctioned country, it may be the full name, abbreviation, or national standard code. For the sanction time, some count the number of sanction policies by year, while others count by month. For the type of sanctions, there are industrial classifications, and there is also the Harmonized Commodity Description and Coding System, an international general commodity classification and coding system presided over by the World Customs Organization (WCO).
The data sources related to sanction policies are scattered, and there are various forms of attribute identification, which bring certain difficulties to the analysis and judgment of policies and seriously affect the processing efficiency of policy analysis. This paper focuses on how to use some of the quantifiable information to predict the effect of sanctions. Based on the Global Sanctions Data Base - Release 3 (GSDB - R3), this quantifiable information includes:

- Sanction - imposing countries or organizations: Countries or organizations that take the initiative or are forced to participate in the sanctions.
- Sanctioned countries or organizations: The targets of the sanctions, which can be transnational organizations composed of a single country or multiple countries.
- Reasons for sanctions: Including the reasons for which the sanction - imposing party implements the sanction measures.
- Types of sanctions: Including restrictions on financial financing and lending, control over trade imports and

exports, and suspension of military assistance.

- Start time of sanctions: The specific year when the sanctions begin to be implemented.
- End time of sanctions: The time when the sanctions are terminated or suspended upon acceptance of the negotiation results.

There are 5 types of labels for the effect of sanctions:

- Successful sanctions: The purpose of the sanctions is achieved, such as the target party ceasing to invade other countries or accepting a truce agreement.
- Partial sanctions: A type of trade sanction, which includes comprehensive import and export sanctions or special sanctions on some industries.
- Ongoing: The sanctions are still in progress and have not had a substantial impact. For example, the sanctions on Cuba are still part of the U.S. sanction plan and have not been lifted.
- Failed sanctions: The sanctions fail to achieve the goal of stopping the target party's infringement, resulting in the failure of the sanctions.
- Negotiated settlement: Negotiations are facilitated through a third party, and the sanctioned party accepts the negotiation results, thus achieving the purpose of imposing the sanctions.

3 PROBLEM SOLVING

3.1 Technical Framework of Strategic Sanction Effect Prediction Agent

The multi - agent technology processing flow for data - driven strategic sanction effect prediction is mainly divided into two main processes: training and application, as shown in Figure 1. The sanction prediction model is trained based on historical sanction data, with iterative training conducted to learn and update model parameters and boundary constraints, and continuous approximation and fitting performed to develop a sanction prediction model that is sensitive to sanction data, based on data evidence, and achieves optimal sanction prediction results. This model can then be applied to practical policy evaluation scenarios such as sanction prediction.

In the training module, first, massive amounts of unstructured data are acquired and stored from multi - source information. Second, data preprocessing processes such as data encoding, cleaning, screening, and feature extraction are carried out. Then, the features extracted in the preprocessing stage are input into the sanction impact prediction model for iterative training, and the neural network parameters and training algorithms are continuously improved to form an effect prediction model.

In the application module, first, information about the actual sanction scenario is obtained and feature extraction is conducted. Second, real - time dynamic sanction information is imported into the sanction policy prediction Agent, and a sanction policy evaluation report is generated in accordance with the sanction prediction processing flow.

