Intelligent Assessment and Empirical Analysis of the Resilience of Shandong Province's Manufacturing Industry Chain under the Impact of Tariff Policies

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ABSTRACT This paper develops an intelligent assessment framework for evaluating the resilience of Shandong Province's manufacturing industry chain under tariff policy shocks by integrating a dynamic CGE model, industrial complex networks, and a random forest algorithm. Against the background of digital manufacturing and intelligent industrial systems, resilient production networks supported by reliable information transmission and sensing infrastructures are essential for stable industrial operation. The proposed framework quantifies the influence of tariff fluctuations on the structural stability and recovery capability of regional manufacturing clusters. Specifically, a dynamic CGE model based on the 2020 input-output table is established to simulate the macroeconomic transmission effects of tariff shocks ranging from 5% to 15%, while a directed weighted complex network identifies critical industrial links through node degree and betweenness centrality. Furthermore, a random forest model incorporating 20 economic and networkrelated variables predicts the dynamic evolution of resilience. The results show that tariff shocks reduce industry output by an average of 3.7%, with import-dependent sectors experiencing the greatest losses, while key hub industries play a dominant role in system stability. The resilience index exhibits a V-shaped recovery, improving from 0.52 to 0.68 within three years through enhanced R&D intensity and digitalization, providing quantitative support for intelligent industrial risk assessment and resilient manufacturing systems.

INDEX TERMS manufacturing industry chain resilience, dynamic CGE model, complex network analysis, random forest, intelligent industrial systems

I. INTRODUCTION

WITHIN the context of radical changes in the global trade environment and increased policy unpredictability, external shocks pose a severe threat to the stability of regional manufacturing systems and their underlying production security. These fluctuations necessitate a more robust framework to protect the structural integrity of industrial clusters against volatile international market shifts. Being an essential means to intervene in the trade, tariff policies due to alterations in the cost and channel of demands are transferred and sensitized in the interrelated industrial systems, which directly affects the strong functioning and sustainable growth of industrial chains. Hence, the scientific evaluation of transmission modes of tariff shocks, the correct determination of weak links in industry chains, as well as the dynamic measurement of their resilience have become central to the issues of the economic security of the industrial zone in the region and the construction of regional policy.

The paper develops a smart assessment system for the industry that integrates a dynamic CGE model, complex network analysis, and machine learning to realize a complete analytical chain from trade impact simulation to the prediction of industrial resilience. This framework enables the precise identification of structural vulnerabilities within manufacturing clusters, ensuring a data-driven approach to maintaining production stability under external economic shocks. Second, in the sense of empirical depth, selecting 28 manufacturing sub-sectors in Shandong Province as a research object, and using a highly timely data on it, does not only quantify the various impacted industries and paths of transmission of tariff events, but closes the most important industries and susceptible connections vital to the stability of the system, and dynamically determines the most important driving factor of resilience recovery. Thirdly, with regards to decision-making value, the research findings enable the local governments with theoretically effective and practical decision support to implement the process of precise industrial risk early warning and draw variousiated policies that would contribute to industrial chain resilience.

II. RELATED WORK

Against the backdrop of a deep adjustment in the global supply chain and increased uncertainty in regional economic and trade policies, the resilience of the manufacturing industry chain has become a core issue of concern. Sheng et al. [1] found that although China's manufacturing industry has made some progress in adopting GSCM, the overall level is still uneven and it faces multiple challenges such as cost pressure, technology gap, weak regulatory implementation and insufficient supplier capabilities. Against the backdrop of global value chain restructuring and frequent external shocks, Wei et al. [2] constructed a comprehensive evaluation index system to measure the resilience of the industry chain from multiple dimensions such as resistance, recovery, adaptation and learning. Hanaysha and Alzoubi [3] used partial least squares structural equation model (PLS-SEM) to analyze the data and tested the direct impact of digital supply chain on operational and financial performance. Tian and Hou [4]. Zhang et al. [5] systematically evaluated the opportunities and challenges brought by restructuring to China's high-end equipment manufacturing industry from multiple dimensions such as technology acquisition, market access, cost structure and industry chain security.

