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Multimodal high-dimensional heterogeneous Transformer deconstructs the nonlinear cascading effects and dynamic chain reactions of global trade networks.

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Abstract Under the current development trend of global economic integration, countries around the world are interconnected and influenced by each other in international trade, and the connection of world trade forms a complex network. This paper constructs a global trade network based on global trade theory and social network analysis theory, and selects indicators such as the number of network nodes and network diameter to characterize the topological structure of the global trade network. The Transformer model is designed based on the gating mechanism unit and dynamic attention mechanism to analyze the multimodal, high-dimensional and heterogeneous global trade time series data. The empirical analysis finds that the characteristics of the global trade network structure change over time, the trade network between countries and regions becomes more and more close, and there is an impulse effect of the country's GDP and other influencing variables on the structure of the global trade network. This paper reveals the multi-path influence effect of global trade network through empirical analysis, and improves the related research on the structural change and positive evolution of global trade network, with a view to providing useful reference and guidance for the formulation of national trade countermeasures.

Index Terms transformer model, attention mechanism, gating mechanism, impulse response, global trade network

I. Introduction

Since the middle of the 20th century, the international trade pattern has been continuously diverging, which is manifested in the multipolarization of international trade development and the continuous rise of developing countries, and the global trade network shows a strong heterogeneous distribution, including the distribution of the total trade volume of each country, as well as the distribution of the number of trading partners of each country [1], [2]. However, until 2012, the U.S. had occupied the position of a core trade country, being the largest trading partner of the largest number of countries and regions in the world [3]. Since the 21st century, the global trade network structure has undergone two important changes: first, China has gradually replaced Japan's trade “core” position in the Asian region [4]. Secondly, China has become the largest trading partner of Japan, South Korea and other major trading countries in the Asian region, the United States as the core of the global trade network structure is gradually replaced by China, the United States, Germany and the three countries dominated by the new global trade structure, the global trade pattern is undergoing profound changes [5].

The global trade network is composed of transactions between individual countries, each country is regarded as a node in the system, and the trade relations between individual countries constitute the connecting edges of the network [6]. In order to adapt to the rapid development of global economic integration, more and more countries and regions are integrated into the network of trade liberalization. The emergence of international trade cooperation organizations from the World Trade Organization, the Economic Cooperation Organization, and the Asia-Pacific Economic Cooperation in the 20th century to the Trans-Pacific Strategic Economic Partnership, the Regional Comprehensive Economic Partnership, and the Transatlantic Trade and Investment Partnership Agreement in the 21st century has led to the formation of a huge and complex economic network between countries through trade exchanges [7]-[10]. Truly economically powerful countries will seek to harmonize and match and synchronize their financial market influence with their trade position in the international arena [11]. Unlike traditional manual connections, online trade is more convenient and faster, allowing many people to trade internationally more easily. China has also taken a series of measures to steadily build a global FTA network, and has signed 19 FTAs with 26 countries and regions by 2022, and the proportion of FTA partners in China's foreign trade has increased from 12.3% in 2012 to 35% [12], [13]. The evolutionary trend of the global trade network in many ways is consistent with the process of globalization, international experience shows that production, trade dependence, distance, cultural similarity, and political relations are the main determinants of determining the member countries of the FTA, and these factors also reflect the intricate trade network relationships in the current world economic system [14]-[17]. It can be seen that in the context of trade cooperation, the deepening of the division of labor and the formation of the global trade network, the country's trade position in the global network is particularly important. However, the international situation is changing, regional conflicts continue to escalate, trade protectionism, unilateralism, emerging economic powers injected, the pattern of the game of the countries to further intensify [18]-[21].

With the United Kingdom's exit from the European Union and the United States and China trade friction, the phenomenon of “anti-globalization” is becoming increasingly obvious, coupled with the new crown pneumonia epidemic in 2020, a serious impact on the process of globalization [22]-[24]. At the same time, emerging technologies such as the development of spring, reshaping the shape of economic development, emerging market economies and the group rise of developing countries is contributing to the shift in the center of gravity of the world economy, scientific and technological innovation, economic changes in the long term, which in turn promote the continuous adjustment of the international trade pattern [25]-[28]. Therefore, in the context of changes in the international trade pattern, analyzing the intrinsic mechanism of the global trade network and the evolution of the law, measuring the multimodal, high-dimensional data, heterogeneity of the network under the emerging characteristics of the country and the mutual influence of foreign trade, will help to correctly locate the country's trade position and influence, to grasp the opportunities brought about by the restructuring of the international trade pattern, so as to optimize the trade structure and enhance the competitive advantage of trade.

In the analysis of global trade networks, many scholars have gone forward and adopted different advantageous analytical tools to study various types of global trade networks. Literature [29] explored the evolution of the international trade network of automobiles, and the change of trade structure of regionalization of automotive parts and components and its associated impacts through the descriptive network measurement method. In the analysis of global trade networks, the social network analysis method is usually used to measure the characteristics of global trade networks. And in literature [30], the social network analysis method was used to analyze the financial flows between countries in the international trade network, the frequency of transactions, and obtain the core countries and the countries that benefit the most from the trade network. Literature [31] focuses on the main connectivity characteristics and trade dynamic process of countries in the world trade network according to the network analysis method, which is characterized by clustering, and the characteristics were not affected by the international financial crisis in 2008, but this crisis became a turning point in the evolution of the trade network. Differently, literature [32] used network analysis to explore the structural characteristics and spatio-temporal dynamics of grain trade network among countries along the “Belt and Road”, presenting a core-edge structure, with India, Russia and Ukraine as the absolute core nodes. In addition, the exponential random graph model, based on random graph theory, has the advantage of simulating the connection between nodes and the information dissemination process in the network. For this reason, the literature [33] has been curious about the differences in export patterns of core and edge nodes in the global trade network, using the exponential random graph model, whose high and low technological products lead to significant differences in exports. Literature [34] explored the relationship of countries in the structure of the global wheat trade network through descriptive and statistical inference methods and captured the determinants of their relationship with an exponential random graph model. Literature [35] analyzed the spatial correlation among countries in the global rare earth trade with the global Moran index, analyzed the influencing factors and evolution law of the trade network with the time-exponential random graph model, and analyzed the response of the trade network structure to the network topology with the network modal analysis, which together revealed the structure of the global rare earth trade network, the intrinsic mechanism, and the evolution law.

In recent years, complex network analysis has been widely used by academics, which is a graph structure composed of nodes and edges, and models and analyzes the structure and dynamic behavior of complex networks through its degree distribution, clustering coefficients, modularity and other features. Literature [36] created a complex network model of global coal trade during 1996-2015 based on the complex network analysis method, focusing on the characteristics of the evolution of this network under continuous time series and multi-angle comparisons, and the global coal trade presents scale-free characteristics. And literature [37] used the complex network analysis method to explore the global agricultural trade network evolution process, and in the cumulative distribution function curve to obtain the trade trend direction, the total trade growth is significant, with the largest increase in oil crops, but there is an import risk. Literature [38] carries out all-round analysis of the international agricultural trade network transaction mode, specifically, designing the international agricultural trade network according to the complex network theory, analyzing the import sources of each node and the position of the node in the network through the Herfindahl-Hirschman index and the network indexes, and then discovering the response of the transaction mode in the trade network to the country risk by the layout regression method.