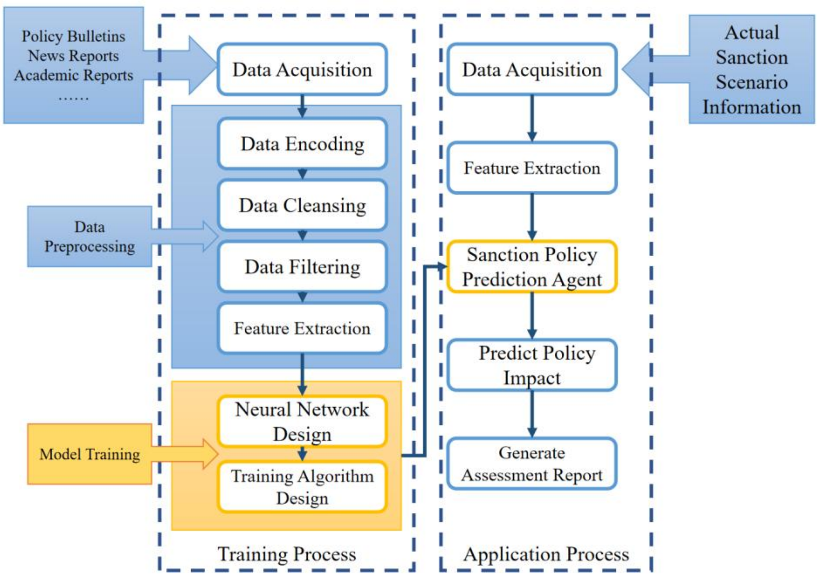

Figure 1 Technical Framework of Strategic Sanction Effect Prediction Agent

3.2 Data Preprocessing

The Global Sanctions Data Base - Release 3 (GSDB - R3) contains a total of 1325 sanction case records, including elements such as the start and end times of the sanction cases, the classification of the sanction - imposing parties, the reasons for the sanctions, the types of sanction measures, and the results of the sanctions. The original sanction data is shown in Table 1.

Table 1 Variables and Descriptions of the Original Dataset

Variables	Dscriptions
case_id	Sanction case ID.
sanctioned_state	Sanctioned (target) country/region.
sanctioning_state	Sanction - imposing (initiating) country/region.
begin	Sanction start year.
end	Sanction end year. The value of 2022 may have a dual meaning for ongoing sanctions.
arms	Arms sanction indicator variable, with a value of 1 if it is an arms sanction.
military	Military assistance sanction indicator variable, with a value of 1 if it is a military assistance sanction.
trade	Trade sanction indicator variable, with a value of 1 if it is a trade sanction.
descr_trade	Type of trade sanction. "exp_compl" denotes comprehensive export sanctions; "imp_compl" denotes comprehensive import sanctions; "exp_part" denotes partial export sanctions; "imp_part" denotes partial import sanctions.
financial	Financial sanction indicator variable, with a value of 1 if it is a financial sanction.
travel	Travel sanction indicator variable, with a value of 1 if it is a travel sanction.
other	Other sanction indicator variable, with a value of 1 if it is another type of sanction.
target_mult	Multilateral target sanction indicator variable, with a value of 1 if it is a multilateral target sanction
sender_mult	Multilateral initiator sanction indicator variable, with a value of 1 if it is a multilateral initiator sanction
objective	Sanction objectives. If multiple objectives are assigned to the same case, there is no ranking among these objectives.
success	Sanction impact. If there are multiple objectives, the success sequence corresponds to the objective sequence.

Based on the analysis in Chapter 2 and the understanding of the GSDB - R3 dataset, this section focuses on designing the values of each indicator in the dataset according to the characteristics of the strategic sanction effect prediction problem. According to the original dataset, the indicators are further processed into discrete numerical variables. The indicators and their value ranges are designed as follows:

1. Sanction initiator: In the original data, the initiator is a string variable representing the country or organization that initiates the sanctions. The initiator includes at least one country or organization, and a sanction can be jointly initiated by multiple countries or organizations. In the dataset, different countries or organizations are separated by commas. This study examines the relationship between the number of initiators and the sanction effect. Therefore, after processing, this indicator is a positive integer representing the number of countries or regions participating in the sanctions.
2. Sanctioned party: Similar to the initiator, the sanctioned party is a string variable representing the country or organization being sanctioned. The sanctioned party of a sanction policy can also be multiple countries and organizations, which are separated by commas in the dataset. This study examines the relationship between the number of sanctioned countries and the sanction effect. Therefore, after processing, this indicator is a positive integer representing the number of sanctioned countries or regions.
3. Sanction start time: The original dataset uses a 4 - digit integer, with values ranging from 1949 to 2022, representing the calendar year when the sanctions begin.
4. Sanction end time: Similar to the sanction start time, the data range is from 1951 to 2022. When the end time is 2022, it may have a dual meaning, that is, the sanctions have not ended after the statistical year.
5. Sanction type: There are 6 types of sanctions, including trade, arms, military assistance, financial, travel, and others. Among them, trade is described in a separate column, distinguishing 4 subtypes of sanctions: partial import, partial export, comprehensive import, and comprehensive export, which are separated by commas. The rest are represented by 0 or 1 variables indicating the presence or absence of such sanctions. This study examines the relationship between the type of sanctions and the effect of sanctions. Therefore, after processing the trade description, the 4 trade subtypes are counted one by one, represented by 0 or 1 indicating their presence or absence, which is the same as the representation of other types of sanctions.
6. Sanction objective: The sanction objectives include territorial conflicts, policy changes, war termination, war prevention, human rights, democracy, regime change, and others, which are represented by strings. When there are multiple sanction objectives, they are separated by commas.
7. Sanction effect: In the dataset, there are 5 types of sanction effects, represented by strings: successful sanctions, partially successful sanctions, failed sanctions, acceptance of negotiation results, and ongoing sanctions. When there are multiple sanction objectives, the sanction effects correspond to the sanction objectives one by one, separated by commas. This study examines the relationship between the type of sanctions, the sanction objectives, and the sanction effects. Therefore, the sanction effects are counted one by one corresponding to the sanction objectives, and 0 or 1 is used to indicate the presence or absence of various sanction effects.

After the above data processing, the data represented by strings in the original sanction dataset are uniformly converted into discrete data represented by integers. In addition to facilitating calculation and analysis, this will provide a basis for subsequent feature extraction and the selection of appropriate sanction prediction effect models and methods, resulting in a new dataset shown in Table 2.

Table 2 Newly Processed Dataset

Variable	Name	Value Range	Variable	Name	Value Range
X_1	Number of sanctioned parties	1-4	X_2	Number of sanction initiators	1-18
X_3	Sanction start year	1949-2022	X_4	Sanction end year	1951-2022
X_5	Partial import sanctions	0/1	X_6	Partial export sanctions	0/1
X_7	Comprehensive import sanctions	0/1	X_8	Comprehensive export sanctions	0/1
X_9	Arms sanctions	0/1	X_{10}	Military assistance sanctions	0/1
X_{11}	Financial sanctions	0/1	X_{12}	Travel sanctions	0/1
X_{13}	Other sanctions	0/1	X_{14}	Multilateral sanctioned parties	0/1
X_{15}	Multilateral initiators	0/1	X_{16}	Sanction objective: Territorial conflict	0/1
X_{17}	Sanction objective: Human rights	0/1	X_{18}	Sanction objective: Policy change	0/1
X_{19}	Sanction objective: War termination	0/1	X_{20}	Sanction objective: War prevention	0/1
X_{21}	Sanction objective: Democracy	0/1	X_{22}	Sanction objective: Terrorism	0/1
X_{23}	Sanction objective: Regime change	0/1	Y_1	Sanction result: Success	0/1
Y_2	Sanction result: Partial success	0/1	Y_3	Sanction result: Failure	0/1
Y_4	Sanction result: Acceptance of negotiation results	0/1	Y_5	Sanction result: Ongoing	0/1

3.3 Neural Network Design

In the problem of predicting the impact of sanctions, due to the participation of multiple parties in sanctions and the overlap of factors such as sanction types and purposes, it is difficult to obtain accurate prediction results using a general linear function that predicts the impact of sanctions based on these variables, making it difficult to support strategic - level macro - decision - making. Artificial intelligence neural networks have better advantages over other methods in fitting and predicting complex functions. Therefore, this study adopts a fully connected network to describe the value function for predicting the effect of sanctions.

