Research Article

Import and Export Trade Prediction Algorithm of Belt and Road Countries Based on Hybrid RVM Model

Yang Zhao and Zhiqiang Li

1School of Commerce, Yangzhou Polytechnic Institute, Yangzhou 225127, China
2College of Information Engineering, Yangzhou University, Yangzhou 225127, China

Correspondence should be addressed to Yang Zhao; zhaoy@ypi.edu.cn

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1. Introduction

The relevance vector machine (RVM) theory was proposed by American scholar Michael in 2001 by combining support vector machines (SVM) and machine learning algorithms. This algorithm employs Bayesian learning theory to train algorithm models in high-dimensional space, which can be used for regression prediction, pattern recognition, and model classification [1]. In [2], RVM was used to predict medium and long-term runoff of rivers, and a relatively accurate prediction effect was achieved. Literature [3] uses RVM to recognize speech signals and has achieved high recognition accuracy. Literature [4] systematically discusses the application of RVM in high-spectral image classification. Compared with SVM, RVM requires fewer association vectors and has stronger generalization ability. However, RVM also needs to use kernel function selection and parameters ultimately affect the prediction and classification accuracy of RVM. In addition, there is no previous theory that can be used in kernel function category and parameter selection [5]. The import and export trade volume fluctuate greatly, and there are many factors affecting the import and export trade. It is difficult for ordinary prediction algorithms to obtain more accurate prediction results. Aiming at the problem that import and export trade are difficult to predict accurately, and combined with the problem that the optimal kernel function of the RVM model and kernel function parameters are difficult to determine, this paper constructs the import and export trade prediction algorithm based on Particle Swarm Optimization (PSO) hybrid RVM model. The algorithm can obtain more accurate prediction results of import and export trade through principal factor extraction, hybrid kernel construction, and PSO optimization.
Compared with the existing literature, this article contribution lies in two aspects: The first is a more rigorous econometric research paradigm, analyzing as many countries’ trade behavior as possible and analyzing the common language of factors affecting behavior, such as people’s pursuit of complete details of content. The second is to select the appropriate empirical analysis method and verify the robustness of the estimated results through different forms of the regression equation. In addition to the standard static panel estimation, dynamic panel estimation and generalized moment estimation are used to fully introduce dynamic factors and solve potential endogeneity problems. The rational choice of regression method and the mutual verification of multiple regression results make the empirical results of this paper have high credibility and make the corresponding policy recommendations more rational.

The Belt and Road Initiative will create a new trade model in the context of the current global economic recession and the need to adjust China’s foreign trade situation. China is faced with the establishment of a new model of foreign trade cooperation, economic development structure adjustment, and a series of new topics, making full use of this opportunity, which can effectively help China out of the current foreign trade dilemma, for economic development to bring vitality and power. Trade among “Belt and Road” countries is a relatively new research topic. Based on the trade data among “Belt and Road” countries in 2015, this paper analyzes the characteristics of trade value and trade exchanges between countries and in real-time. The clustering method is used to discuss the trade situation. For example, feedforward cycles have been shown to be fundamental to understanding transcriptional regulatory networks. Triangles are the key to social network, with open bidirectional cuneiform structure with center and two jumping paths. It is important to understand the air traffic model. Although the network theme has been recognized as the basic unit of the network, the high-level network organization at the network theme level is still a problem to be solved to a large extent.

In foreign trade cooperation, the economic benefit is the goal of trade contacts, and high-quality trade contacts are the premise of high-level cooperation and opening to the outside world. As China has entered a new era and entered a critical stage of high-quality and quantitative development, improving trade efficiency has become one of the key issues of concern. In recent years, scholars have made great achievements in the study of trade efficiency. Fuchs and Wohlrabe [2] found by using the gravity model that the synergy of new members to the EU standard framework promoted the trade cooperation of traditional members. Ravishankar and Stack [3] measured the trade efficiency of European countries. In China, Shi Bingzhan et al. [4] used the stochastic frontier model for the first time to study the growth of China’s export trade from the perspective of trade efficiency. Lu Xiaodong et al. [5] estimated the “frontier” export level of China with the stochastic frontier model, found that China’s export was in a state of low efficiency, and also indicated the huge potential of China’s export. Si Zengchuo et al. [6] believed that the overall level of China’s trade efficiency was low but showed an upward trend. He Shufeng et al. [7] estimated and compared the trade potential under the traditional trade environment and the navigable conditions of the Arctic waterway, respectively.