In complex network analysis, community detection, dynamic tracking, and anomaly detection are commonly used methods to reveal hidden groups and organizations in the network, reveal dynamic change patterns in the network, and discover anomalous patterns and potential threats in the network, respectively. For example, literature [39] uses anomaly detection to model and analyze the complex phenomenon of dynamic wireless features of entities and cascading of dynamic features in a network using social networks as objects. In trade networks, literature [40] analyzes the topological relationship between different trade communities in the global trade network under the "Belt and Road" initiative with a community detection algorithm, where China is the core of the community in the "Belt and Road" trade network and Europe is the center of the global trade network. The "Belt and Road" trade network is centered on China and the global trade network is centered on Europe. Literature [41] analyzed the global e-waste trade network by graph theory method, mainly based on the United Nations Commodity Trade Statistics Database (UN Comtrade), utilized the Springlass community detection algorithm to generate the community trade network on the annual trade data, compared the multifactorial and multilevel country clusters, and evaluated the key factors affecting the trade network by random effect linear regression method. Literature [42] constructs a visualization and analysis framework of spatio-temporal global trade networks, which is realized by anomaly detection, network analysis and spatio-temporal visualization methods to obtain the characteristics of global trade networks and their correlation with regional conditions under spatio-temporal dynamics.

However, with the gradual deepening of global economic integration, the global trade network has become more complex, showing complex and diverse new characteristics such as multimodal, high-dimensional, and heterogeneous [43]. It is difficult for these traditional analytical methods to accurately and comprehensively capture these characteristics, and a new analytical tool is urgently needed to capture these characteristics and analyze the complex relationships in the global trade network.The Transformer model is a neural network model that utilizes a multi-layer information fusion and a white-adaptive learning mechanism to generate the final output, and its main idea is to convert the input sequences into vectors, and encode and decode the inputs using a multi-layer Transformer structure. Transformer structure for encoding and decoding, thus it has the advantages of handling multimodal data, capturing long-term dependencies, and parallel computing [44]. Applying the Transformer model to the analysis of multipath effects in global trade networks can reveal the complex internal mechanisms and evolutionary laws of global trade networks, while structuring the nonlinear cascades and dynamic chain reactions therein.

In this paper, global trade theory and complex network theory are taken as the theoretical basis of the research, and network scale, network density and clustering coefficient are used as the feature indicators to analyze the overall network characteristics and specific topological features of the global trade network. Subsequently, based on the Transformer algorithm, the TFT model is designed to analyze the multimodal, high-dimensional and heterogeneous time series data in the global trade network, the gated residual network is introduced into the model to improve the processing performance of the nonlinear data, and the multi-head dynamic attention mechanism is embedded to realize the analysis and prediction of the time series data in the global trade network. Finally, we analyze the evolution of global trade network size and structural characteristics, and then test the path effect of GDP and other variables on the global trade network through the impulse response model.

II. Theoretical foundations

II. A.Global trade theory

Global trade theory [45] has gone through four stages in its more than 200 years of research history, classical trade theory, neoclassical trade theory, new trade theory and new neo-trade theory. In the 1870s, Adam Smith put forward the theory of international division of labor and free trade in his representative work, "An Inquiry into the Nature and Causes of National Wealth", and created the theory of absolute advantage, becoming the free trade theory's the founder of the theory of free trade. Thereafter, David Ricardo put forward the famous theory of comparative advantage in his Principles of Political Economy and Taxation published in 1817, which was greatly respected by the mainstream of international trade research. It can be said that the theory of comparative advantage is the inheritance and development of the absolute cost theory, which further improves the classical trade theory. In a certain period of time, the classical trade theory has become the main theoretical basis for foreign trade of all countries in the world. Until today, this theory still provides an important theoretical basis for the formulation of foreign trade policies of many countries, especially developing countries.

With the further in-depth development of the international division of labor and trade, import and export enterprises play an extremely important role in international trade. The research focus of classical trade theory, neoclassical trade theory and new trade theory is based on macro and meso countries or industries, and seldom pays attention to the reality of micro enterprises directly engaged in trade activities. Since entering the 21st century, some economists have concluded through a large number of empirical analyses that there is significant productivity heterogeneity between exporting enterprises and non-exporting enterprises and other related conclusions. These studies have provided a solid theoretical foundation for the proposal of the new new trade theory. It mainly focuses on three research directions, enterprise product quality differences, product diversification and intra-firm trade. Starting from the heterogeneity of enterprises, the new new trade theory proves that free and open trade is conducive to raising the productivity level of a country's industry, and also reflects the dominant role of multinational corporations in international trade.

Global trade theories evolve with the development of trade practices, and the theories of various eras are well suited to and explain the trade phenomena and characteristics of the time. For example, the comparative advantage in classical trade theory and the factor endowment in neoclassical trade theory can explain the inter-industry trade in the initial stage of international trade. The dynamic comparative advantage brought about by economies of scale and imperfect competition emphasized by the new trade theory can well explain the expanding intra-industry trade. And the new neo-trade theory explains new phenomena such as associated trade and intra-product trade within multinational enterprises in terms of enterprise heterogeneity.

II. B.Complex Systems Theory

Global trade networks are typically complex systems. In the global trade network, there are extremely complex game relations between countries as the basic components, and the strong development capacity of countries to broaden the space of activities and even have an impact on the global trade network, which make the complexity of the global trade network is much higher than the physical system.

The complex system of the global trade network is a system composed of a large number of interacting, interdependent components with unpredictable system behavior. These components can be simple or complex, and their interactions and dependencies are highly complex, thus making the properties, behaviors and nature exhibited by the system as a whole difficult to accurately predict and understand. Complex systems are usually not composed of a single component or parts, but are formed by complex interactions in which each part has its own dynamic properties and is in turn affected by the dynamic properties of other parts. In nature, many systems are complex systems, such as climatic, biological, and geological systems. In the social field, economic systems, urban systems, etc. are also typical representatives of complex systems. The characteristics of complex systems such as multiple circuits, multiple inputs, and multiple outputs lead to the high complexity and diversity of system behaviors, which makes them different from the simplicity and predictability of general simple systems [46]. At the same time, complex systems are also characterized by nonlinearity, uncertainty, self-similarity, openness, multi-temporality, internal and external perturbations, chaotic phenomena and dynamic structure. Among them, openness, dynamics, adaptivity and nonlinearity are the most essential features of complex systems. Openness is mainly manifested in the fact that complex system is an open system interacting with the environment, and maintains its own homeostasis by exchanging energy, material and information with external system and environment, and this openness makes the complex system adaptive and evolutionary, and able to adapt and adjust dynamically with the external environment. Dynamics is mainly manifested in the complex system is a system with change and dynamics, its behavior and state can be with the passage of time and constantly changing, constantly evolving, the interaction and feedback between the components of the complex system, as well as changes in external inputs can lead to corresponding changes in the behavior and state of the system. Nonlinearity refers to the property that the nature of a part or the whole of a complex system cannot be described by a linear mathematical model. Because of the nonlinear interactions between the parts of a complex system, the behavior of the system as a whole is unpredictable and tends to produce nonlinear effects that do not satisfy the superposition principle. This characteristic is the cause of the uncertainty and diversity of complex systems, but also provides rich possibilities for the dynamics and evolution of complex systems, and nonlinear interactions are the key markers for distinguishing between simple and complex systems, as well as one of the most essential characteristics of complex systems. The system consists of interacting individuals, which have the ability of self-adaptation and self-organization, etc. Through interaction and communication with the outside world and other individuals, it can continuously learn and adapt to the environment, and adjust its state and behavior according to different situations. Adaptivity allows for a high degree of complexity in the behavior of the system, and this complexity is driven by interactions and adaptations within the system rather than simply accruing to the behavior of a single individual, and adaptivity allows individuals to adapt to changes in uncertain and dynamic environments, leading to more complex system behaviors, and ultimately, this adaptivity promotes the evolution and continuous development of the system. Adaptivity helps to improve the dynamics and controllability of the system, allowing the system to dynamically adjust and adaptively change as needed to adapt to the ever-changing environment. It can be seen that openness, dynamics, self-organization and non-linearity are the most essential features of complex systems, and these features are interconnected and interact with each other, making complex systems able to adapt to environmental changes, spontaneously generate orderly structures and behaviors, and present diverse and complex behavioral patterns.