The manufacturing industry chain is a complex network composed of numerous enterprise nodes and supply and demand relationships. Xu and Zhu [6] used machine learning algorithms such as random forest to comprehensively evaluate and rank the importance of nodes, thereby detecting the key nodes that have the greatest impact on the stability of the industry chain. The optimization model and algorithm developed by Beheshtinia and Fathi [7] can effectively provide decision-makers with a series of optimal supply chain configuration schemes under the trade-offs of energy, environment and economy. Sharma et al. [8] studied and determined that supplier concentration, geopolitical environment, and information system security are the most critical factors leading to the vulnerability of the manufacturing supply chain. Dwivedi et al. [9] identified key business recovery challenges and used the ISM model to determine the hierarchical structure and interdependence among these challenges. Al Kurdi et al. [10] used partial least squares structural equation model (PLS-SEM) to test the hypothesis and focused on analyzing the relationship between SC 4.0, supply chain risk and organizational performance. This study constructs an intelligent assessment framework that integrates dynamic CGE models, industrial complex networks, and machine learning algorithms. It empirically analyzes the transmission path of tariff policy shocks in the manufacturing industry chain of Shandong Province, the identification of vulnerabilities in key links, and the dynamic evolution of resilience levels. The aim is to provide an academic reference with both theoretical depth and decision support value for risk warning and precise policy intervention in the regional industry chain.

III. METHODS

A. CONSTRUCTION OF DYNAMIC CGE MODEL

In order to capture the macroeconomic transmission impact of tariff policy shocks on the manufacturing industry in Shandong Province, this paper uses this concept to create a dynamic computational general equilibrium (CGE) model that includes many sectors. The model data mainly relies on the 2020 Shandong Province input-output table, supplements the 2015-2023 Shandong Province Statistical Yearbook data, supplements the customs import and export data, and conducts in-depth enterprise surveys to make the data timely and representative. The model is considered industry representative because it covers 28 sub-sectors, accounting for more than 95% of the province's total manufacturing added value, and is therefore considered sufficiently representative of the industry.

In terms of model structure design, this paper constructs four economic entity behavior models: a household sector that establishes consumption behavior based on the Stone-Giri utility principle; a corporate sector that determines three nested layers of constant elasticity of substitution of production factors; a government sector whose behavior is constrained by fiscal equilibrium; and a foreign sector that adopts the small-country assumption. The first-layer production function describes the combination relationship between value added and intermediate input factors, and its elasticity of substitution between value added and intermediate inputs ($\sigma 1$) is set between 0.8 and 1.2 according to the technological characteristics of each industry. Value added is further decomposed into two major factor inputs: capital and labor. The elasticity of substitution between capital and labor ($\sigma 2$) ranges from 0.5 to 1.5 based on existing research results and industry differences. For example, the elasticity of substitution between capital and labor is 0.8 in the general equipment manufacturing industry and 1.3 in food processing, as shown in Table 1. The elasticity of substitution ($\sigma 3$) within the third-layer intermediate input structure is set to 0.9. The trade module adopts the Armington assumption, and the Armington elasticity of substitution ($\sigma 4$) between local goods and imported goods is set to 2.5.

The capital accumulation equation and adaptive expectations realize the dynamic process of the model, in which the investment adjustment coefficient is 0.3 and the expectation adjustment coefficient is 0.6. The exogenous variable introduced in the model is the tariff shock. Taking the existing tariff level as the baseline scenario, the shock scenarios are 5%, 10% and 15% to analyze the changes in the impact of different shock levels. The model is solved with the help of the GAMS/MPSGE software package. Comparative statistical analysis is used to measure short-term effects (within one year), and dynamic analysis is used to examine medium- and long-term effects (3-5 years). This study also conducted rigorous parameter sensitivity analysis to ensure the reliability of the research results. The results show that

TABLE 1. Changes in Output by Sector in Shandong Province's Manufacturing Industry under the Impact of Tariffs (%)

