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EDITED BY
Yongxiang Xia,
Hangzhou Dianzi University, China

REVIEWED BY
Kehui Sun,
Central South University, China
Gang Diao,
Lishui University, China

*CORRESPONDENCE
Liangli Yang,
yangliangli1997@163.com
Jieqi Lei,
leijieqi@bupt.edu.cn
Ruijie Wu,
wu@bnu.edu.cn
Yixiu Kong,
yixiu.kong@bupt.edu.cn

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Imports matter more than you think: a complexity-weighted reassessment of trade and GDP growth

Yutai Zhang[1], Yihua Zhou[1], Niuniu Fan[2], Xinyue Sun[1], Siqing Pang[1], Liangli Yang[1]*, Jieqi Lei[3]*, Ruijie Wu[4]* and Yixiu Kong[1,5]*

[1]School of Physical Science and Technology, Beijing University of Posts and Telecommunications, Beijing, China, [2]School of Statistics and Data Science, Shanghai University of Finance and Economics, Shanghai, China, [3]School of Humanities, Beijing University of Posts and Telecommunications, Beijing, China, [4]Department of Systems Science, Faculty of Arts and Sciences, Beijing Normal University, Zhuhai, China, [5]Hangzhou International Innovation Institute, Beihang University, Hangzhou, China

Gross Domestic Product (GDP), as a key indicator of a country's economic performance, is often assumed to have a positive correlation with Net Exports based on the expenditure approach to GDP calculation. However, by introducing the product complexity that integrates a product's technological content and scarcity of international trade, we investigate the impact of trade complexity on GDP growth across all countries within our data. Our findings reveal a significant negative correlation between net Complexity-Weighted Exports and GDP, contrasting with traditional belief. Further analysis discovers that Complexity-Weighted Imports (CWI) has a more pronounced effect on GDP than Complexity-Weighted Exports (CWE), underscoring the crucial role of imports in driving economic growth. To establish a universal model for analyzing the impact patterns of CWE and CWI on GDP, we employed a Long Short-Term Memory (LSTM) neural network to model and analyze relevant data from the majority of countries worldwide. Through this model, we explored the import and export adjustment strategies a country should adopt at different stages of economic development. Our study demonstrates a significant positive correlation between the importation of high-complexity products and a nation's GDP, which also suggests that imported products may facilitate non-linear GDP growth within the domestic economy. These findings offer a reference for how countries can formulate macroeconomic strategies for imports and exports to stimulate economic growth.

KEYWORDS

economic complexity, machine learning, complex networks, nonlinear dynamics, simulation analysis

1 Introduction

Economic growth, a central focus of nations worldwide, is a complex and multifaceted phenomenon. Gross Domestic Product (GDP), the total monetary value of goods and services produced within a country's borders, serves as the most widely used indicator of economic performanceAshley and Sun [1]. Understanding the factors that drive GDP growth is crucial for informing economic policies and strategies. Traditionally, based on the expenditure approach to calculating GDP, net exports (exports minus imports), or balance of trade, are considered to have a positive correlation with economic growthSong and Song [2]; Dunaev [3]; Landefeld et al. [4]; Akalpler and SHAMADEEN [5]; Tsen [6]. However, this perspective oversimplifies the complex dynamic relationship between international trade and economic development.

In recent years, an increasing amount of research has called into question the limitations of focusing solely on aggregate trade volumes as a determinant of economic growth. These studies argue that the traditional approach fails to capture the heterogeneous nature of traded goods and their varying impacts on economic complexity. Economic complexity, a measure of the combined effect of technology and diversity of an economy's production structure, has emerged as a powerful predictor of economic growthTacchella et al. [7]; Hidalgo and Hausmann [8]; Hidalgo [9]; Mao and An [10]. Countries with higher economic fitness tend to have more sophisticated capabilities, allowing them to produce products with higher complexity. This complexity reflects the embedded knowledge, technologies, and productive know-how within an economy.

Inspired by these insights, we adopt a new approach to analyzing the impact of international trade on economic growth. We introduce the concept of economic complexityCardoso et al. [11] and design two simple indicators: Complexity-Weighted Exports (CWE) and Complexity-Weighted Imports (CWI). These measures go beyond simple trade volumes by integrating the concept of product complexity. Product complexity quantifies the technology intensity and scarcity of a product based on the diversity and fitness of the countries that export it. By weighting trade flows with product complexity, CWE and CWI provide a more nuanced picture of the technological content and economic sophistication of a country's exports and imports.

In this study, we aim to investigate the impact of CWE and CWI on economic growth, which is measured by GDP. We hypothesize that these complexity-adjusted trade indicators will reveal new insights into the growth dynamics of economies. By considering not just the quantity but also the quality of traded goods, we expect to uncover the hidden dimensions of international trade that shape economic development. This approach aligns with the growing recognition that economic growth is driven not merely by factor accumulation but also by the upgrading of production structures and the acquisition of new productive capabilities.