II. C. Global trade network construction and analytical methods

II. C. 1) Trade network construction

Using the social network analysis method, the complex network of global trade is constructed by industrial chain, and the evolution of the network is analyzed through characteristic indicators. The global trade network is divided into a physical network and a logical network, and the logical network is an abstracted network from the actual visual transportation network, and this study only considers the logical network based on trade data. By selecting countries as the "nodes" of the network, the import-export relations between countries as the directed "edges", and the weighted trade volume as the edge weights, the directed and unentitled networks and the directed weighted networks of global trade are constructed respectively, the unentitled networks can show the connection modes and network topologies between nodes, and the weighted networks can reflect the characteristics of the interrelationship and strength of trade links. The constructed network is represented as $G=(N,S,A,W)$, where $N=\left(n_1,n_2,\ldots,n_j\right)$ represents the countries participating in the trade, i.e., the "nodes". $S=\left\{s_{ij}\right\}$ indicates the relationship between trading countries, i.e. "edges". $A=A(t)$ is the unentitled, adjacency matrix. $W=w(t)$ is the entitlement adjacency matrix.

In a directed unweighted network, if node i does not trade with node j in year t, then $a_{ij}(t)=0$. If node i trades with node j in year t, then $a_{ij}(t)=1$. Eq:

$$A(t)\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \cdots & \cdots & \cdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix}$$
$$a_{ij}=\begin{pmatrix} 1 & \text{If there is trade between node } i \text{ and node } j \\ 0 & \text{If there is no trade between node } i \text{ and node } j \end{pmatrix} \tag{1}$$

In the above equation, n is the number of network nodes, i.e., the number of countries/regions participating in global trade. a_{ij} is the number of edges of node i pointing to node j, i.e., the number of global exporting countries/regions of node i. a_{ji} is the number of edges pointing from node j to node i, i.e., the number of global importing countries/regions at node i.

In a directed weighted trade network, w_{ij} is represented by the value of import/export trade between node i and node j, i.e.:

$$w_{ij}=\left(e_{ij}+m_{ji}\right)/2 \tag{2}$$

In the above equation, e_{ij} is the export value of node i to node j and m_{ji} is the import value of node j to node i.

II. C. 2) Network Characterization Methods

In this study, the overall network characteristics of the global trade network are portrayed through indicators such as network size, network density, clustering coefficient, average path length, network diameter and small world index.

(1) Node in-degree and out-degree

The degree of a complex network node K_i refers to the number of connecting edges that exist between the node and other nodes, and in directed complex networks, the degree of a node can be further categorized into in-degree K_i^{in} and out-degree K_i^{out} based on the direction of the connecting edge arrows. By adding the consideration of connected edge weights w_{ij} and w_{ji}, the in-degree and out-degree of a node can be expanded to weighted in-degree WK_i^{in} and weighted out-degree WK_i^{out}, respectively. Equations are given below:

$$K_i=K_i^{in}+K_i^{out} \tag{3}$$

$$K_i^{in} = \sum_{j=1}^{N} a_{ji}; \left(a_{ji} \in \{0,1\}, i \neq j\right) \tag{4}$$

$$K_i^{out} = \sum_{j=1}^{N} a_{ij}; \left(a_{ji} \in \{0,1\}, i \neq j\right) \tag{5}$$

$$WK_i^{in} = \sum_{j=1}^{N} w_{ji} a_{iji}; \left(a_{ji} \in \{0,1\}, i \neq j\right) \tag{6}$$

$$WK_i^{out} = \sum_{j=1}^{N} w_{ij} a_{ij}; \left(a_{ij} \in \{0,1\}, i \neq j\right) \tag{7}$$

where N is the total number of nodes in the network, $a_{ij} = 1$ when there is a connecting edge from node i to node j, otherwise $a_{ij} = 0$. $a_{ji} = 1$ when there is a connecting edge from node j to node i, otherwise $a_{ji} = 0$.

In a global trade complex network, the degree of a node represents the total number of trade objects of the node country (region) in that kind of trade. Correspondingly, the in-degree of a node refers to the number of importing source countries of that node, and the out-degree of a node refers to the number of its export objects. For a node country (region) involved in international trade, the greater the degree of its node, the more trading partners it has in the network, and the greater its structural influence in the network accordingly.

(2) Degree distribution of network nodes

The degree distribution of a complex network is an overall description of the number of degrees of all nodes in the network. For random networks, the degree distribution of the network refers to the distribution probability of the degree of the nodes in the graph, and for fully connected complex networks, the degree distribution of the network is the average distribution. The degree distribution of complex network models based on real data is generally scale-free, the connectivity between nodes is severely uneven, a few nodes have larger degree fingers, while most nodes have smaller degree values, and thus their degree distribution is severely right-skewed or left-skewed (depending on the axes). By portraying the degree distribution of complex networks, the network structure characteristics can be analyzed macroscopically.

(3) Degree centrality of nodes

In the research related to the importance of nodes in complex networks, scholars have proposed a variety of indicators for evaluating the importance of nodes based on the topological structure of nodes in the network. The degree centrality of the base C_i is calculated as the ratio of the degree k_i of the node to the degree of the node's theoretical existence in the network (i.e., the degree when the network is fully connected), $C_i = k_i / N - 1$, where N is the total number of nodes in the network.

The centrality of a node measures the relative connectedness of the node in the network. The centrality of nodes can be ranked by comparing the centrality calculation results of each node horizontally. Applied to the study of global trade network pattern, the centrality of nodes shows the trade closeness of nodes to a certain extent, and the higher the centrality of nodes, the greater their contribution to the topological stability of the trade network.

(4) Median centrality of nodes

Based on link analysis of complex networks, the other main metric for node importance is the median centrality of a node. The median centrality $c_B(v)$ of a node v is defined as the proportion of times the node occurs in all shortest connection paths in the network. A node with high median centrality plays an important role in mediating the connectivity of links in the network, and the smooth flow of a large number of paths depends on the effective mediation of this node. The calculation formula is:

$$c_B(v) = \sum_{s,t \in \mathrm{V}} \frac{\delta(s,t \mid v)}{\delta(s,t)} \tag{8}$$

where V is the set of nodes, $\delta(s,t)$ is the number of shortest paths between all pairs of nodes, and $\delta(s,t \mid v)$ is the number of shortest paths through all nodes v.

III. Prediction of high dimensional data based on Transformer structure

III. A. Model Architecture

In this paper, based on the Transformer algorithm [47], we propose a TFT model suitable for analyzing multimodal, high-dimensional and heterogeneous data in the global trade network to analyze and predict various types of complex time series economic data in the global trade network, the TFT model architecture is shown in Fig. 1, and the main structural principles of the model are introduced as follows.

(1) Gating Mechanism

Skips any unused components of the architecture, providing adaptive depth and network complexity to accommodate a wide range of datasets and scenarios.

(2) Variable selection network

Selects relevant input variables at each time point within the step range.

(3) Static covariate coding

Integrate static features into the network to regulate temporal dynamics through encoding of contextual environment vectors.

(4) Temporal Fusion Processing

Learning long-term and short-term temporal relationships from the input data, a sequence-to-sequence layer is used through local processing, while long-term dependencies are recognized by an interpretable multi-head attention module.

(5) Output module of prediction

Determine the range of target values by quantile prediction.