The trade gravitation model is a theoretical hypothesis based on Newton’s universal gravitation formula. In the study of international trade, Dinbogen [8] studied the asymmetry of trade flow in a world composed of multiple countries and regions, that is, the proportion of trade volume of a big country in GNP is smaller than that of trade volume of a small country in ONP.

The global trade analysis model, or Global Trade Analysis Project (GTAP) model, is a general equilibrium model based on neoclassical economic theory and is applied to many countries and sectors. The model was originally developed from the Global Trade Analysis Project (GTAP) by Thomas W. Hertel [9]. In the GTAP model, a general equalization submodel is established for each country or region’s economic behaviors such as production, consumption, and government expenditure, and then each submodel is connected into a multicountry and multisector general equilibrium model through bilateral trade relations between countries. GTAP model considers the interaction between countries and domestic economic sectors, so when using the GTAP model to conduct policy simulation, it can discuss the impact of the policy on the production, trade, commodity prices, factor supply and demand, factor remuneration, gross domestic product (GDP), and social welfare level of various countries. Based on this, the GTAP model can provide specific suggestions and evaluation for policy quantitative analysis and decision-making, so the GTAP model has been widely used in the World Bank, World Trade Organization (WTO), International Monetary Fund (IMF), and other major international economic cooperation organizations.

The constant market share model, referred to as CA/IS model, in Information System (IS) is the main method to study trade fluctuation factors. It was first proposed by Tyszynski in 1995 [10] and then modified and perfected by Learner [11], Stern [12], Jepma, and Milana [13]. The model has become one of the important models to study the factors of foreign trade growth and the international competitiveness of export commodities.

On the one hand, labor cost drives the price level of a country by influencing the production cost of the production department of a country; on the other hand, labor cost, as labor remuneration, can directly affect the income level of a country. Labor economics theory has shown that the growth rate of real wages should be the same as the growth rate of labor productivity. When wages rise at the same rate as labor productivity, there is no change in the level of product prices and therefore no pressure on inflation. However, if wages rise faster than labor productivity, the difference will be made up at the expense of higher product prices, which is called wage-pushed inflation. Li Haibin [14] used a vector autoregressive model to investigate the relationship between the labor price level and price. Firstly, the
increase of labor price will stimulate consumption by increasing residents’ disposable income, thus expanding domestic demand. Second, in the short term, the rise of labor price level has little impact on the price level, but in the medium and long term, it will exert pressure on inflation; that is, it will promote the rise of a country’s price level. Huang Zhizhua [15] used the Granger causality test and impulse response function and other empirical methods to study the relationship between the labor price level and price level. It is found that there is a one-way causal relationship between labor price and price level, labor price is the Granger cause of price level, and there is a significant positive correlation between the two [16].

In the development of international trade theory, the importance of technical factors is increasing. Technological factors mainly reduce the production cost of a country’s production department by improving the total factor productivity of a country’s production department and then affect the product price level of a country and ultimately the overall price level of a country. Li Xinhe [17] pointed out that there was an obvious correlation between technology and cost. If the equipment of the enterprise is too old and the process is relatively backward, it will lead to high raw material consumption in the production process, increase the production loss, reduce the production efficiency, and improve the production cost level [18]. When Xiaogang and Zhang Ning [19] explored the driving force of China’s economic growth and transformation from the perspective of cost, they found that, among various factors causing cost changes of enterprises, the scale expansion effect was the most influential, followed by technological progress, price adjustment of production factors, and finally efficiency improvement [20–23].

Investment and trade cooperation is a traditional field, pushing the construction of “area” is promising in the heavy, all parties need to focus on solving the problem of investment and trade facilitation and trade and investment barriers and build a good business environment, the common commercial building free trade area, and China will go along with the country to strengthen the partnership in the following aspects.

Further, expand trade areas, optimize trade structure, explore new growth points of trade, and promote trade balance. We will establish a sound system for promoting trade in services, consolidate and expand traditional trade, and vigorously develop modern trade in services. We will create new forms of trade and develop cross-border e-commerce and other new forms of business. We should integrate investment with trade and promote trade through investment.