To test our hypotheses, we employ a combination of econometric techniques and machine learning methods. We first calculate CWE and CWI using detailed trade data and product complexity measures. Then we examine the correlations between these indicators, traditional trade measures, and GDP growth across a large sample of countries. Through ridge regression analysis, we estimate and compare the impact of CWE and CWI on GDP growth while controlling for other relevant factors. Finally, to capture the potential non-linear and country-specific effects of trade complexity, we employ a Long Short-Term Memory (LSTM) neural network. This enables us to construct a universal model for predicting GDP growth based on historical and current trade patterns, while accounting for the economic complexity of individual countries. We conducted simulation experiments using this universal model to investigate the effects of the CWE and CWI on GDP across different stages of economic development in a country.

The remainder of this paper is structured as follows. Section II presents the methodology, including the data sources, the calculation of CWE and CWI, and the econometric and machine learning techniques used. Section III reports the main findings, including the correlations between trade indicators and GDP growth, the regression results, the performance of the LSTM neural network, and the simulation analysis results. Finally, Section IV discusses the implications of our findings for understanding the complex relationship between international trade and economic growth.

2 Methods

2.1 Dataset

We use the CEPII-BACI database to calculate country fitness and product complexity. This dataset covers trade data for over 200 countries in 5,000 products, which are classified according to a six-digit code (Harmonized System 200,723). To simplify the analysis, we only consider the first four digits of the code, thereby reducing the product set to approximately 1,200 types.

The GDP data come from the World Bank database Greshake [12], which includes GDP data for over 200 countries and regions from 1960 to 2023.

2.2 Revealed Comparative Advantage

To understand whether a country can be considered a producer of a specific product, the criterion used is Revealed Comparative Advantage (RCA) Hoen and Oosterhaven [13], which is the proportion of country c's exports of product p relative to global exports of p by all countries. This quantity is then divided by the proportion of country c's total exports to the total world exports. These ideas are summarized as Equation 1:

$$RCA_{cp} = \frac{\frac{q_{cp}}{\sum_{c'} q_{c'p}}}{\frac{\sum_{p'} q_{cp'}}{\sum_{c'p'} q_{c'p'}}} \tag{1}$$

We construct a binary matrix M using the RCA rule, where if $RCA_{cp} > 1$: $M_{cp} = 1$; otherwise: $M_{cp} = 0$.

2.3 Product complexity

Each year's relationship between countries and their exported products can be modeled as a bipartite network, with countries and products as its two disjoint sets of nodes. An edge connects a country and a product if an export relationship exists; we construct this network using the global trade data of the corresponding year. To eliminate the differences in scale between countries, we have adopted the concept of RCA to process this network. We have retained only the connections between countries and products that have a relative comparative advantage in a particular export product, creating a bipartite matrix M.

Subsequently, we apply nonlinear dynamics equations for iterative calculations Tisdell and Zaidi [14]. In this process, the fitness of each country is defined as the sum of the complexity of export products in which it has a relative comparative advantage from the previous round. Meanwhile, the complexity of each product is determined by the inverse of the sum of the inverses of the fitness of countries that have a relative export comparative advantage in that product. In each round of iteration, we perform standardization to ensure the consistency and comparability of the data. These ideas are summarized as formula:

$$\begin{cases} \tilde{F}_c^{(n)} = \sum_p M_{cp} Q_p^{(n-1)} \\ \tilde{Q}_p^{(n)} = \dfrac{1}{\sum_c M_{cp} \frac{1}{F_c^{(n-1)}}} \end{cases} \rightarrow \begin{cases} F_c^{(n)} = \dfrac{\tilde{F}_c^{(n)}}{\left\langle \tilde{F}_c^{(n)} \right\rangle_c} \\ Q_p^{(n)} = \dfrac{\tilde{Q}_p^{(n)}}{\left\langle \tilde{Q}_p^{(n)} \right\rangle_p} \end{cases} \tag{2}$$

From Equation 2, the iterative method consists of two steps: in each iteration, we first calculate the intermediate variables $F_c^{(n)}$ and $Q_p^{(n)}$, and then normalize them. The initial conditions are $Q_p^{(0)} = 1$ for all products p and $F_c^{(0)} = 1$ for all countries c. The element M_{cp} is the element of the binary country-product matrix M: if country c exports product p, the element M_{cp} is 1, otherwise it is 0. After iterative computations, we obtained the fitness of each country and the complexity of each product for that year.

By this calculation method, country fitness is associated with product complexity, which is dominated by the less developed countries that produce the product.

2.4 Complexity-weighted imports and exports calculation

Based on the product complexity data obtained for the year through iterative calculations as described above, we further conducted a weighted treatment of the import and export values of all products for each country's trade. This process enabled us to calculate the CWI and CWE for each country in that year. The specific calculation formulas are as follows Equations 3–5:

$$CWE = \sum_e Q_e \times V_e \tag{3}$$

$$CWI = \sum_i Q_i \times V_i \tag{4}$$

$$NCWE = CWE - CWI \tag{5}$$

Where CWE represents Complexity-Weighted Exports, CWI represents Complexity-Weighted Imports, Q stands for product complexity, derived from the iterative calculations above, and V stands for the total import/export value of the product for the country, obtained from CEPII-BACI database. The subscripts e and i represent imported and exported products, respectively. $NCWE$ stands for Net Complexity-Weighted Exports.