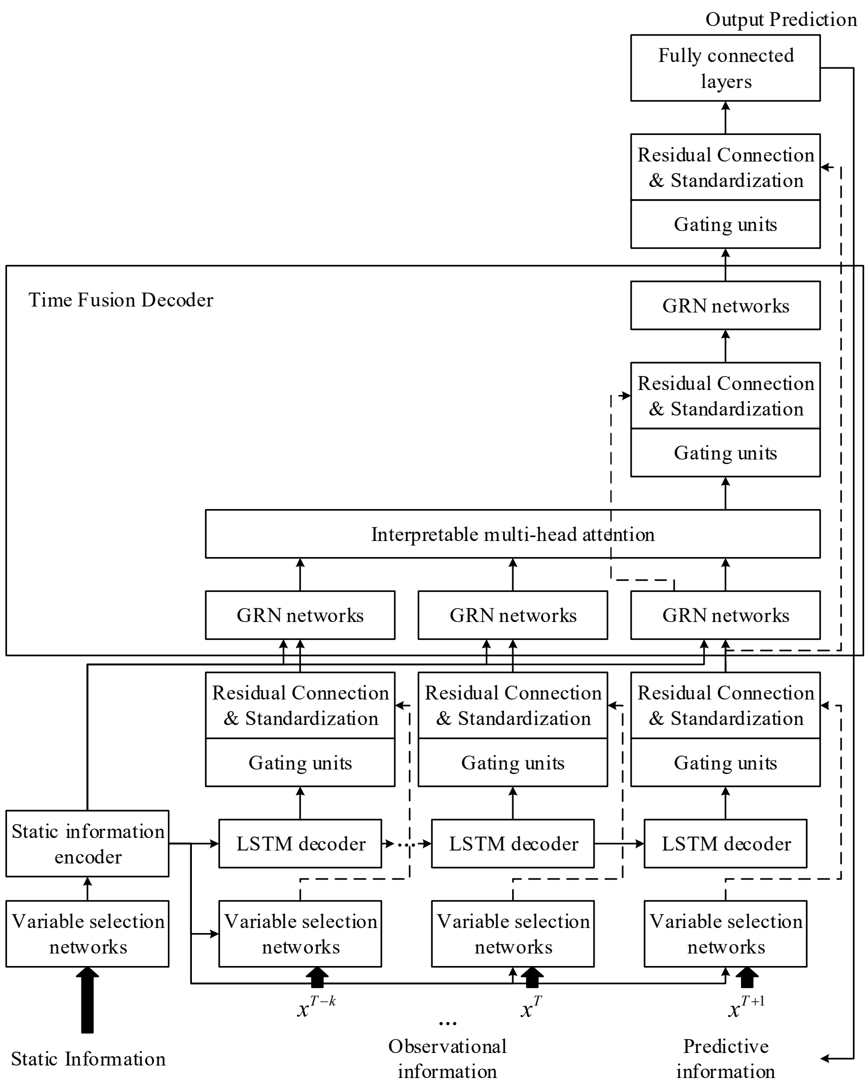


Figure 1: Space time fusion converter model structure

III. B. Module Unit Design

III. B. 1) Gate control mechanisms

When building predictive models based on multimodal, high-dimensional, and heterogeneous Transformer structures, researchers do not know in advance the exact mapping relationship between explanatory and interpreted variables, thus making it difficult to determine in advance the degree of nonlinear treatment between indicators, and many related studies have illustrated that modeling effects do not necessarily improve with increasing complexity. In order to make the model can be more flexible, rather than forced to use the determined nonlinear treatment. Therefore, the gated residual network (GRN) [48] is proposed in this paper and used as a central part of the TFT structure.

Let the inputs of the gated residual network be a and c, then:

$$GRN_{\omega}(a,c) = layerNorm\left(a + GLU_{\omega}\left(\eta_1\right)\right) \tag{9}$$

$$\eta_1 = W_{1,\omega}\eta_2 + b_{1,\omega} \tag{10}$$

$$\eta_2 = ELU\left(W_{2,\omega}a + W_{3,\omega}c + b_{2,\omega}\right) \tag{11}$$

where ELU is the exponential linear activation function, $layerNorm$ represents the layer normalization operation, and ω represents the index of shared weights.

In order to suppress non-essential model substructures from having an impact on the overall model operation, TFT introduces the GLU setting. Let $\gamma \in \mathbb{R}^{d_{model}}$ be the information input, then GLU can be defined as:

$$GLU_{\omega} = \sigma\left(W_{4,\omega}\gamma + b_{4,\omega}\right) \odot \left(W_{5,\omega}\gamma + b_{5,\omega}\right) \tag{12}$$

where $\sigma(\cdot)$ represents the sigmoid activation function and $\odot$ the Hadamard product.

Thanks to the introduction of the GLU, the TFT can capture the degree of control that the GRN has over the original input variables: if necessary, the model can even skip the layer altogether to suppress the degree of nonlinearity, since the GLU output can be close to 0. Without external environment vectors, the GRN can be set directly in Eq. (11) $c = 0$. For training, an intermediate exit setting can also be added between Eq. (9) and Eq. (10).

III. B. 2) Variable selection network

Let $\xi_t^{(j)} \in R^{d_{model}}$ be the transformation of the j nd variable at moment t, then $\Xi_t = \left[\xi_t^{(1)T}, \cdots, \xi_t^{(m_\chi)T}\right]^T$ is the vector of all input combinations at moment t after beat flat processing. In GRN network input Ξ_t and external environment vector c_s will get a variable selection weight after processing by Softmax function. The formula is:

$$v_{\chi t} = Soft\max\left(GRN_{v_\chi}\left(\Xi_t, c_s\right)\right) \tag{13}$$

where v_{χ_t} represents the variable selection weight vector, $v_{\chi_t} \in \mathbb{R}^{m_x}$, c_s are the environment vectors, and the environment vectors c_s are obtained by a static covariate encoder.

At each time point the input $\xi_t^{(j)}$ is processed into $\tilde{\xi}_t^{(j)}$ by a nonlinear GRN network as shown in Eq. (14):

$$\tilde{\xi}_t^{(j)} = GRN_{\tilde{\xi}_t^{(j)}}\left(\xi_t^{(j)}\right) \tag{14}$$

The final features are obtained by weighted summation of each variable with its variable selection weights, as shown in equation (15), where $v_{\chi_t}^{(j)}$ is the j rd element of $v_{\chi t}$:

$$\tilde{\xi}_t = \sum_{j=1}^{m_x} v_{\chi t}^{(j)} \tilde{\xi}_t^{(j)} \tag{15}$$

III. B. 3) Dynamic Attention Mechanisms

(1) Encoder and decoder

The model's masked multinomial attention [49] prevents it from learning about subsequent locations in advance of the prediction of a location word, which ensures that the prediction of location i can only rely on known output information for locations less than i . In the case of time-series forecasting of global trade data, this also means that the model cannot learn future information that has occurred after the point to be predicted that it should not have known when backtesting historical points in time.

Each layer in the encoder and decoder contains an independent and consistent fully-connected feed-forward network that consists mainly of two linear transformations and the ReLU activation function in between, as shown in the following equation:

$$FFN(x) = \max\left(0, xW_1 + b_1\right)W_2 + b_2 \tag{16}$$

(2) Attention weighting

A weight is calculated by multiplying Q by K and dividing by $\sqrt{d_k}$, followed by a Softmax function:

$$Attention\left(Q,K,V\right) = Soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{17}$$

It is more efficient to execute the attention mechanism several times in parallel and recombine it according to certain weights than to execute it only once. Because each head is assigned a different Q, K, V weight, a different Q, K, V matrix is obtained, as shown in the following equation:

$$MultiHead\left(Q,K,V\right) = Concat\left(head_1, \cdots, head_h\right)W^O \tag{18}$$

$$head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{19}$$

where $W_i^Q \in \mathbb{R}^{d_{model} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{model} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{model} \times d_v}$, $W_i^O \in \mathbb{R}_v \times d_{model}$.