We will strengthen consultations with relevant countries on bilateral investment protection agreements and double taxation avoidance agreements, remove investment barriers, and protect the legitimate rights and interests of investors. We will coordinate and resolve issues such as work visas, investment environment, financing needs, and preferential policies.

We will strengthen the division of labor and cooperation with relevant countries in the industrial chain, promote the coordinated development of upstream and downstream industries and related industries, and enhance the supporting capacity and overall competitiveness of regional industries. We will further open the service sector to each other. Actively cooperate with relevant countries to build overseas economic and trade cooperation zones and cross-border economic cooperation zones to promote the development of industrial clusters. China welcomes foreign enterprises to invest in China and encourages Chinese enterprises to participate in infrastructure construction and industrial investment in countries along the Belt and Road.

We will continue to promote in-depth cooperation in agriculture, forestry, animal husbandry, fishery, production, and processing and actively promote cooperation in mariculture, far-ocean fishery, seawater desalination, marine engineering technology, and environmental protection industries. We should step up in cooperation in the exploration and development of traditional energy and resources, actively promote cooperation in hydropower, nuclear power, wind power, solar energy, and other clean and renewable energies, and promote cooperation in the processing and conversion of energy and resources locally, so as to form an upstream and downstream industrial chain of energy and resources cooperation. We will strengthen cooperation in deep-processing technology, equipment, and engineering services of energy and resources. We will promote in-depth cooperation in emerging industries such as next-generation information technology, biology, new energy sources, and new materials and promote the establishment of cooperation mechanisms for venture capital investment.

First of all, whether from the number of countries linked to the “Belt and Road” or the full angle of relevant supporting policies, it shows that China attaches great importance to the construction of this strategy. From the perspective of the current situation of trade along the Belt and Road, it is not difficult to deduce the following: First, there is a huge potential for trade development in the “Belt and Road”; second, countries along the Belt and Road are likely to become China’s major investment partners in the future. Secondly, it is not difficult to conclude from the summary and analysis of the existing theories and models of international trade or the existing research literature that labor, resources, capital, and technology have always been recognized as the core, T, ma E dynamic factors of international trade. Among them, in the original classical trade theory, labor was considered the only factor of production at that time. However, in some new trade theories, resources, capital, and technology gradually appear as important factors of production. With technological progress, human labor will gradually be replaced by machines, and the importance of labor as a factor of production will gradually be weakened, while the importance of technology, capital, and resources as factors of production will be highlighted.

The following is a summary of the research: Section 2 contains PSO optimization mixed RVM model, Section 3 discusses the research experimental analysis, data analysis, and import and export trade forecast in detail. Finally, the conclusion brings the paper to a finish in Section 4.
2. PSO Optimization Mixed RVM Model

Particle Swarm Optimization (PSO) is a computational method for optimizing a problem by iteratively trying to improve a candidate solution in terms of a specific quality measure in computational science. The algorithm was modified, and it was discovered that it was optimizing.

2.1. RVM Model. In the Bayesian framework, RVM removes irrelevant data points through active correlation decision theory and then obtains nonzero parameter correlation vectors. The RVM prediction model is shown in (1).

\[ Y = \sum_{i=1}^{N} \omega_i K(X, X^*) + \omega_0, \]

where \( Y \) is the predicted output value, \( X \) is the correlation vector, \( X^* \) is the input vector value, \( \omega_0 \) is the model weight, and \( K(X, X^*) \) is the RVM kernel function.

2.2. Multicore Mixed Weighting. Similar to SVM, RVM also uses kernel function and kernel mapping in the process of recognition and realizes nonlinear mapping from data space to feature space through kernel function method in the process of algorithm learning. The kernel functions of RVM include Gaussian kernel function, Laplace kernel function, polynomial kernel function, homogeneous polynomial kernel function, spline kernel function, etc. Different kernel functions correspond to different fitting characteristics of RVM.