CWE and CWI have significant economic implications. CWE can be seen as a measure of the overall quality of a country's exported products. It encompasses not only the absolute monetary value of the products but also integrates abstract factors such as technological content and scarcity that are difficult to quantify. It reflects a country's level of industrial production. CWI, on the other hand, reflects the total quality of products imported into a country. These imported products and technologies can be used to upgrade and transform various industries within the country, thereby becoming an internal driving force for GDP growth Dahlman [15].

2.5 Multivariate linear ridge regression analysis

To compare the impact of CWE and CWI on GDP, we conducted multiple linear ridge regression modeling for each country. We used the CWE and CWI data from 1995 to 2021 as independent variables and the GDP data as the dependent variable. The regression coefficients were interpreted as the partial derivatives of GDP with respect to CWE and CWI for each country. To ensure consistency in the scale of the data, we normalized the time-series data of these three variables using 0–1 normalization. The regression model is as shown in Equation 6:

$$GDP_C = a_C \times CWE_C + b_C \times CWI_C + c_C \tag{6}$$

Where, a and b represent the regression coefficients of CWE and CWI on GDP. c denotes the constant term in the regression. The subscript C indicates that the parameters are based on different countries.

The loss function for multivariate ridge regression is as follows Brown and Zidek [16]:

$$L\left(\hat{\mathbf{k}}\right) = \left(\mathbf{y} - \mathbf{X}\hat{\mathbf{k}}\right)^{\mathbf{T}} \left(\mathbf{y} - \mathbf{X}\hat{\mathbf{k}}\right) + \alpha \|\hat{\mathbf{k}}\|_2^2 \tag{7}$$

From Equation 7, $\mathbf{y}$ is the vector of dependent variables, $\mathbf{X}$ is the matrix of independent variables with a column of 1 as the last column, $\hat{\mathbf{k}}$ is the vector of coefficients, and α is the regularization coefficient, which is set to 1 in this paper.

The solution that minimizes the loss function can be obtained by setting the gradient of the loss function with respect to $\hat{\mathbf{k}}$ to zero. Setting the gradient to zero yields the normal equation for ridge regression, as shown in following Equation 8:

$$\left(\mathbf{X}^{\mathbf{T}}\mathbf{X} + \alpha\mathbf{E}\right)\hat{\mathbf{k}} = \mathbf{X}^{\mathbf{T}}\mathbf{y} \tag{8}$$

The solution of ridge regression can be obtained as shown in Equation 9:

$$\hat{\mathbf{k}}^* = \left(\mathbf{X}^{\mathbf{T}}\mathbf{X} + \alpha\mathbf{E}\right)^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{y} \tag{9}$$

2.6 Long short-term memory neutral network

The impacts of CWE and CWI on GDP measured by the ridge regression are different across countries. To build a universal model applicable to all countries, we deploy a LSTM neural network. The reasons for model selection are as follows: Considering that the CWE, CWI, and GDP data of various countries have temporal characteristics, this paper selects recurrent neural network models that perform well in processing time-series data for modeling. We compared multiple recurrent neural networks and finally chose the LSTM network with the relatively best performance. See the Appendix 3 for the comparison results. The specific details of this approach are as follows: Firstly, in terms of data processing, we independently normalize the 1995–2021 time-series data of *CWE*, *CWI*, and *GDP* for every country to the 0–1 range. *GDP* is taken as an example, as shown in Equation 10:

$$\overline{GDP}_t^C = \frac{GDP_t^C - GDP_{\min}^C}{GDP_{\max}^C - GDP_{\min}^C} \tag{10}$$

Where, superscript C denotes a specific country, subscript t denotes a given year, and *CWE* and *CWI* are normalized in the same way.

Then, we merged these three columns of data for each country in the order of *CWE*, *CWI*, and *GDP*, with each country's data formatted as: CWE_{1995}, CWI_{1995}, GDP_{1995}, CWE_{1996}, CWI_{1996}, GDP_{1996}…After mixing, we sliced the dataset with a window size of 6 and a step size of 3, resulting in 26 data segments for each country, structured as CWE_{t-1}, CWI_{t-1}, GDP_{t-1}, CWE_t, CWI_t, GDP_t. Subsequently, we mixed the data from 160 countries to form our training set and mixed the data from 14 countries to form our test set. During the training and testing process, CWE_{t-1}, CWI_{t-1}, GDP_{t-1}, CWE_t, CWI_t served as input variables, with GDP_t as the output variable. Abstracted into the formula as shown in Equation 11:

$$GDP_t = LSTM\left(CWE_{t-1}, CWI_{t-1}, GDP_{t-1}, CWE_t, CWI_t\right) \tag{11}$$