Industry categories	Short-term impact (within 1 year)	Long-term impact (within 3 years)	Resilience index	Import dependence (%)	Alternative elasticity
High-end equipment manufacturing	-5.2	-3.1	0.62	32.5	0.8
Electronic Information	-4.8	-2.9	0.60	35.2	0.9
Chemical raw materials	-4.1	-2.5	0.61	28.7	0.7
General equipment manufacturing	-3.9	-2.3	0.59	26.4	0.8
Electrical machinery	-3.5	-2.1	0.58	24.3	0.9
Metal products	-3.2	-1.8	0.55	22.1	1.0
Food processing	-1.8	-0.9	0.50	12.3	1.3
Textiles and Apparel	-1.5	-0.7	0.47	15.6	1.4

the substitution elasticity parameter is the most sensitive of the model results. Therefore, this study uses Monte Carlo simulation to test the robustness and randomly generates 1000 parameter combinations to test the stability of the conclusion. Special consideration was given to data quality and consistency during data collection and processing. The input-output table data for 2020 was significantly affected by the COVID-19 pandemic and may deviate from the long-term trend. To mitigate this structural bias, this study combined data from the Shandong Provincial Statistical Yearbook (2015–2023), customs import and export data, and enterprise survey information for multi-source validation and calibration, and conducted sensitivity analysis on key parameters to ensure the robustness of the model results. This study accurately measures industry parameters through business interviews, expert consultation, etc., so that the model can accurately reflect the actual operation of the manufacturing industry in Shandong Province. In addition, this study also summarizes industry technological innovation levels, digitalization level indicators, etc., to provide complete data support for further resilience assessment [11,12].

B. INDUSTRIAL COMPLEX NETWORK ANALYSIS

Based on the data provided by the 2020 Shandong Province Input-Output Table, this study constructs a directed weighted industrial chain network model. In this network, nodes represent 28 manufacturing industries, edges represent the supply and demand relationship between industries, and the weights of the edges are standardized and quantified by intermediate input coefficients. In order to fully characterize the topological features of the network, this study calculates a series of network indicators: node degree measures the number of direct connections between industries, reflecting the scope of direct association between industries; node strength considers the connection weight factor, which better reflects the importance of the connection; betweenness centrality measures the mediating role of nodes in the shortest path of the network, and identifies key hub industries in the industrial chain. In addition, this study also introduces clustering coefficient to measure the local compactness of the network, and reflects the information transmission efficiency in the network by average path length [13].

This study uses multi-index comprehensive evaluation to name important nodes. In the first step, degree centrality, proximity centrality, and eigenvector centrality are calculated as classic indicators of each node network. The PageRank algorithm is then used to score the node's impact on the world as a whole. Finally, simulate randomly reducing nodes to see how network efficiency changes. A weighted comprehensive assessment of nodes is performed to determine the vulnerability index Vi of node i, which consists of a set of different dimensions, including the centrality of the node, indicators based on industry characteristics (such as foreign trade dependence), and indicators based on the impact of disruptions. The entropy weight method is a scientific method to derive the weight coefficient of each indicator.

The community detection algorithm is applied to establish the organizational form of industrial clusters in the industrial chain. The Louvain algorithm is used, which exploits the condition of maximizing modularity to find the natural communities of the network. The objective measure of modularity Q value is an expression of the significance of network community structure; Q value exceeding 0.3 means that the network has substantial community structure characteristics. This discussion helps to understand the structure and interactions of subsystems within the industrial chain.

Empirical analysis found that there are significant structural characteristics in the manufacturing network of Shandong Province. The network has a density length of 0.36, an average path length of 2.8, and a clustering coefficient of 0.41. All these indicators indicate that the network is a small-world network, that is, a network with high information transmission efficiency but high local clustering. This high efficiency typically translates to a rapid response capability of the supply chain under normal circumstances, but it can also be accompanied by low redundancy, making it vulnerable to shocks. However, in the context of tariff shocks, high efficiency becomes a positive characteristic that enhances resilience—because companies can more quickly leverage existing close connections to allocate alternative suppliers or adjust production plans, thereby buffering the spread of cost shocks. Therefore, the efficient information transmission and resource allocation capabilities endowed by the small-world nature of Shandong Province are an important source of resilience for the province's manufacturing industry in the face of tariff fluctuations. The node degree distribution is a power law distribution (goodness of fit $R^2 = 0.87$), which means that there is a lot of heterogeneity in the network, because a few important nodes can have many connections, while most nodes have only few connections. This is an important structural feature related to the stability of the industrial chain, and is also the basis for further elasticity analysis in this article.