The Gaussian kernel is a typical local kernel with good partition property, and its expression is shown in (2).

\[ G(x_i, y_j) = \exp\left(-\frac{\|x_i - y_j\|^2}{\sigma^2}\right). \]

Polynomial kernel functions are typical global kernel functions, and their expressions are shown in (3).

\[ P(x_i, y_j) = \left| x_i \left(\frac{y^*}{\sigma^2}\right) + 1 \right|^2. \]

In order to integrate the advantages of the local kernel and global kernel, Gaussian kernel function and polynomial kernel function are adopted in this paper to form the mixed kernel function, and the expression \( K \) of the mixed kernel function is shown in (4).

\[ K = \lambda G(x_i, y_j) + (1 - \lambda)P(x_i, y_j), \]

where \( \lambda \) is the coefficient between \([0, 1]\).

2.3. PSO Optimization of Mixed RVM Model Parameters. PSO is a typical swarm optimization technology. The algorithm was first proposed by Kennedy and Eberhart. The algorithm was derived from the study of bird predation. Compared with genetic algorithms, Particle Swarm Optimization has the advantages of simple operation, high search efficiency, and fast search speed.

This paper adopts the RVM model in the RVM-MATLAB toolbox. In this toolbox, for the RVM regression model based on a single core, the selection of alpha, beta, and scale parameters has an important influence on the quality of the prediction results. In this paper, PSO was used to optimize the parameters of mixed RVM mode. Since the mixed kernel model includes two single cores, namely, Gaussian kernel and polynomial kernel, with a total of six real parameters, a real coding method was adopted for particles. The length of each particle was 6, and the minimum training sample error was taken as the optimization target. According to (5), the optimal kernel parameters are obtained through iterative optimization.

\[ v_{i+1} = \omega \times v_i + c_1 \times rand \times (P_{\text{best}}(i)) + c_2 \times rand \times (G_{\text{best}} - x_i), \]

\[ x_{i+1} = x_i + v_{i+1}, \]

where \( x_i \) is the individual particle, \( \omega \) is the inertia weight, \( P_{\text{best}}(i) \) is the individual optimal particle of particle \( I \), \( G_{\text{best}} \) is the global optimal particle, and \( c_1 \) and \( c_2 \) are the increasing velocity factors.

Stochastic frontier analysis was first proposed by Aigner, and the gravity model is the most commonly used method to measure trade efficiency. In recent years, the stochastic frontier analysis method has been applied to the traditional force drawing model to determine the “frontier level” of bilateral trade, that is, the trade potential. Bilateral trade efficiency is obtained by calculating the ratio of actual trade to trade potential.

The basic form of trade gravity model is as follows:

\[ T_{ijt} = f(x_{ijt}, \beta) \exp(v_{ijt}) \exp(-u_{ijt}), u_{ijt} \geq 0, \]

\[ T^*_{ij} = f(x_{ijt}, \beta) \exp(v_{ijt}), \]

\[ TE_{ijt} = T_{ijt} \frac{T^*_{ij}}{T_{ijt}} = \exp(-u_{ijt}). \]

Among them, \( T_{ijt} \) represents the actual trade volume of country \( i \) and country \( j \) in \( t \) years, \( T^*_{ijt} \) represents the potential trade volume of country \( i \) to country \( j \), and \( TE_{ijt} \) represents the bilateral trade efficiency of country \( I \) and country \( J \) in \( t \) years. \( X_{ijt} \) represents the core variables that affect the actual trade volume, including economic scale (GDPIT, GDPJT), geographical distance (DISIJ), per capita income (PGDPIT, PGDPJT), etc. \( U_{ijt} \) is a nontrade efficiency term, which is independent of \( V_{ijt} \), indicating nontrade efficiency factors that are not included, including tariff, cultural difference, institutional difference, and many other aspects.

3. Experimental Analysis

First, this paper tests the existence of the threshold effect of cultural distance, and the test results are shown in Table 1. Test results can be found from Table 1, samples of all countries and the different development degree economies show obvious single threshold effect, with the developed
estimation, and the regression results are shown in Table 2. To select a single threshold regression model for parameter estimation, and transition economies and developing economies are all through the 10% significance level. In order to further study the difference in the influence of economies by 1% of the effect of single threshold level examination and all economies by 5% significance level verification, and transition economies and developing economies are all through the 10% significance level. In order to further study the difference in the influence of cultural distance on the threshold effect of trade efficiency of different levels of development, this paper selects a single threshold regression model for parameter estimation, and the regression results are shown in Table 2.