3.3.1 Network structure

According to the characteristics of the dataset, the ANN neural network algorithm shown in Figure 2 is intended to be adopted. Data in the dataset—including sanction types, sanction times, and sanction purposes—are designed as the input layer, while data corresponding to sanction impacts serve as the output layer. The hidden layers are set to [10, 10], indicating that the neural network includes two hidden layers. The first hidden layer has 10 neurons, and the second hidden layer has 10 neurons. The number of training times is designed to be 1000.

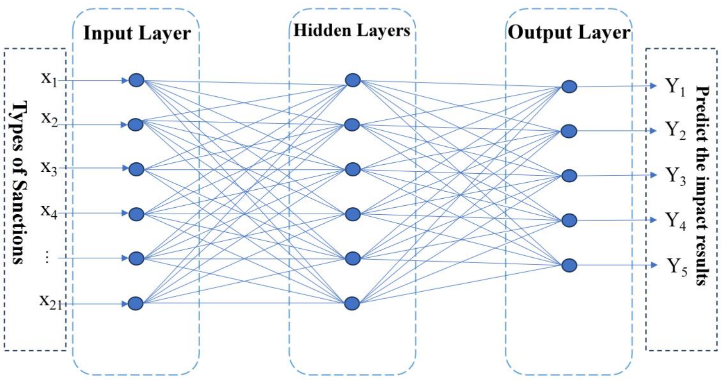

Figure 2 Design of Fully Connected Artificial Neural Network (ANN)

3.3.2 Training process

According to the attribute characteristics of global economic sanctions dataset (such as sample size, feature type and data distribution), the appropriate training method is selected from data characteristics and prediction tasks.

Predicting sanctions impact is essentially a supervised learning task. The input characteristics include sanctions involved, sanctions start and end time, sanctions type and sanctions purpose. The data of this dataset has the following characteristics:First, the number of samples is limited, and the number of major global economic sanctions events (unilateral sanctions by major powers) is small, far lower than the large-scale data sets of massive Social networks information such as images and texts;Second, the sample correlation is strong: the impact degree of sanctions is highly correlated with "sanctions intensity"(sanctions type + multilateral sanctions),"time window"(whether sanctions duration covers key time nodes),"purpose feasibility"(trade sanctions are easier to achieve than subversion), etc.;Third, there is data noise in the sample, the definition of "success rate" of some sanctions is vague (such as "partial success" is difficult to quantify), and in addition, there is no record of threat leading to success of sanctions in the original data set. The sanctions prediction neural network training algorithm is as follows:

Firstly, the data acquisition unit will collect the contents related to sanctions in government bulletins, major news media reports and major academic databases of various countries, extract the relevant sanctions time, country or region, sanctions initiator and its joint sanctions organization, and disclose the reasons for various sanctions in the information bulletin; Secondly, according to the set rules, the acquired data is distinguished from the sanction time, object, content, mode, etc., and the basic content of each piece of information is recorded according to the information elements, and corresponding labels are given;However, when incomplete information data is encountered, key information collected from other sources documenting the same sanctions case assists each other in verifying the authenticity of the sanctions incident and assessing the quality and completeness of the information; Finally, when the number of recorded sanction cases reaches a certain level, the common sanction methods, sanction targets and impact effects in the sanction cases are analyzed, the sanction rules hidden in the information are captured, and key variables with influence weights are formed, and then the data features closely related to the prediction effects of sanctions are extracted.

According to the characteristics of data features, combined with artificial neural network design specifications, the classical fully connected neural network is selected. The 21 sanction variable features after pretreatment are used as the input of neural network. Different number of hidden layer parameters are continuously tested. Through less times of testing, training data such as accuracy, recall and error distribution are recorded, and the data parameters are continuously adjusted to construct the best prediction model.