C. APPLICATION OF MACHINE LEARNING ALGORITHMS

To improve the predictive accuracy of supply chain resilience assessment, this study uses the random forest algorithm to construct a resilience index prediction model. In terms of feature variable selection, this study comprehensively considers three types of indicators: the first type comes from the simulation output of the dynamic CGE model, including macroeconomic variables such as industry output change rate and price volatility; the second type is the structural indicators obtained based on complex network analysis, such as network characteristic parameters such as node degree and betweenness centrality; the third type is the industry's own characteristic variables, including R&D intensity, digitalization level, talent structure, etc., for a total of 20 feature dimensions. The resilience index is used as the target variable for prediction. Its definition comprehensively considers the two dimensions of recovery speed and recovery degree after the shock, and is obtained by weighted calculation [14,15]. This study uses Shandong Province manufacturing panel information from 2000 to 2020, covering 588 valid observations in 28 industries in 21 years. Since the resilience index is a continuous variable, directly applying SMOTE (Synthetic Minority Oversampling Technique) presents methodological obstacles. Therefore, this approach first discretizes the resilience index into five levels based on quintiles. Then, within the classification framework, SMOTE is applied to generate synthetic samples. Finally, the levels of the synthetic samples are restored to their corresponding median resilience values, resulting in 1000 effective training samples. This strategy effectively mitigates the overfitting problem caused by small sample sizes while preserving the original data distribution characteristics. An oversampling strategy is used to manage data imbalance, and a SMOTE strategy is used to generate 1000 training samples. During the training of the model, we applied tenfold cross-validation to optimize important hyperparameters such as the number of decision trees and the maximum depth. Measure feature significance based on the reduction in Gini impurity and use partial dependence plots to analyze the marginal effects of variables to increase model interpretability.

In order to determine the effectiveness of the model, this paper proposes support vector machines, gradient boosting trees, and backpropagation neural networks as baseline models used in comparative experiments. The measures evaluated consider the various dimensions of root mean square error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2). Specifically, this paper adopts Shapley value decomposition, aiming to estimate the role of each feature in the final prediction output. This approach not only enhances the transparency of the model but also provides in-depth information on the mechanisms of elasticity formation.

Empirically, the random forest model showed very good predictive performance, with a goodness-of-fit R^2 of 0.83 and a root mean square error of 0.04. In the feature importance analysis, the three factors of node centrality, R&D intensity and digitalization level play the most critical role in the elasticity of the industrial chain. Additional inspection with the help of partial dependence graphs shows that the variables are not related to each other in a linear manner; node centrality and elasticity have a non-linear inverted U-shaped relationship. This means that a moderate centrality of the industrial chain network can help resist risks, while an excessively high centrality may lead to the concentration of systemic risks. In the specific layout of Shandong Province's manufacturing industry, sectors such as general equipment manufacturing and chemical raw materials play a key pivotal role (both with betweenness centrality greater than 0.3). They connect numerous upstream and downstream industries, and moderate centrality helps coordinate resources and diversify risks. However, if the centrality is too high, it means that the industry is too core in the network. Once a tariff shock causes its production to be disrupted, the risk of disruption will be rapidly amplified through dense connections, thus becoming the root of systemic vulnerability. Therefore, moderate industrial chain network centrality helps to resist risks, while excessive centrality may lead to the concentration of systemic risks. These results confirm the reliability of the model and provide scientific basis for post-event policy analysis.

IV. RESULTS AND DISCUSSION

A. ANALYSIS OF THE TRANSMISSION PATH OF TARIFF SHOCKS

The output of the Shandong manufacturing industry is clearly indicated by simulation outcomes of the dynamic CGE model that there will be an average reduction of 3.7% in the overall output when a tariff shock is created by 10 percent but the extent is much different with various industries. Regarding the transmission mechanism, mainly there are two channels of spreading the shock, and they are the cost and demand channels. The effect of raising the tariff on the cost path is that it directly increases the price of imported intermediate goods and the impact of this effect is compounded by an intricate input-output network. According to simulations, any industry that has bigger share of imported inputs suffers more in cost of its products; in electronics manufacturing industry, intermediate goods that were imported in the country take 35.2 percent of the total industry and the cost of production of the industry has gone up by 4.8 percent. The demand side policy has the effect of reducing the consumption and investment demand on the demand side, especially affecting the export industries, due to the tariff which raises the final products price.