IV. Empirical analysis of the multipath effects of global trade networks

IV. A. Data sources and selection

In order to more comprehensively analyze the overall and individual characteristics of the global trade network and its changes, so as to analyze the multipath effect of the global trade network. This paper analyzes the current major global trade databases by comparing and contrasting them, and finally selects UN Comtrade, the United Nations Commodity Trade Statistics Database. The reasons for the selection mainly include the following three aspects, first, UN Comtrade database includes all the trade and import and export data of up to 235 economies in the world that have been registered in the statistics from 1962 to 2024, which has a long time span and involves a large number of economies to meet the research demand. Secondly, the database is obtained annually through the collection of official trade data provided by more than 200 economies to the United Nations Statistical Office (UNSO), and the data are original rather than estimated, interpolated or otherwise processed, so the data are authoritative and scientific in nature. Thirdly, the database basically covers 99 per cent of global trade transactions and can effectively calculate the two-way flow of trade, and in terms of unit processing, the trade volume is uniformly denominated in United States dollars, which facilitates data processing.

In terms of data selection, the trade of all statistically registered economies with records of imports and exports is included in all calculations, without setting a threshold, so that countries with a low trade impact but of strategic importance to certain countries (such as some small-volume Pacific island countries and African countries, etc.) are taken into account, and the completeness of the global trade network can be better reflected. In addition, in the case of missing data on exports from one economy to another, the latter's imports to the former are used as a substitute, e.g., if there is missing data on imports from initiator country A to trading partner country B, the export data from initiator country B to trading partner country A is utilized to supplement the data using a reverse query. After processing, there may still be a small amount of missing data for individual countries, but since the missing countries generally have a small trade volume and are basically non-core countries, they basically do not constitute a major impact on the results of the study. The data used in this paper were downloaded from UN Comtrade as of January 31, 2024, and although the data for 2024 have been partially updated, the statistics are still incomplete, and the amount of missing data is large, so this paper selects the trade data from 1962 to 2023, a total of 62 years, to construct the global trade network.

IV. B. Characterization of global trade networks

IV. B. 1) Changes in the overall size of trade networks

(1) Results of network size analysis

The evolution of the size of the global trade network is shown in Figure 2, which shows that the number of countries and regions involved in the network is increasing in terms of the number of nodes. It increased from 150 nodes in 1962 to 235 nodes in 2023, indicating that more and more economies in the context of economic globalization are participating in the world market, establishing trade relations with other economies, and the scale of the network is expanding. In terms of the number of trade relations in the network, it increases from 10,280 in 1962 to 27,870 in 2023, with the number of trade relations edges increasing by a factor of 2.7. The number of connections in the overall network increases, and trade exchanges between countries and regions become closer.

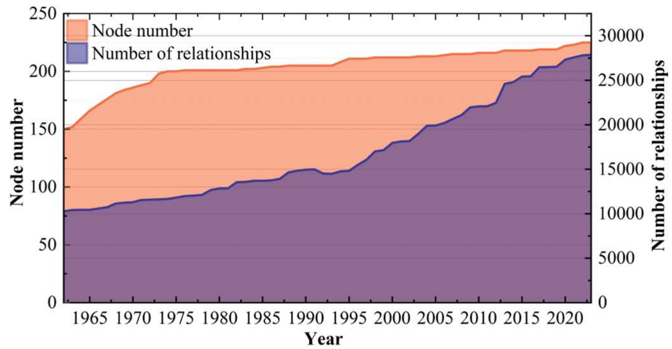


Figure 2: The overall scale of the global trade network in 1962-2023

Table 1: 1962-2023 global trade network density

Year	Network density	Year	Network density	Year	Network density
1962	0.3	1983	0.39	2004	0.36
1963	0.3	1984	0.39	2005	0.38
1964	0.3	1985	0.39	2006	0.38
1965	0.31	1986	0.4	2007	0.39
1966	0.31	1987	0.4	2008	0.39
1967	0.31	1988	0.4	2009	0.39
1968	0.32	1989	0.4	2010	0.4
1969	0.32	1990	0.29	2011	0.4
1970	0.33	1991	0.28	2012	0.4
1971	0.33	1992	0.23	2013	0.41
1972	0.33	1993	0.2	2014	0.42
1973	0.34	1994	0.25	2015	0.44
1974	0.34	1995	0.26	2016	0.44
1975	0.34	1996	0.27	2017	0.52
1976	0.35	1997	0.27	2018	0.53
1977	0.37	1998	0.28	2019	0.54
1978	0.37	1999	0.29	2020	0.56
1979	0.37	2000	0.29	2021	0.56
1980	0.38	2001	0.33	2022	0.56
1981	0.39	2002	0.34	2023	0.59
1982	0.39	2003	0.36	——	——

(2) Results of the analysis of changes in network density

The evolution of the global trade network density is shown in Table 1, and since 1962, the global trade network density has been on an overall increasing trend. It is mainly divided into two stages, the first stage is the slow increase before 1990, mainly due to the “Cold War” policy of the United States and the Soviet Union, which restricted the development of the global trade network and the freedom of trade. Although network density declined in the early 1990s, from 0.40 in 1989 to 0.20 in 1993, this is mainly attributed to the fact that between 1990 and 1993, major developed countries entered into an economic recession, and global trade was hit by the economic downturn. The second stage is 1993 (0.20) 2023 (0.59), the network density shows a rapid growth trend, each country (region) began to carry out economic reforms and open up to the outside world, and vigorously carry out foreign trade, the world's countries (regions) have existing trade relations of the highest nearly accounted for the potential trade relations of the whole 65%. Overall, the number and density of connecting edges are increasing, indicating that the economies in the global trade network tend to establish more links between each other, trade relations are deepening, and the degree of trade closeness between different countries and regions is on the rise. With the deepening internationalization of the division of labor, individual countries (regions) have formed a tightly connected community, which also means that the network as a whole will be less and less affected by changes in the economic cycle.

IV. B. 2) In-depth analysis of network topology characteristics

In order to deeply analyze the topological features of global trade network, firstly, the period of 2003-2023 is selected as the time period for in-depth study, which is divided into two identical time periods, i.e., 2003-2013 and 2013-2023, as well as three key time nodes, i.e., 2003, 2013 and 2023. Secondly, by building a complex network model, the trade network statistical characteristic quantities for 2003, 2013 and 2023 are calculated.The global trade network statistical characteristic quantities for 2003 are shown in Table 2, the global trade network statistical characteristic quantities for 2013 are shown in Table 3, and the global trade network statistical characteristic quantities for 2023 are shown in Table 4, and due to the limitation of space, the calculations are only retained for 18 countries. Based on the calculation results, it is found that the trend of “multipolarity” in global trade is becoming more and more obvious, showing a hierarchical development of “core-periphery”.

Table 2: 2003 global trade network statistics feature quantity

Country	Weighted strength center	Centrality	Proximity	Intermediate number center	Clustering coefficient	Eigenvector center
Germany	13926081	198	0.98	940.36	0.41	0.99
The UK	12528961	197	0.95	930.62	0.42	0.99
France	10364905	184	0.95	818.15	0.52	0.98
The United States	10009288	171	0.91	794.27	0.53	0.96
Switzerland	8390888	164	0.87	766.67	0.33	0.95
Belgium	7451516	160	0.86	651.1	0.26	0.93
Italy	7276928	159	0.78	613.18	0.5	0.92
Ireland	7081602	145	0.77	604.05	0.34	0.87
Netherlands	7069175	143	0.77	254.62	0.5	0.85
Sweden	6966866	136	0.77	423.03	0.56	0.81
Denmark	6845202	127	0.75	150.41	0.34	0.79
Spain	6009867	123	0.74	293.72	0.48	0.78
Japan	5635957	116	0.74	455.15	0.52	0.74
Japan	5124529	115	0.64	199.08	0.25	0.7
India	4504211	106	0.72	100.98	0.28	0.7
China	3665465	92	0.71	415.61	0.45	0.7
Greece	2230063	84	0.73	109.81	0.26	0.66
Israel	1968086	74	0.63	184.83	0.46	0.61

In order to facilitate the analysis of different network statistical characteristic quantities, the statistical characteristic indicators are divided into 3 parts, which are network size, small-worldness, and centrality, and the results of the in-depth analysis of the characteristic quantities of the global trade network topology in 2003, 2013, and 2023 are shown in Table 5, which is discussed in the following segments.