In order to obtain higher accuracy and reduce the error of sanctions prediction, regularization and boundary restriction are adopted to optimize the model, so as to obtain the convergence characteristic of function faster. With the increasing iteration times, when the error rate decreases to meet the requirements and the accuracy has high accuracy, the training is stopped, and the model will approach the actual sanctions effect function more closely and reach the optimal parameters of sanctions prediction model. The detailed sanctions prediction neural network training algorithm is shown in Algorithm 1:

Algorithm 1 Training Algorithm for Sanctions Prediction Neural Network

Randomly initialize weights w and thresholds θ
Set the error convergence threshold ε
Initialize total training steps total_steps $= 0$
loop ▷ Training loop (until error meets requirements)
  total_steps $\leftarrow$ total_steps $+ 1$
  Initialize current round total error round_error $= 0$
  for each sample sample $\in$ training set do
    input $\leftarrow$ sanction types as input features
    target $\leftarrow$ predicted sanction impacts as target outputs
    h_input $\leftarrow \sum(w_{\text{in}\to\text{hid}} \cdot \text{input}) + \theta_{\text{hid}}$
    h_output $\leftarrow \sigma(\text{h\_input})$ ▷ Activation function σ (e.g., Sigmoid)
    o_input $\leftarrow \sum(w_{\text{hid}\to\text{out}} \cdot \text{h\_output}) + \theta_{\text{out}}$
    o_output $\leftarrow \sigma(\text{o\_input})$
    $\delta_{\text{out}} \leftarrow (\text{target} - \text{o\_output}) \cdot \sigma'(\text{o\_input})$
    round_error $\leftarrow$ round_error $+$ MSE(target, o_output) ▷ Accumulate mean squared error
    $\delta_{\text{hid}} \leftarrow (\sum(w_{\text{hid}\to\text{out}} \cdot \delta_{\text{out}})) \cdot \sigma'(\text{h\_input})$
    $w_{\text{hid}\to\text{out}} \leftarrow w_{\text{hid}\to\text{out}} + \eta \cdot \delta_{\text{out}} \cdot \text{h\_output}$
    $\theta_{\text{out}} \leftarrow \theta_{\text{out}} + \eta \cdot \delta_{\text{out}}$
    $w_{\text{in}\to\text{hid}} \leftarrow w_{\text{in}\to\text{hid}} + \eta \cdot \delta_{\text{hid}} \cdot \text{input}$
    $\theta_{\text{hid}} \leftarrow \theta_{\text{hid}} + \eta \cdot \delta_{\text{hid}}$
  end for
  if round_error $< \varepsilon$ then
    break ▷ Error meets requirements, terminate training
  end if
end loop
Output: Training completed (total steps: total_steps)

The basic optimization framework selection is based on the Levenberg-Marquardt(LM) algorithm, considering that the sample size is limited and the sample size is medium. Combined with the sample size of the global economic sanctions dataset (GSDB-R3), it can handle the problem of "large difference between sanctions type and data characteristic gradient", and the convergence speed is fast. It does not need to manually adjust parameters frequently, and is suitable for nonlinear fitting task scenarios such as sanctions impact prediction.

The core idea of LM algorithm is to balance the characteristics of Newton method and gradient descent method through damping factor, and balance the performance of the above optimization methods through the following update rules. The core formula is:

$$\xi_{k+1} = \xi_k - (\Psi^T \Psi + \lambda I)^{-1} \Psi^T e \tag{1}$$

Based on this formula, the parameters in the network can be iteratively updated, and finally the neural network can be used to predict the effect of sanctions.

3.3.3 Application process

Taking the historical sanction data set as the input of neural network, the model continuously modifies the parameters and prediction effect boundaries of neural network, and the sanctions prediction model can obtain better fitting effect through continuous iteration and upgrading. The main purpose of this paper is to design this model. Facing the complex international situation, when new sanction events occur, how to obtain the prediction effect evaluation report with high accuracy based on the sanction events obtained by data mining. Therefore, in the design and application stage, Sanction cases occurred after 2000 were taken as test set, and the training effect of cases before 2000 was tested as training set. The prediction effect obtained by applying the model was tested respectively, and the related data such as accuracy rate and recall rate were distinguished to evaluate the performance and effect of the model.