From the final regression results, it can be found that cultural distance has obvious heterogeneity on trade efficiency between China and economies at different development levels along the Belt and Road, and the corresponding threshold values also have great differences. From the perspective of all sample countries, cultural distance has a negative influence coefficient on bilateral trade efficiency, which has a significant hindrance effect with the threshold value of 2.146, and the hindrance effect on countries with cultural distance less than 2.146 is stronger than that of countries with a cultural distance greater than 2.146. The possible reason is that countries with a large cultural distance are mainly concentrated in Africa and other economically backward regions. Compared with Asia and neighboring countries, China started its trade cooperation with them later. Meanwhile, it also indicates that China and these countries have great potential for future trade cooperation, so it is necessary to continuously expand cooperation areas and improve cooperation efficiency. In short, due to the differences in geographical location, historical origin, development path, development stage, and even development concept of countries along the line, cultural distance ultimately leads to the great differences.

Specifically, the threshold value of developed economies is 2.141, which is similar to that of all sample countries. It is not difficult to find that when the threshold value is greater than 2.141, cultural distance has a positive impact on the trade efficiency of developed economies, while when the threshold value is less than 2.141, cultural distance has an inhibitory effect. The threshold value of developing economies is 0.776. It is worth noting that when cultural distance is greater than 0.776, the impact on bilateral trade efficiency is significantly negative. However, when the cultural distance is less than 0.776, this effect is significantly positive, indicating that, in the ranks of developing economies, when the cultural distance with China exceeds 0.776, bilateral trade will be hindered. In the transition economies, the highest threshold value of the cultural distance is 2.741, which has a significant negative effect on bilateral trade efficiency. The transition economies have a relatively low degree of industrialization and a single economic structure and tend to lag behind the development of foreign trade. In addition, these countries have rich natural resources. China, like a big energy demand country, has strong economic complementarity, which has become an important driving force for bilateral trade cooperation in the future.

### 3.1. Data Analysis.

The index correlation coefficient matrix was calculated after the normalization of the 8 indexes, and it was found that the indexes $X_1$-$X_5$ had a great correlation, and $X_6$-$X_8$ had a great negative correlation. $X_1$ and $X_3$ are mutually close to sex because these five indexes in Shenzhen development refer to the national economy, so the correlation between indicators is stronger; $X_6$ has big negative correlation by 8 because the country needs to set up the floating tariff regulating import and export, in the international environment under the condition of poor need by reducing tariffs to increase the import and export.

Due to the large correlation of indicators, principal component analysis was adopted to extract the characteristic values, and the contribution rate of the characteristic values obtained was shown in Figure 1.

As can be seen from Figure 1, the contribution rate of the first 4 factors selected for principal component analysis to the principal component is more than 99%; that is, the first 4 factors can represent 99% of the information of the original index, so the first 4 factors are used to replace the original 8 indicators to forecast the total import and export trade of Shenzhen.

### 3.2. Import and Export Trade Forecast.

PSO-based hybrid RVM model is optimized to predict Shenzhen's import and export trade. The data used are the total import and export trade. The existence test of a cultural distance threshold effect.

| Country           | The threshold number | F   | P     | The critical value | The sampling frequency |
|-------------------|----------------------|-----|-------|--------------------|------------------------|
|                   |                      |     |       |                    | 10% | 5%  | 1%  |                          |
| Total economy     | Transition economy   | 40.91* | 0.0667 | 36.99 | 44.568 | 65.196 | 300 |
|                   | Triple threshold     | 17.43 | 0.1533 | 70.212 | 83.207 | 112.549 | 300 |
|                   | The threshold number | 18   | 0.51  | 62.563 | 75.542 | 116.296 | 300 |
| Transition economy| Transition economy   | 24.190* | 0.074 | 22.204 | 29.046 | 44.793 | 300 |
|                   | Triple threshold     | 22.63 | 0.413  | 42.143 | 52.411 | 75.948 | 300 |
|                   | The threshold number | 29.28 | 0.337 | 70.947 | 103.905 | 145.442 | 300 |
| Developing economies| Transition economy   | 60.730* | 0.092 | 58.926 | 73.682 | 114.275 | 300 |
|                   | Triple threshold     | 58.27 | 0.48  | 122.773 | 164.922 | 276.339 | 300 |
|                   | The threshold number | 39.79 | 0.343 | 74.075 | 90.405 | 201.385 | 300 |
| Developing economies| Transition economy   | 103.330* | 0.002 | 46.928 | 57.883 | 78.145 | 300 |
|                   | Triple threshold     | 44.79 | 0.66  | 98.15  | 131.35 | 166.43 | 300 |
|                   | The threshold number | 50.01 | 0.57  | 134.91 | 172.670 | 257.94 | 300 |
volume of Shenzhen from 1979 to 2013 and the four main factors obtained through Section 2 of this paper. Among them, the four main factors are the input parameters of the model, and the total import and export volume is the output parameter of the model. In addition, 25 groups of data from 1979 to 2003 were selected as training data and 10 groups of data from 2004 to 2013 were selected as test data to test the prediction accuracy of the model. Firstly, single Gaussian kernel RVM and polynomial kernel RVM are trained with training data, respectively. Then, the nonlinear programming method is used to iterate two single kernels of RVM into hybrid kernel RVM with the minimum error of the hybrid model as the target. Finally, the PSO algorithm is used to optimize the parameters of hybrid kernel RVM, so as to obtain a better prediction effect. The prediction errors of two single-core RVM are shown in Figure 2.