The neural network we employ is a sequence-prediction model that incorporates a two-layer LSTM architecture with Dropout regularization. The model is composed of the following components: First, there is an LSTM layer with 32 units to process the input sequence and retain time-dependent information, followed immediately by a Dropout layer to reduce overfitting. Next is a second LSTM layer with 16 units to further refine features, followed again by a Dropout layer. The model concludes with two fully connected layers, the first with 2 neurons and the second output layer with 1 neuron, both using the ReLU activation function to increase the model's nonlinear expressive power Zhang et al. [17]. The detailed network diagram is provided in Appendix 1. After repeated learning on the training dataset, the network is able to accurately analyze the historical data of CWE, CWI and GDP, thereby identifying different types of economic development in various countries and predicting GDP more accurately, and it performs excellently on the randomly selected test set.

3 Results

To calculate the annual CWI and CWE for each country, taking 2019 as an example, we first constructed a country-product bipartite network based on global trade data, using export relationships and the RCA criterion. A partial structure of this network is shown in Figure 1a. Building upon this framework, we applied the nonlinear iterative method mentioned earlier for computation. Through this process, we successfully calculated two key variables: the fitness of each country and the complexity of each product. By weighting the product complexity with the import and export volumes of corresponding products from each country, we further derived the two core variables: CWI and CWE. Now, let's focus on product complexity. As anticipated, products characterized by high technological content and scarcity exhibit a higher degree of product complexity. Conversely, those with lower technological content and scarcity demonstrate a lower degree of product complexity, as illustrated in Figure 1b.

When delving deeper into the concept of CWI and CWE, we have uncovered a few fascinating phenomena. For instance, a few countries that are traditionally Net Exporters appear as Net Complexity-Weighted Importers when measured with Complexity-Weighted, while others that are Net Importers have an advantage in CWE. This situation is observed in both developing countries, such as Nigeria, and developed countries, such as Austria, which is shown in Figure 2. This finding further confirms that CWI and CWE can more effectively integrate multi-dimensional economic information, providing a more accurate and comprehensive assessment of trade conditions.

The global economic output and the total volume of trade have been continuously increasing since 1995. To eliminate the impact of the growth in global economic and trade values, we use the proportion of each country's GDP or import-export value to the total worldwide to conduct correlation analysis, what we call the relative GDP or r-GDP.

Similarly, we adopt the share of trading volume of countries, to measure the relative imports and exports of a country, namely, r-Import and r-Exports. By analyzing the correlation coefficients between r-GDP and r-NE of different countries, we can find that there is no obvious distribution pattern in their correlation, as depicted in Figure 3a. This distribution indicates that the relationship between GDP and NE is much more complex than we might intuitively think. Furthermore, Imports should not be merely regarded as a subtraction in GDP. Although imports do reduce the value of NE, they have a significant positive impact on the economy in several key areas. Imports help to meet domestic market demands, facilitate the introduction of technology and capital goods, stimulate market competition, integrate into global supply chains, create job opportunities, and influence prices Gereffi and Sturgeon [18]. These functions can enhance consumption levels, improve production efficiency, and increase overall economic productivity, thereby driving GDP growth. Therefore, contrary to common understanding, imports often exhibit a positive correlation with GDP, which is shown in Figure 3b.

Similarly, in order to eliminate the interference of the annual increase in the total amount of each variable on the correlation analysis, we use the annual proportion of each variable to the total amount in the subsequent correlation analysis for research. After analyzing the linear relationships between NCWE, NE, CWE, CWI and GDP for different countries over the period from 1995 to 2021, we made a few interesting findings. Unlike the linear relationship between NE and GDP, which shows no clear pattern, when we take into account abstract factors such as technology, the relationship between NCWE and GDP generally shows a negative correlation, as shown in Figure 4a. At the same time, the linear relationships between CWE and CWI with GDP are generally positively correlated, which is shown in Figure 4. These results indicate that, after incorporating the effects of technology and other factors, the statistical impact of imports on GDP is generally more