4 EXPERIMENT

In this paper, the real historical dataset is divided into training data and test data. The dataset is provided by institutions such as the LeBow College of Business at Drexel University in the United States, the Austrian Institute of Economic Research, and the Konstanz University of Applied Sciences, and is used to verify the effectiveness of the above - mentioned prediction method. The experiment is run on a personal laptop with the following main performance parameters: CPU model is 13th Gen Intel® Core™ i9 - 13900HX, memory is 32G, and graphics card is Nvidia 4080.

4.1 Experimental Scenario Design

4.1.1 Data preparation

The Global Sanctions Dataset records the statistical data of global sanction policies from 1949 to 2022. This database covers unilateral and multilateral sanctions and details attributes such as the type of sanctions, political objectives, and success level, with a total of 1325 data entries. According to the design in Chapter 3 of this paper, the original data are sorted into 21 quantitative attributes, including the sanction case ID, the sanction initiator and target, the type of sanctions, the start and end times of the sanctions, the purpose of the sanctions, and the results of the sanctions, as shown in Table 2.

4.2 Preliminary Data Analysis

4.2.1 The variation of the number of various sanction policies over time

The data are sorted in ascending order of the start time of the sanctions, and the number of various sanctions implemented each year is counted. The variation trend of the types of sanctions over time can be intuitively obtained, as shown in Figure 3.

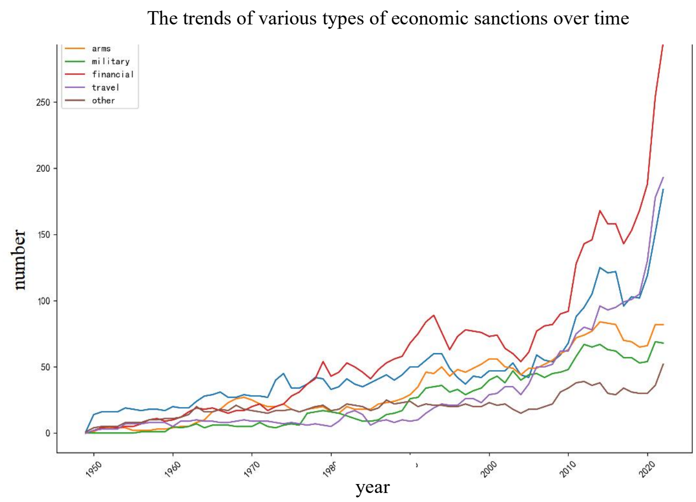

Figure 3 Trend of Various Types of Sanctions Over Time

Through the analysis of Figure 3, it can be clearly found that the number of various sanction policies shows an increasing trend, especially after 2020, the number of sanctions has increased sharply. Among them, the number of financial and trade sanction policies has been higher than that of other types of sanctions for a long time. The growth rate of travel sanctions is relatively high, and the gap between the number of these three types of sanctions and other types is becoming larger and larger. This indicates that military sanctions are not the mainstream type of sanctions, and it reflects that non - military means of sanctions have become the mainstream in the current world development.

4.2.2 Correlation analysis between sanction types and sanction results

Based on the information in the dataset, we first analyze the correlation between sanction types, the correlation between sanction types and sanction results, and the correlation between sanction results. By calculating the correlation indicators of each statistical indicator, Figure 4 can be obtained.