(1) Characterization of topology from 2003-2013

The total number of nodes in the global trade network grew from 213 to 218 during 2003-2013, indicating that the size of the network has expanded. The number of export nodes increased from 148 to 159, indicating an increase in the number of exporting countries or regions in the network. The density of the trade network increased from 0.2360 in 2003 to 0.410 in 2013, indicating that the nodes in the network are more closely connected to each other, which may mean that more countries or regions are involved in global trade. It can be concluded that the size of the global trade network has been expanding and its density has been increasing steadily from 2003 to 2013.The average path length of the global trade network has slightly decreased from 1.732 to 1.678 during the period of 2003-2013, but it is lower than that of the random path length during the same period, which suggests that the nodes in the network still have the short-path characteristics, even though the distances between them have been reduced. It can be concluded that the global trade network from 2003 to 2013 is characterized by high clustering coefficient and short average path length, and the network shows small-world nature. The average proximity centrality slightly increased from 0.5890 to 0.590, indicating that the number of neighboring nodes of the nodes in the network also increased, which suggests that the nodes have become more closely connected to each other, or it is because some more isolated nodes have been connected to the network. Overall, there were structural and compositional changes in the global trade network from 2003 to 2013, and although the overall connectivity and density of the network increased, the importance of certain nodes may have declined, while trade relations between some countries or regions were strengthened, reflecting the dynamics of the global trade market and the occurrence of inter-country or inter-regional trade relations Changes.

Table 3: 2013 global trade network statistics feature quantity

Country	Weighted strength center	Centrality	Proximity	Intermediate number center	Clustering coefficient	Eigenvector center
Germany	6951763	108	0.91	563.86	0.97	0.95
The UK	28961296	119	0.88	546.78	0.96	0.92
France	41155567	162	0.73	742.08	0.92	0.91
The United States	76166160	140	0.75	122.2	0.91	0.89
Switzerland	57004627	114	0.88	594.98	0.87	0.88
Belgium	8711199	90	0.82	607.65	0.86	0.85
Italy	10845393	148	0.65	169.91	0.85	0.85
Ireland	60745754	188	0.92	185.76	0.85	0.84
Netherlands	22533965	155	0.75	137.96	0.82	0.8
Sweden	78990766	100	0.72	302.63	0.8	0.79
Denmark	42529722	174	0.97	640.28	0.8	0.78
Spain	61905094	102	0.81	340.07	0.77	0.77
Japan	74492386	153	0.76	283.7	0.75	0.77
Japan	57374148	120	0.66	443.71	0.74	0.72
India	85748960	93	0.96	281.12	0.74	0.69
China	43193103	99	0.81	685.21	0.73	0.66
Greece	52290906	188	0.72	659.99	0.72	0.63
Israel	25237540	100	0.77	247.77	0.7	0.61

(2) Characteristics of topology from 2013-2023

The total number of nodes and the number of export nodes in the size of the global trade network changed from 218 and 159 to 220 and 136, respectively, during the period 2013-2023, which indicates that although the size of the global trade network has expanded, the number of exporting countries or regions in the network has decreased. The network diameter stabilized at 3, indicating that the core nodes in the global trade network are more connected to each other, but the connections between more distant nodes remained unchanged. From the aspect of small worldliness, the average clustering coefficient slightly increases from 0.795 to 0.824, but it is higher than the random clustering coefficient in the same period, indicating that the nodes in the network are still characterized by high clustering coefficients, although the degree of closeness between the nodes has weakened. The average path length slightly decreases from 1.678 to 1.662, but is lower than the random path length in the same period, which indicates that the nodes in the network still have short path characteristics although the distance between them has decreased. From this, it can be concluded that the global trade network has high clustering coefficients and short average path length characteristics from 2013 to 2023, and the network continues to show small-worldness. From the results of the global trade network centrality feature analysis, the average degree centrality of the global trade network rises from 58.942 to 59.632, indicating that the connectivity of the nodes in the whole network (i.e., the number of nodes connected to other nodes) increases, and the overall connectivity and interaction of the network is also strengthened, implying that more countries or regions are involved in international trade. The average proximity centrality and eigenvector centrality slightly increased from 0.5900 and 2.112 to 0.598 and 2.635, respectively, indicating that the importance of the nodes and the number of neighboring nodes in the network have increased, that the nodes are more tightly connected to each other, and that the increase in the importance of certain nodes has made the trade closer and more intensive on a global scale. The average median centrality, although not much improved, also increased from 69.532 to 69.958, indicating that the average shortest path length between nodes increased, while certain nodes became less interactive with each other.

Table 4: 2023 global trade network statistics feature quantity

Country	Weighted strength center	Centrality	Proximity	Intermediate number center	Clustering coefficient	Eigenvector center
Germany	25496343	178	0.8	459.27	0.98	0.95
The UK	27578464	176	0.86	938.99	0.98	0.88
France	115776927	175	0.85	834.28	0.97	0.92
The United States	46445457	170	0.92	781.05	0.97	0.99
Switzerland	24032857	168	0.79	882.29	0.96	0.96
Belgium	94289646	167	0.79	756.34	0.95	0.98
Italy	110296327	165	0.82	715.41	0.95	0.99
Ireland	140711997	161	0.92	480.09	0.94	0.96
Netherlands	141908664	161	0.84	531.71	0.93	1
Sweden	114379812	159	0.85	287.96	0.92	0.95
Denmark	15835854	156	0.86	370.56	0.92	0.89
Spain	103162290	151	0.78	448.58	0.92	0.88
Japan	13476451	151	0.86	853.64	0.9	0.98
Japan	102105964	150	0.78	429.18	0.9	0.94
India	82067650	150	0.92	630.49	0.9	0.93
China	20713639	150	0.78	643.84	0.89	0.92
Greece	108992106	148	0.83	934.96	0.88	0.97
Israel	36219889	140	0.82	708.48	0.88	0.91

Table 5: The amount of presidential features of the global trade network

Statistical characteristics	Statistical index	2003	2013	2023
Network size	Total node number	213	218	220
	Exit number	148	159	136
	Side number	6598	7784	8265
	Density	0.360	0.410	0.590
	Network diameter	3	3	3.000
Small world	Average clustering coefficient	0.784	0.795	0.824
	Random clustering coefficient	0.533	0.549	0.597
	Mean path length	1.732	1.678	1.662
Centrality	Average degree	52.635	58.942	59.632
	Average proximity	0.589	0.590	0.598
	Eigenvector center	2.415	2.112	2.635
	Average number center	74.825	69.532	69.958

IV. C. Model Construction and Empirical Tests

IV. C. 1) Selection of variables

This study utilizes autoregressive modeling to explore the multipath effects of global trade networks in terms of nonlinear cascade and dynamic chain reaction deconstruction. The global trade network is affected by multi-scale drivers and path effects in the process of structural evolution. This paper takes China as the object of empirical analysis, selects global and national data at two scales as explanatory variables, and selects RCA Displayed Comparative Advantage Index as the explanatory variable to carry out the research on the multipath effect of global trade network.

(1) Explanatory variables

Global-scale data are divided into global high-tech exports (as a percentage of manufactured exports) (export), global total imports and exports (import(export)), and global per capita GDP. Each of the measures is closely related to the evolution of the structure of the global trade network, so it is chosen to characterize the global scale, and the data for the three indicators are obtained from the United Nations Merchandise Trade Database (UN Comtrade). The national scale data include China's Productive Capacity Index (PMCI), China's National Policy and Institutional Assessment Index (CPIA), and China's Restrictions on Foreign Investment Index (RSI). These indicators represent the strength of national policy support in the economic and trade sectors, which is conducive to the promotion of national trade and exports and the protection of national trade markets.