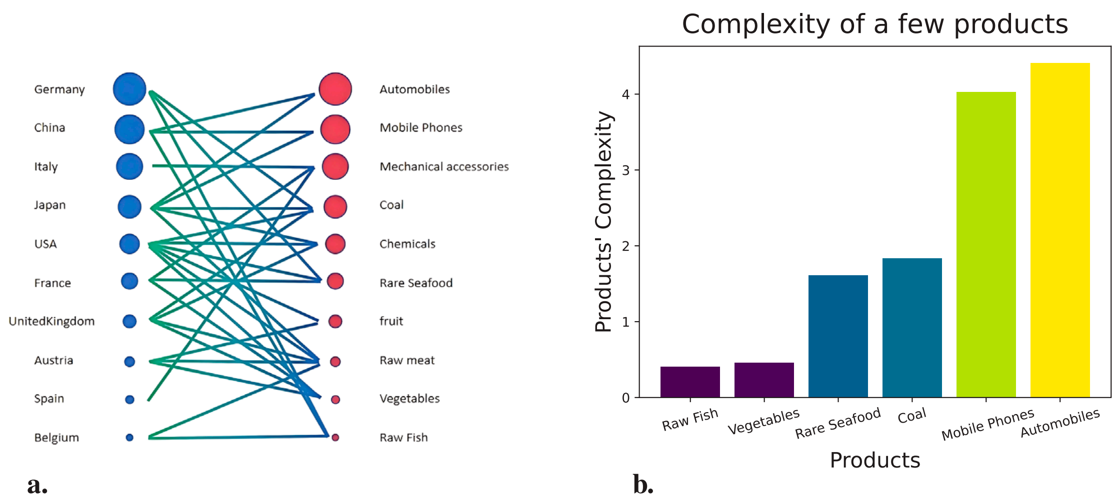

FIGURE 1
The partial results of Countries' Fitness and Products' Complexity. **(a)** A bipartite network diagram of a few countries and products under the RCA criterion. The points on the left represent countries, with the size of the points indicating the level of country fitness; the points on the right represent products, with the size of the points indicating the level of product complexity. **(b)** A bar chart of product complexity for a few products. Products with low complexity are mostly raw fish (excluding rare varieties) and vegetables. Products with moderate complexity mainly include rare seafood, coal, and industrial products with low technological content. Products with high complexity are primarily high-tech industrial products, such as mobile phones and automobiles.

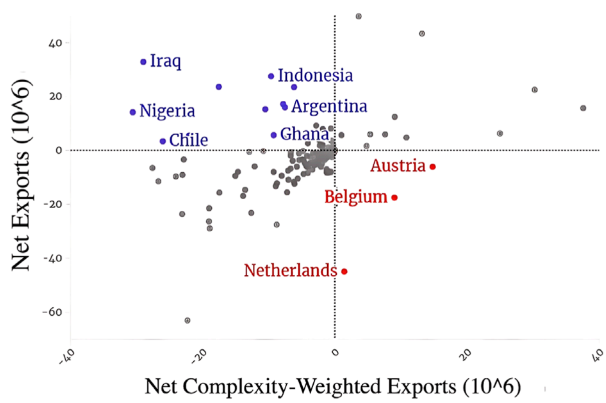

FIGURE 2
Scatter plot of NCWE and Net Exports (NE) for countries. It can be observed from the figure that countries which are actually net importers but are Complexity-Weighted exports exporters are mostly developed countries, such as Belgium, the Netherlands, Austria, etc.; countries which are actually net exporters but are Complexity-Weighted importers are mostly developing countries, such as Iraq, Chile, Nigeria and so on.

significant than that of exports. This finding challenges the intuitive understanding of traditional trade indicators and emphasizes the important role of imports in promoting economic growth in the context of globalization Bertucci and Alberti [19].

By analyzing the distribution of linear relationships between r-GDP and r-CWE, as well as r-CWI, we can observe a significant trend: as shown in Figure 4b, the positive correlation between r-CWI and r-GDP is more pronounced. This indicates that the connection between CWI and economic growth is statistically more robust. However, this does not mean that the role of CWE can be overlooked, as CWE also generally shows a positive correlation with GDP.

To further compare the effects of CWE and CWI on GDP, we conducted a multiple linear regression analysis for 174 countries and regions. To avoid overfitting, we employed the ridge regression method and standardized the data to eliminate the impact of different data scales. The results of the study show that the ridge regression coefficient of CWI is generally higher than that of CWE, as illustrated in Figure 5. The significance test is presented in Appendix 2. This finding further confirms the significant contribution of imports to GDP growth. These results highlight the key role of imports in promoting national economic growth, especially when considering multi-dimensional factors such as product complexity and diversity.

From the above research findings, by examining the linear relationship between NCWE and GDP, as well as analyzing the regression coefficients of CWI and CWE on GDP, it is evident that the driving effect of CWI on economic growth is significantly higher than that of CWE. Further review of the expenditure approach formula for GDP: GDP = Consumption + Government Spending + Investment + Net Exports. The theoretical framework posits a positive correlation between GDP and net exports; however, empirical data do not substantiate this claim. This indicates that the domestic component of GDP–namely, the sum of consumption, government spending, and investment, is subject to a nonlinear enhancement effect from imports. This effect not only offsets the monetary or value outflow caused by net imports but also generates significant surplus value.