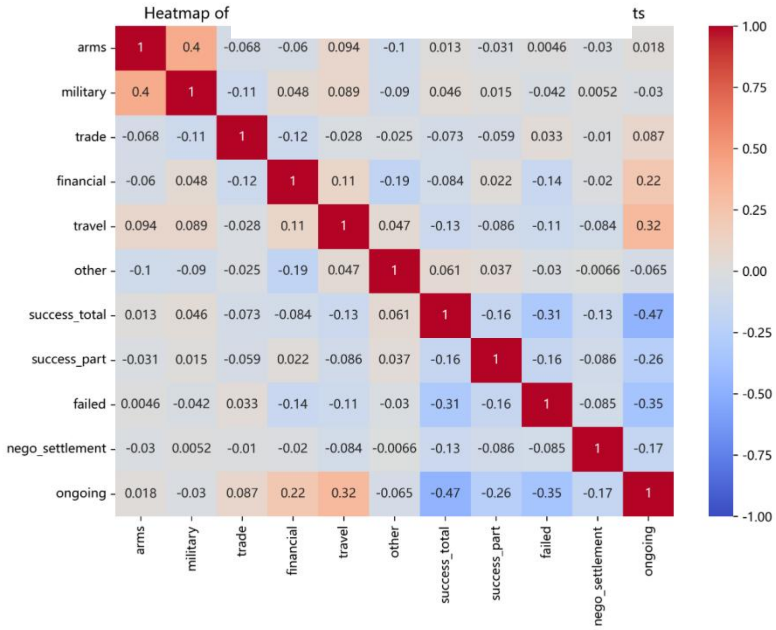

Figure 4 Correlation Heatmap of Sanction Types and Sanction Results

The absolute values of the correlations between the various attributes shown in Figure 4 are all less than 0.5, and most of them are between - 0.2 and 0.2. It is worth noting that intuitively, arms sanctions (arms) and military sanctions (military) should have a strong correlation, but the data shows that the correlation is only 0.4. There is no obvious negative correlation between cases where the sanction result is failure (failed) and those where it is success. The absolute value of the correlation between ongoing sanctions (ongoing) and other indicators is higher than 0.2 for the most attributes, but it is still difficult to summarize obvious rules through simple correlation analysis. Focusing on the sanction results of the three types of sanction policies, namely financial, trade, and travel visa sanctions, it is found that there is no obvious difference from the sanctions in other fields. Therefore, it is difficult to study the relationship between different sanction policies and sanction results only through correlation analysis.

4.2.3 Relationship between sanction measure combinations and success rate

To discuss the effect of the combined use of 6 types of sanctions, namely trade, arms, military, financial, travel visa, and other sanctions, we have drawn Figure 5. Figure 5 shows the correlation analysis between the combined use of different types of sanctions and the impact of sanctions. It can be seen from the figure that when multiple types of sanctions are used in combination, their correlation is less than 50%.

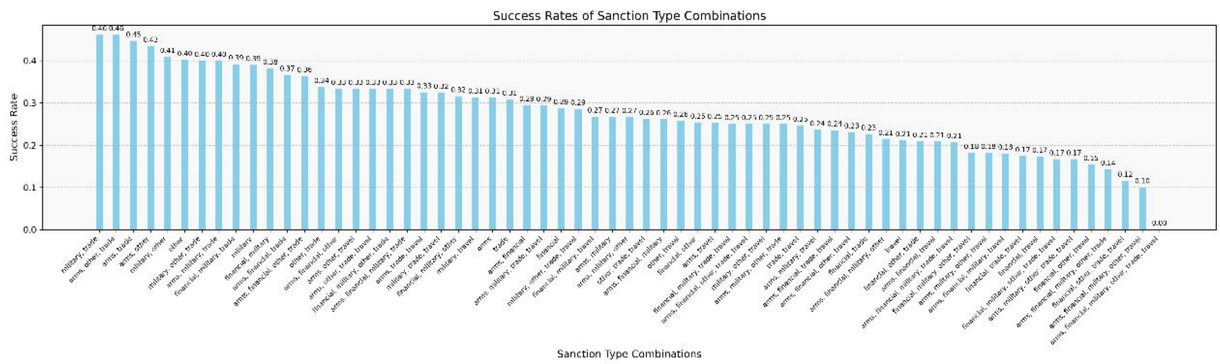

Figure 5 Correlation Between Combined Use of Sanction Types and Their Success Rates

Based on the above discussion, it is difficult to accurately judge the effect of sanctions through simple data analysis methods. Therefore, machine learning methods are introduced to predict the effect of sanctions.