(2) Explained variables

RCA index, RCA can effectively measure the competitiveness performance or development level of a country's products or industries in the international market, and can well represent the international competition level of a country. Researchers and scholars in the fields of geo-economics, international relations, and international trade often use this index to assess a country's trade performance when conducting international trade or country studies. China's RCA index is calculated from the trade data in the UN Comrade database, and the years of the RCA index to be calculated in this paper are all the years of the RCA indicative comparative advantage index from 2003 to 2023. In conclusion, global-scale data and national-scale data are selected as the explanatory variables, and the RCA indicative comparative advantage index is selected as the explanatory variable of this study.

IV. C. 2) Time-varying smoothness tests

Before constructing the vector autoregressive model for variance decomposition and impulse response analysis, the data need to be subjected to dimensionless processing, principal component analysis, and smoothness test. Dimensionless processing performs dimensionless processing on all data. Principal component analysis, that is, the use of principal component analysis to extract the principal components of the main body of different scales, respectively, after calculating the 2 scales have passed the KMO and Bartlett's test in principal component analysis, thus each obtaining a set of data characterizing the main body of different scales. In addition, before building the VAR model, because the time series of data in the global trade network are often non-stationary, if the estimation is carried out directly, it will cause pseudo-regression. Therefore, individual variables should be tested for smoothness before modeling. This study uses the unit root test (ADF) to determine whether the time series is smooth or not, and the results of the time smoothness test are shown in Table 6. After testing that the difference series is smooth after 1st order differencing, the cointegration test is continued and Johansen test shows that all variables passed the cointegration test at 1% level. Therefore, the processed data can be modeled as a VAR model.

Table 6: Stability test results

Variable	ADF test	Test value at a significant level			P	Test result
		1%	5%	10%		
Export	-1.3653	-4.185	-2.3042	-2.1002	0.2612	Uneven stability
Import(export)	-0.7034	-4.4229	-3.5858	-2.6305	0.578	Uneven stability
GDP	-1.9422	-3.0302	-3.0695	-2.7377	0.3279	Uneven stability
PMCI	-2.1169	-3.03	-2.7159	-2.867	0.6161	Uneven stability
CPIA	-2.5988	-3.4081	-2.2774	-1.868	0.3538	Uneven stability
RSI	-0.7223	-4.0355	-2.1582	-2.4054	0.322	Uneven stability
D(Export)	-4.8852	-3.0025	-2.9535	-2.8923	0.000	Smoothness
D(Import(export))	-4.747	-3.3066	-2.2725	-1.8391	0.0001	Smoothness
D(GDP)	-4.8091	-3.1148	-2.9756	-2.6943	0.0004	Smoothness
D(PMCI)	-3.7648	-3.7839	-3.2154	-1.9121	0.0003	Smoothness
D(CPIA)	-3.6699	-3.4895	-3.1215	-3.027	0.0008	Smoothness
D(RSI)	-4.056	-4.2085	-2.7422	-2.8991	0.0007	Smoothness

IV. C. 3) Results of VAR model analysis

(1) Optimal lag coefficient determination

Because the global international trade time series data selected in this paper are not stable in the original data, but after the first-order differencing, the series are stable and satisfy the conditions of first-order monointegration, so when constructing the VAR model, it is necessary to carry out cointegration testing of the time series data to verify whether there is a long-run cointegration relationship between the variables.The two-step method of E-G and the Johansen cointegration test are the two most commonly used methods of cointegration testing of time series. Test and the Johansen cointegration test are the two most commonly used methods for cointegration testing of time series. The Johansen cointegration test has a wider scope of application because it does not need to distinguish between endogenous and exogenous variables and is applicable to multivariate situations. Since this paper explores the relationship between multiple variables, the Johansen cointegration test is chosen to examine the time series data.

Before conducting the cointegration test, the first step is to determine the optimal lag order, and the results of the optimal lag order judgment are shown in Table 7, which is the statistics to be referred to for the selection of the optimal lag order, and among all the six statistics, there are five that show that the optimal lag order is the 2nd order. Therefore, the optimal lag order of the model is determined to be 2nd order.

Table 7: The optimal hysteresis number is the result

Log	LogL	LR	FPE	AIC	SC	HQ
0	-88.539	NA	2.54e-07	7.125	-7.632	7.254
1	105.263	259.451	7.15e-11	-3.529	-0.854	-2.965
2	195.635	79.524	6.95e-12	-7.254	-2.036	-5.695

(2) Cointegration test results

The optimal lag order of the selected variables in this paper is 2, so after setting the lag order to 2, the cointegration test is carried out on the relevant variables. The results of the cointegration test are shown in Table 8. At 95% confidence level, when the original hypothesis is “no cointegration” until the original hypothesis is “up to 4”, the trace statistics values are greater than the critical value, and the P values (P=0.000, 0.000, 0.0005 and 0.0254) are less than 0.05, so the original hypothesis is accepted, that is, there are at most four cointegration relationships between Export, Import, GDP, PMCI, CPIA and RSI, and therefore there is a long-term stable equilibrium relationship between the above variables.

Table 8: Cointegral test results

Hypothesized no.of CE(s)	Eigenvalue	Trace statistic	0.05 critical value	P
None	0.9458	193.2564	125.635	0.0000
At most 1	0.8562	155.2634	85.4263	0.0000
At most 2	0.8125	99.6352	68.5426	0.0005
At most 3	0.5952	48.5241	51.9895	0.0254
At most 4	0.4624	28.5632	24.526	0.0526
At most 5	0.3652	15.2634	12.6352	0.1524
At most 6	0.0251	0.6255	3.0285	0.3625

(3) VAR model stability test

The main purpose of constructing a VAR model is to study the dynamic relationship of variables and impulse response on this basis. Therefore, constructing a stable VAR model is the basis for subsequent analysis, and an unstable VAR model cannot explain the correlation between the data, so after constructing the VAR model, it is necessary to firstly carry out a stability test on it. In the stability test of VAR model, if the modes of all characteristic roots are less than 1, the VAR model is stable. The results of the mode analysis of all characteristic roots are shown in Fig. 3, as long as the points do not exceed the unit circle it means that the mode of the unit root is less than 1, and the model is stable.In the AR root chart test all the points are located in the unit circle, and the modes of all the unit roots are less than 1, which means that the model satisfies the stability.

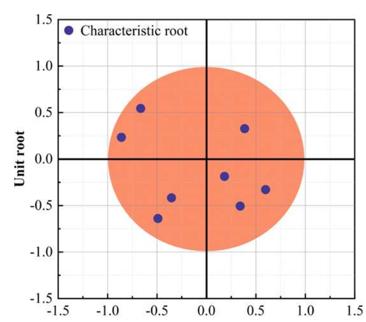


Figure 3: VAR model stability test

(4) Impulse response analysis results

The mechanism of the impulse response function is to capture the dynamic response path of a variable within the model after it is impacted by other variables, so this study analyzes and predicts the relevant time series data in the future global trade network based on the multimodal, high-dimensional, and heterogeneous Transformer model, and conducts the impulse response analysis by combining with the predicted time series data, and uses the results of the impulse response to reflect the global trade network Multi-path effect.

First of all, in order to verify the scientificity and effectiveness of the TFT prediction model proposed in this paper, this paper takes the GDP time series data of China over the years as the dataset, and divides it into training set and test set according to 8:2, and inputs it into the TFT combination model. The TFT model is utilized for single-step prediction of GDP time series data, and the comparison curves of GDP prediction data and actual data are obtained, and the prediction results of the model for GDP time series data on the test set are shown in Fig. 4. It can be seen that the curve trend of the TFT model's predicted and real values of the GDP time series data in the global trade network matches very well, which can basically keep the same with the fluctuation of the real time series of GDP, and the results are in line with the practical needs.