Table 1 describes the change of outputs of various industries due to tariffs. It is also clear that industries that are very intensive in technology like the production of high-end equipment and electronic information reflected a short term output decrease that surpassed 4%. Two main features are typical in these industries, first, there is a high rate of imported intermediate goods where the main components have more than 30 percent of imports; second, their supply chains are very lengthy and have many intermediate links, which increases the additive and multiplied effect on transmission. On the other hand, more resilient industries like the food processing and the industries recorded low output fall of less than 2%. The main characteristic of these industries is that, they serve the local market, where localization rates are above 80, and comparatively low product demand elasticity; such factors altogether help them to resist external shocks. In terms of time, the impact of the shock exhibits a trend of initially rising sharply and then gradually declining. In the short term (over one year), the decline in output is mainly due to supply chain disruptions and inventory changes. In the long term (e.g., over three years), the impact of the shock is gradually absorbed by the processes of capital formation and technological change. The resilience index indicates that technologyintensive industries are more severely affected by shocks in the short term, but their long-term resilience index is higher, directly attributed to their strong technological innovation and capital restructuring capabilities. Further examination of factor substitution elasticity shows that industries with lower factor substitution elasticity (e.g., general equipment manufacturing, with a factor substitution elasticity of 0.8) find it more difficult to cope with rising costs by adjusting the capital-labor ratio, and are therefore more vulnerable to shocks; while industries with lower import dependence or higher Armington substitution elasticity can mitigate tariff shocks by increasing domestic purchases to replace imported intermediate goods. For example, food processing have lower import dependence (12.3% and 15.6%, respectively) and higher Armington substitution elasticity (uniformly set at 2.5), thus experiencing smaller output declines.

B. VULNERABILITY IDENTIFICATION IN CRITICAL LINKS

This paper attempts to explore the structural nature and distribution of vulnerabilities of the manufacturing industry chain in Shandong Province, through advanced network analysis techniques. The results of the analysis indicate that the net density of the network is equal to 0.36, the mean length of the paths is equal to 2.8, and the clustering coefficient is equal to 0.41. The node degree is distributed in a power-law (goodness-of-fit $R^2 = 0.87$) which means that there are highly diverse nodes in the network, with some having a large number of connections and the rest of having the limited number of connections.

The special place of specific industries in the industrial chain is indicated by the recognition of the key nodes. The betweenness centrality indices of the industries like general equipment manufacturing and chemical raw materials have values of more than 0.3, which means that they are very important intermediate in the industrial chain. These are the main similarities they usually possess: first, they are in the middle of the industry chain, closely related to both upstream and downstream industries; second, their products are of high versatility and broad range of applications; third, their technological density is high and the elasticity of substitution is comparatively low. Table 2 combines network structure indicators and industry characteristics to evaluate the vulnerability index of key nodes:

TABLE 2. Vulnerability Assessment Indicators for Key Nodes in Shandong Province's Manufacturing Industry

Industry Name	Node degree	Betweenness centrality	Intensity weight	Foreign trade dependence (%)	Vulnerability Index
General equipment manufacturing	25	0.35	0.18	32.5	0.81
Chemical raw materials	23	0.31	0.16	28.7	0.76
Transportation equipment	22	0.29	0.15	30.1	0.73
Electronic Information	21	0.27	0.14	35.2	0.75
Specialized equipment manufacturing	20	0.26	0.13	29.8	0.70
Metal products	19	0.23	0.12	25.6	0.65
Food processing	18	0.15	0.09	12.3	0.45
Textiles and Apparel	17	0.12	0.08	15.6	0.41

Thorough vulnerability investigations display that those industries which have high node centrality and centrality betweenness tend to have vulnerability indices exceeding 0.7. The dependence of foreign trade can hugely enhance vulnerability; the index of electrical and information industry has the greatest node centrality but a node centrality index of 0.75 because of its foreign trade dependence of 35.2%. To elaborate further, the characteristics of high vulnerable industries are normally that they are highly concentrated in terms of the sources of importation (top 3 suppliers produce more than 60 percent), they can hardly be substituted with other suppliers and their turnover rates are low. Such properties reduce the room of changes that these industries can adopt in the event of tariff shock.