4.3 Sanction Effect Prediction Based on Machine Learning

This scheme adopts a fully connected neural network to predict the effect of sanctions. To further discuss the performance of the network designed in this paper, in addition to the network structure shown in Figure 2 (referred to as ANN1 for short), a comparative experiment is also designed in this section. That is, the parameter of the output layer is set to 1, and the 5 different sanction results are judged respectively, while other network parameters remain unchanged (referred to as ANN2 for short). The accuracy of the two different neural networks in predicting the five different sanction results is counted, as shown in Table 3.

Table 3 Performance Comparison of Two Different Neural Networks

	Accuracy of Y1	Accuracy of Y2	Accuracy of Y3	Accuracy of Y4	Accuracy of Y5	Average accuracy
ANN1	0.75	0.931818	0.80303	0.939394	0.977273	0.880303
ANN2	0.704545	0.795455	0.780303	0.848485	0.931818	0.812121

It can be seen from the data in the table that the accuracy of predicting sanction results using artificial neural networks is far higher than that of traditional correlation analysis methods. Comparing the results of ANN1 and ANN2, the accuracy of ANN1 is higher than that of ANN2 in predicting each indicator, which indicates that the prediction method proposed in this paper has a good prediction effect on the whole.
True Prediction (TP) is defined as the case of correct prediction, False Positive (FP) as the case of predicting 0 as 1, and False Negative (FN) as the case of predicting 1 as 0. The numbers of FP, FN, and TP obtained from the results of the two different network structures in the experiment are counted, as shown in Table 4.

Table 4 Different Neural Networks

	ANN1	ANN2
FP	34	67
FN	45	57
TP	581	536

It can be intuitively concluded from Table 4 that ANN1 has fewer prediction errors, and is superior to the other network structure in terms of FP, FN, and TP.
Based on the above experimental results, this section also counts the number of samples in the test samples where all output parameters (Y1 - Y5) are predicted correctly. The number of prediction error indicators obtained by the two network models is counted, as shown in Table 5.

Table 5 Number of Prediction Error Indicators

Number of Prediction Error Indicators	0	1	2	3	4	5
ANN1	86	17	25	4	0	0
ANN2	59	37	24	9	3	0

A number of 0 prediction error indicators means that the prediction of the sanction result is completely correct. The results in Table 5 show that:
(1) Among the total 132 test samples, 86 are completely correctly predicted by ANN1, with a complete accuracy rate of 65.152%; only 59 are completely correctly predicted by ANN2, with a complete accuracy rate of 44.697%. This indicates that when using this method for complete prediction, ANN1 is still superior to ANN2, but there is still room for improvement in prediction accuracy.
(2) By comparing the prediction error samples of ANN1 and ANN2 one by one, it is found that except that the number of errors of ANN1 is 1 more than that of ANN2 when the number of prediction error indicators is 2, ANN1 is superior to ANN2 in other cases (the number of prediction error indicators is 1, 3, 4).
(3) By analyzing the prediction error samples of ANN1 and ANN2, it is found that in most samples, only 1 or 2 of the five output variables are predicted incorrectly, which indicates that there are very few cases of complete prediction errors. In future research, the prediction accuracy can be improved by fine - tuning the prediction model.

5 CONCLUSION AND OUTLOOK

Aiming at the problem of predicting the effect of sanctions between countries or organizations, this paper creatively proposes a data - driven effect prediction method. Firstly, after fully understanding the relevant characteristics of the formulation of inter - national and inter - organizational sanction policies, a number of pieces of information related to the policies are sorted out. Secondly, this information is quantified, and data are used to describe the characteristics of this information. Thirdly, a neural network is designed to predict the effect of sanctions based on historical statistical data, and the feasibility and effectiveness of the method are verified through experiments.

This paper is only a preliminary attempt to apply AI technology in the field of strategic sanction effect prediction and has achieved good results. However, there are still the following directions for further exploration: (1) Design a deep neural network structure more suitable for such problems to improve the prediction accuracy. (2) Introduce more input information, such as discussing the relationship between the strength of the sanction - imposing and sanctioned parties and the sanction results, and the measures taken by the sanctioned parties to resist the sanctions.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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