From the perspective of data analysis, net imports, which initially showed no consistent pattern in their effects on the economies of various countries, generally exhibit a promoting effect after considering factors such as technology. This indicates that net

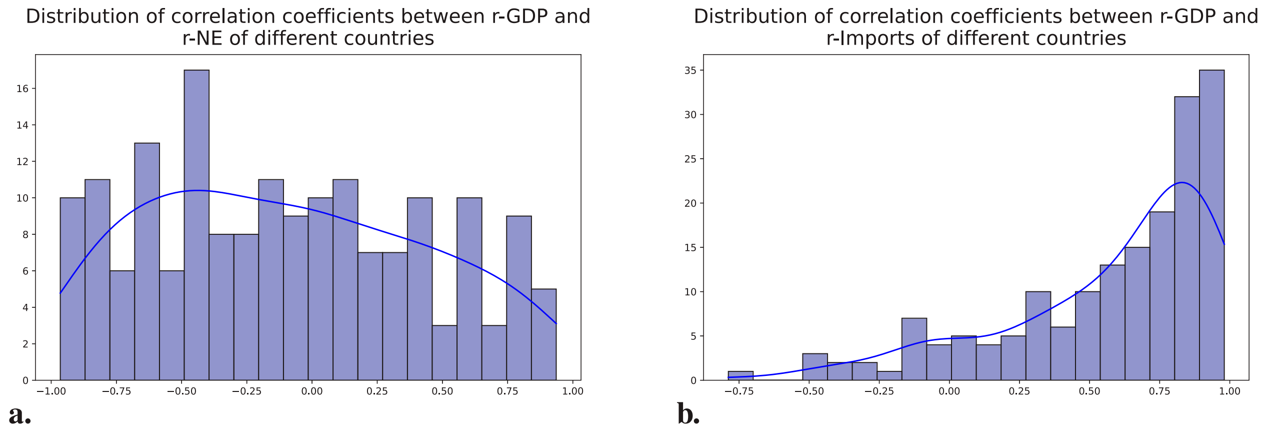

FIGURE 3
The frequency distribution graph of the linear correlation coefficients of 174 countries. The curves in the figures are the Kernel Density Estimation (KDE) curves of the distribution. **(a)** The linear correlation coefficient distribution between r-GDP and r-NE. It can be observed that there is no obvious pattern in the linear relationship between r-GDP and r-NE. **(b)** The linear correlation coefficient distribution between r-GDP and r-Imports. It can be observed that the two variables typically exhibit a positive correlation, which is contrary to the results obtained from calculating GDP using the expenditure approach.

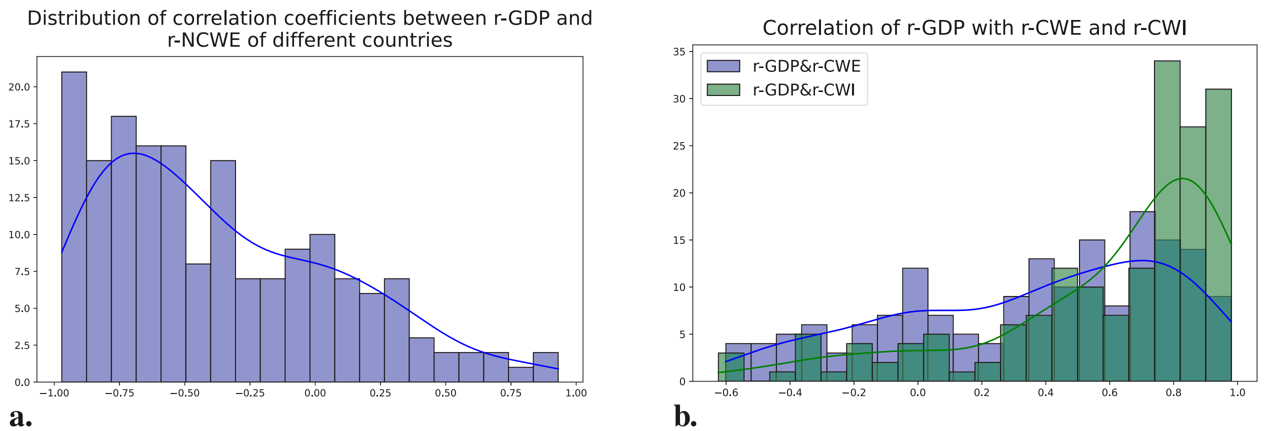

FIGURE 4
Correlation analysis of various variables after eliminating the interference of total volume growth. The curves in the figures represent the KDE of the distribution. **(a)** The distribution chart of the linear correlation coefficient between r-GDP and r-NCWE. It can be observed that there is a generally negative correlation, which is different from the distribution of NE, and even more different from the positive correlation found in the expenditure method of calculating GDP; **(b)** Correlation charts of r-GDP with r-CWE and r-CWI.

imports can effectively boost the internal circulation of the domestic economy and generate positive externalities, and the consideration of technology further amplifies this effect.

Due to the significant differences in linear regression coefficients among different countries, it is not feasible to conduct a single multiple linear regression analysis for CWE, CWI and GDP across all countries. In this case, we can utilize a LSTM neural networks, which is a neural network with the capability of long-term memory Song et al. [20]. This model can identify the types of different countries by analyzing historical data of CWE, CWI and GDP. In this way, the model can utilize the current year's CWE and CWI data along with a few historical data of the country to more accurately fit that country's GDP for the current year. Since CWE and CWI are calculated based on the weighted operations of each country's annual import and export values, there are significant differences in the data among different countries in the same year. Given this, we were compelled to independently normalize the CWE, CWI, and GDP data of each country to a 0–1 scale during the training process. We utilized data from 160 countries and regions as the training set and data from 14 countries as the test set. The loss curve during the training process is shown in Figure 6. Within the test set, we specifically selected a few countries with relatively unique GDP growth trends for illustration. The results indicate that the model achieved satisfactory fitting performance for these four countries. Details can be seen in Figure 7. Meanwhile, in terms of the indicators, the model did not exhibit overfitting and achieved a good fit. Details are provided in Appendix 3.