Policy implications of the network are seen in the strength testing results of the network. The tests demonstrate Shandong manufacturing network is rather resistant to random attacks; in case of the removal of 20% of the nodes there is a mere 18.3-percent reduction in the workability of the network. Nevertheless, targeted attacks are highly vulnerable to the network; a selective deletion of the top 5% of critical nodes leads to the network efficiency reduced by 36.7 percent. This finding is an indication that when industrial policies are being made, special consideration must be given to shielding the critical nodes, which is vital in ensuring the stability of the entire process of the industrial chain. to protecting critical nodes, which is crucial for maintaining the stability of the entire industrial chain.

C. DYNAMIC EVOLUTION OF TOUGHNESS LEVEL

The prediction results of the random forest model indicate the dynamic development of the resilience level of Shandong Province's manufacturing industry (Table 3). Overall, the manufacturing resilience index rose from 0.52 at the beginning of the impact to 0.68 three years later, showing a clear V-shaped recovery pattern. However, the resilience evolution stages of each sub-sector are quite different. Although technology-intensive industries suffered greater damage, they rebounded faster. For example, the resilience index of the high-end equipment manufacturing industry rose from 0.48 to 0.65. Less affected industries such as traditional laborintensive industries recovered slowly. However, it should be noted that the aforementioned V-shaped recovery is based on the premise that the global industrial chain remains basically connected. If the tariff shock continues to escalate, leading to a "decoupling and supply chain disruption" between China and the US or on a broader scale, an L-shaped recovery may occur—industries will be trapped in a low-level equilibrium for a long period, making it difficult to recover to pre-shock levels. In this case, the role of endogenous drivers such as R&D intensity and digitalization may be suppressed by external blockades, and the resilience index will remain at a low level for a long time.

TABLE 3. Dynamic Evolution and Driving Factors of Shandong Province's Manufacturing Resilience Index

Time point	Overall resilience index	High-end equipment manufacturing	Food processing	Key drivers (importance weight)	Changes in main influencing factors	Policy Effectiveness Index
Initial shock phase (T0)	0.52	0.48	0.55	Node centrality (0.35)	Network structure is dominant	0.25
One year later (T1)	0.58	0.54	0.56	Research and development intensity (0.28)	Rising innovation factors	0.30
Two years later (T2)	0.63	0.60	0.57	Digitalization level (0.22)	The role of digitalization is becoming more prominent	0.35
Three years later (T3)	0.68	0.65	0.58	Policy support level (0.15)	Policy effects are evident	0.45

The important reasons affecting the resilience evolution were identified in the analysis of the feature importance. The three most significant drivers were node centrality (weight 0.35), level of R&D (weight 0.28) and level of digitalization (weight 0.22). It is worth highlighting that the significance of these factors evolved over time: during the initial phase of the shock, the characteristics of network structures (centrality of nodes) prevailed in the resilience rates; in the course of time, the role of innovational factors (intensity of R&D) and transformation factors (level of digitalization) gained more and more significance. The comparatively small weight of policy support (0.15) could be a lack of accuracy or the necessity to introduce better efficiency in the existing policies.

V. CONCLUSION

This article develops an intelligent assessment system, combining dynamic CGE models, industrial networks, and machine learning algorithms to conduct an organized assessment of the flexibility of Shandong Province's manufacturing industry chain affected by tariff policies. By integrating these multi-dimensional methodologies, the study quantifies how regional production networks adapt their structural configurations to maintain operational stability amidst shifting international trade barriers. The paper believes that the impact of tariff shocks is highly industry heterogeneous, and industries with high import dependence such as high-end manufacturing will suffer greater short-term losses. It has a small world structure and non-homogeneous industrial chain network, and major hub nodes such as general equipment manufacturing are very fragile. The evolution of resilient recovery is V-shaped, focusing on R&D intensity and digitalization levels. This study provides a quantitative basis for early risk warning and precise intervention within regional industrial chains, ensuring the structural stability of manufacturing networks. By mapping these specific vulnerabilities, the research facilitates the development of data-driven strategies to safeguard the continuity of production against external economic disruptions. However, this model is not effective in capturing non-economic shocks, and the precision of industry classification needs to be further improved. Future research may include a more comprehensive risk likelihood and incorporate current big data to make the assessment dynamic and forward-looking.

AUTHOR CONTRIBUTIONS

Conceptualization –Yuanli Cui and Li Ma; methodology – Yuanli Cui and Li Ma; investigation – Yuanli Cui and Li Ma; writing-original draft preparation – Yuanli Cui and Li Ma. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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