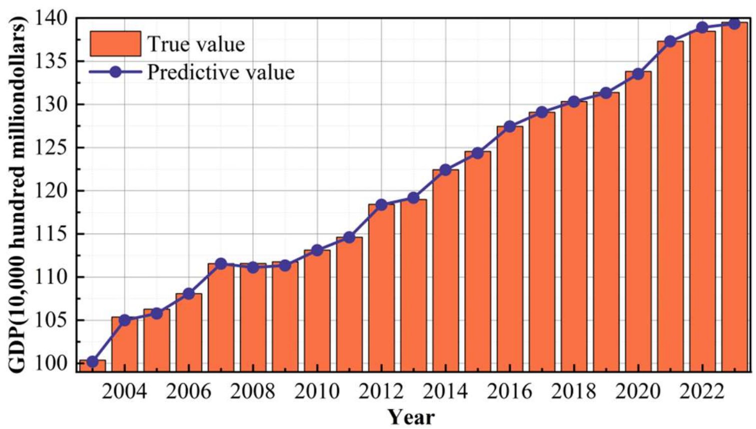
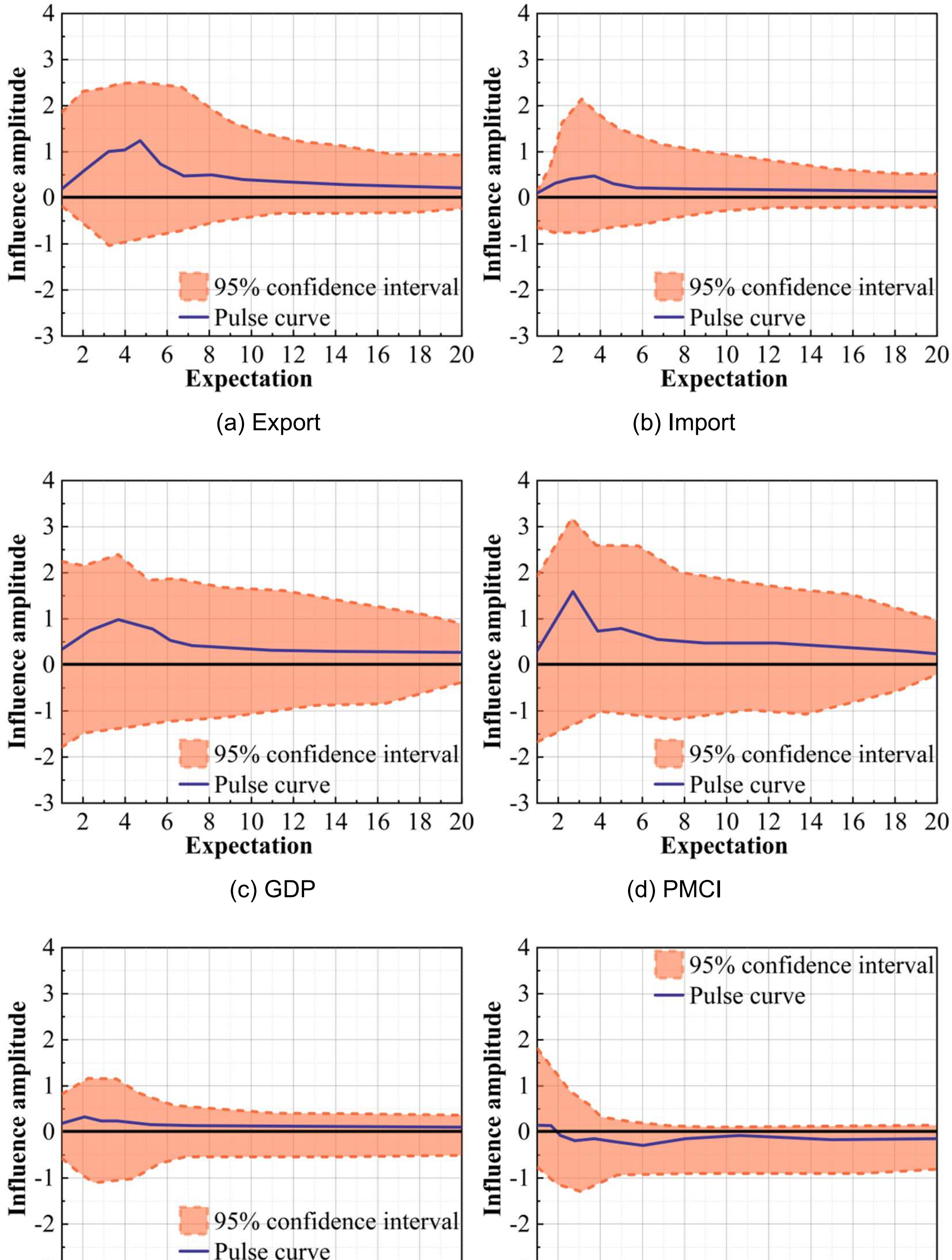


Figure 4: TFT model data prediction results

In order to avoid the influence of the order of variables on the analysis results, this paper adopts the generalized impulse response function, and in order to react to the long-term impact of each explanatory variable on the explained variables, this paper sets the number of response periods to 20, and the results of the impulse response analysis are shown in Fig. 5, and (a)-(f) represent the results of the global trade network of Export, Import, GDP, PMCI, CPIA and RSI, respectively. The horizontal axis of the figure represents the number of response periods of the shock effect, and the vertical axis represents the degree of response of China's weighted degree in the global trade network to the shocks from each explanatory variable, each solid line represents the impulse response function, and each dashed line above and below the solid line represents the positive and negative twofold standard deviation bands, and the impulse response represents the response of the explanatory variables to the shocks of all the endogenous variables, including itself, i.e. the shocks caused by each explanatory variable to the explanatory variables. From the figure, it can be seen that the degree of influence from the Export shock on the structure of the global trade network is positively increasing in the first five periods, and then shows a downward trend and gradually converges to zero.The influence of the Import and GDP variables on the degree of China's weightedness in the global trade network is also positively increasing in the first four or so periods, and then turns into a decline.The influence of the RSI on the explanatory variables as a whole is seen to fluctuate, but overall is in the horizontal axis, and the RSI is in the horizontal axis, and the impulse response is in the horizontal axis. Fluctuates, but is overall below the horizontal axis, suggesting that its impact is consistently negative in the later periods.



(a) Export (b) Import

(c) GDP (d) PMCI

(e) CPIA (f) RSI

Figure 5: Pulse response analysis

V. Conclusion

This paper analyzes the scale and structural evolution of the global trade network by using the global trade network construction method and the characteristic index calculation method, analyzes and predicts the multimodal and high-dimensional time series data in global trade by using the improved Transformer model, and finally explores the multipath effect of the evolution of the global trade network by means of the impulse response model. The analysis finds that the number of trade relationships in the global trade network increases from 10,280 in 1962 to 27,870 in

2023, indicating that the trade network between countries and regions is getting closer. The topological features indicate that the global trade network is characterized by high clustering coefficients and short average path lengths from 2013 to 2023, and the network continues to exhibit small-worldness. Finally, the impulse response model results find that Export, Import, GDP, PMCI, CPIA and RSI variables have path influence effects on the structural evolution of global trade networks.

In summary, fully recognizing the multipath influence effect of global trade network structure is conducive to improving the diversity of global trade networks and economic resilience, and promoting the formation of mutually beneficial and win-win cooperative relationships among countries.

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2.Provincial Key Educational Reform and Research Project:Exploration of Economic and Management Talent Training under the Background of "Double Carbon" and Digital Teaching Based on the EVOS Platform.

3. University-level "Enterprise Strategy Management" teaching innovation team (project No.2023xcxtd01).

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