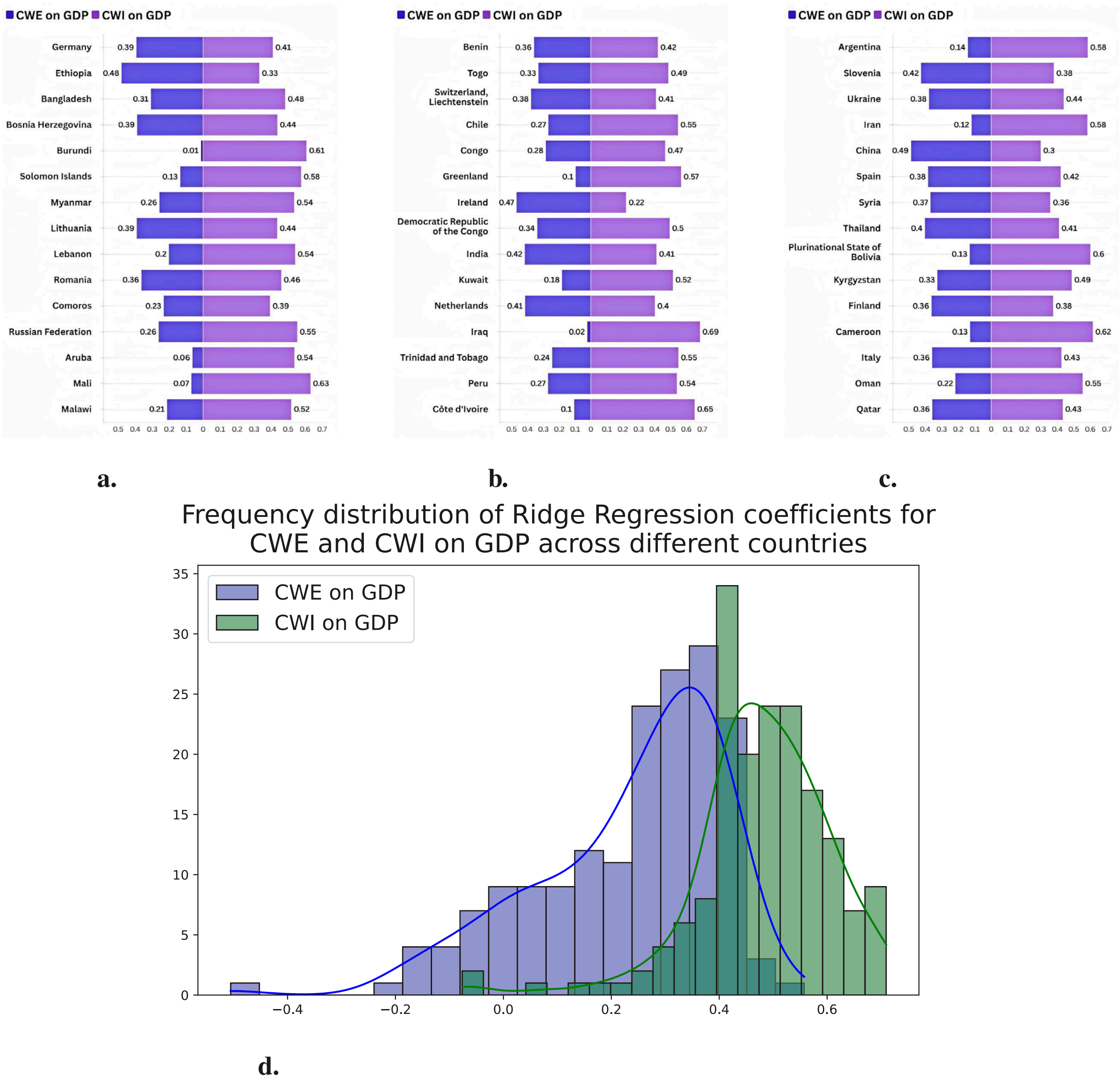

FIGURE 5
The ridge regression coefficient results of CWE and CWI for GDP. **(a–c)** Show the multiple ridge regression coefficients of CWE and CWI on GDP for part countries and regions. The left side is the linear regression coefficient of CWE on GDP, and the right side is the linear regression coefficient of CWI on GDP. It can be observed that the regression coefficient of CWI on GDP is larger, but the role of CWE on GDP should not be overlooked. **(d)** Provides a visual comparison of the frequency distribution of ridge regression coefficients for CWI and CWE on GDP. The curves in the figure represent the KDE curves of their respective distributions.