On the basis of single-kernel RVM prediction, PSO was used to optimize the parameters of the mixed kernel model. The number of particle swarm was 40, the number of iterations was 100, and the individual particle length was 6, representing the nuclear parameters of Gaussian kernel and hybrid kernel. In the calculation of particle fitness value, the kernel parameters were first assigned according to the particle parameters, and then the two single-kernel RVM models were optimized separately. According to the prediction error of the single-kernel RVM model, the nonlinear programming method was adopted to find the weight of the single kernel in order to minimize the error of the mixed model. The optimization process of the PSO algorithm was shown in Figure 3.

The weight of the two single models in the optimal hybrid kernel model is 0.39 for multiterm kernel RVM and 0.61 for Gaussian kernel RVM. The final prediction results of the hybrid kernel RVM model are shown in Figure 4. The comparison of prediction errors between the single-core prediction model and the mixed-core prediction model is shown in Table 3.

As can be seen from Figure 4 and Table 3, the prediction accuracy of the hybrid RVM model based on PSO optimization proposed in this paper is higher than that of the general method and can obtain a more accurate prediction value.

| Variable | All countries | Transition economy | Developing economies | Advanced economies |
|----------|--------------|--------------------|----------------------|-------------------|
| dc ≤ 2.146 | dc ≤ 2.741 | dc ≤ 0.776 | dc ≤ 2.141 |
| Te | -0.188* (-0.89) | -0.051" (-1.570) | 0.005* (0.130) | 0.025" (0.460) |
| dc ≥ 2.146 | dc ≥ 2.741 | dc ≥ 0.776 | dc ≥ 2.141 |
| -0.037* (-1.72) | -0.066 (2.040) | -0.0397" (-1.04) | -0.025" (0.470) |
| gdppt | -0.004 (-0.76) | 0.0039 (0.610) | -0.018 (-1.650) | -0.024 (-2.170) |
| gdpit | 0.007 (1.960) | -0.0015 (-0.320) | 0.021 (2.610) | 0.007 (1.370) |
| Constant term | 0.386 (4.540) | 0.478 (3.980) | 0.377 (2.460) | 0.706 (3.540) |
| R' | 0.494 | 0.622 | 0.645 | 0.567 |
| Sample size | 1242 | 450 | 468 | 324 |

Figure 1: Principal component analysis of indicators.
Figure 2: Prediction error of single-core RVM model.

Figure 3: PSO optimization process.

Figure 4: Prediction error of hybrid kernel RVM model.
4. Conclusion

This research provides a trade forecast method based on the PSO optimization hybrid RVM model when examining the complexity of import and export trade forecasts. Based on the prediction of single-kernel RVM, the PSO algorithm is used to optimize the kernel function, and the weight of a single kernel is found by the nonlinear optimization method, so as to build the optimal hybrid RVM model. The example of the Shenzhen import and export trade forecast shows that the combined forecast model in this paper has a high forecast precision and puts forward a new method for foreign trade import and export forecast. Cutting graphs and K-means clustering methods are used to classify the 65 trading countries, and the classification results are achieved by running relevant MATLAB routines. The lattice graph is used to represent the results.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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