We conducted a simulation analysis of the trained LSTM model, regarding the trained LSTM model as a universal model that captures the underlying patterns of the relationship between CWE, CWI, and GDP from 1995 to 2021. We observed the changes in GDP with variations in CWE and CWI, given the fixed historical data of the previous year. Given that the training approach we employed involved normalizing the relevant data for each country to a 0–1 scale, from a historical perspective, the global economy as a whole exhibited a developmental trajectory characterized by an initial takeoff, a period of relatively high growth, and a subsequent slowdown from 1995 to 2021. For specific details, please refer to Figure 8. Based on this, we selected the normalized GDP values of 0.25, 0.5, and 0.75 to correspond to the aforementioned three stages. From the perspective of national economic development, the overall evolutionary trajectory of the global economy over the past 27 years closely aligns with the pattern of an underdeveloped country that begins with economic takeoff, experiences a period of rapid growth, and ultimately moves towards stable development. Therefore, these three GDP values not only have clear demarcation significance in the historical context of data normalization but also can respectively represent the development

FIGURE 6
Loss change graph during training. In this paper, our epoch parameter is set to 100, and the batch size parameter is set to 128.

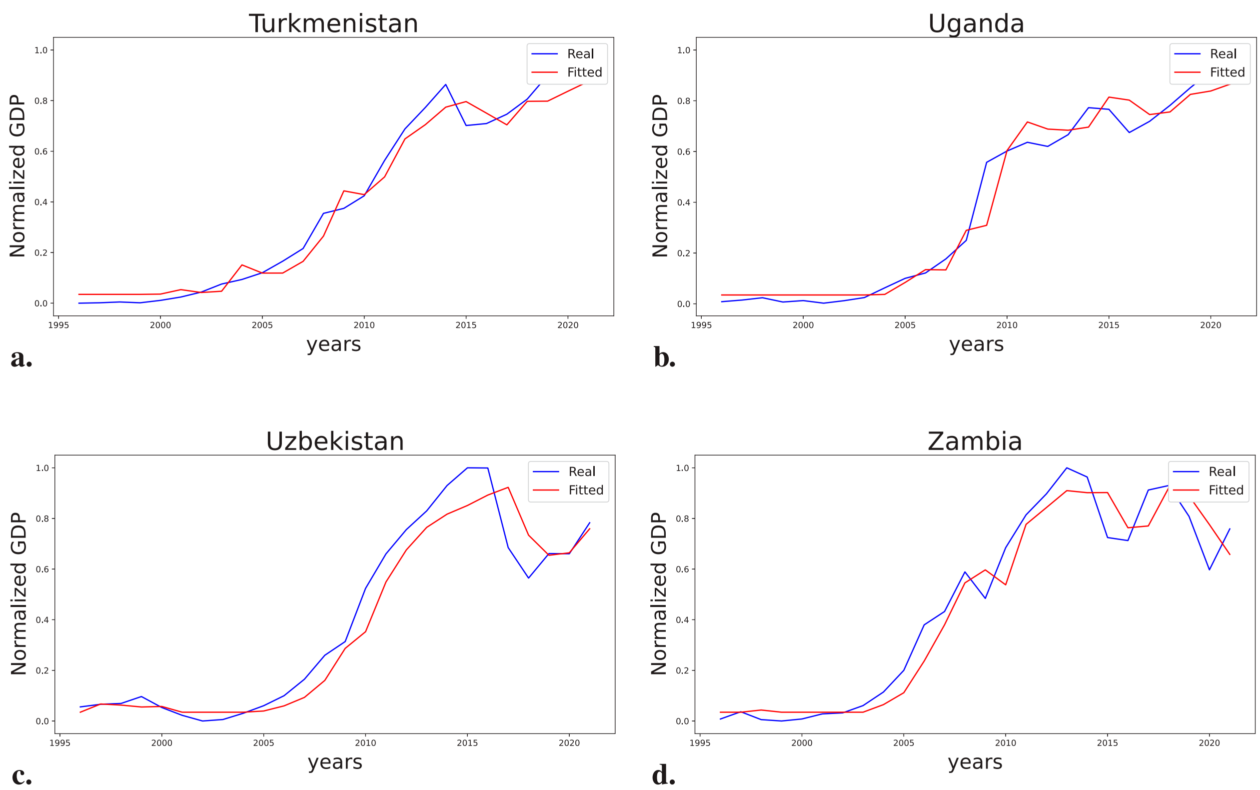

FIGURE 7
Comparison between actual values and fitted values for a few test set data. **(a–d)** The prediction generated by the LSTM model for four countries (Turkmenistan, Uganda, Uzbekistan, and Zambia). The blue curve represents the true value of the country's normalized GDP, and the red curve represents the fitted value of the LSTM model.

status of currently underdeveloped countries, currently developing countries, and currently more developed countries in practical terms.

Given the high correlation between CWI and CWE and GDP, after determining the value of the normalized GDP for the previous year, we selected the strategy of adding a small random perturbation

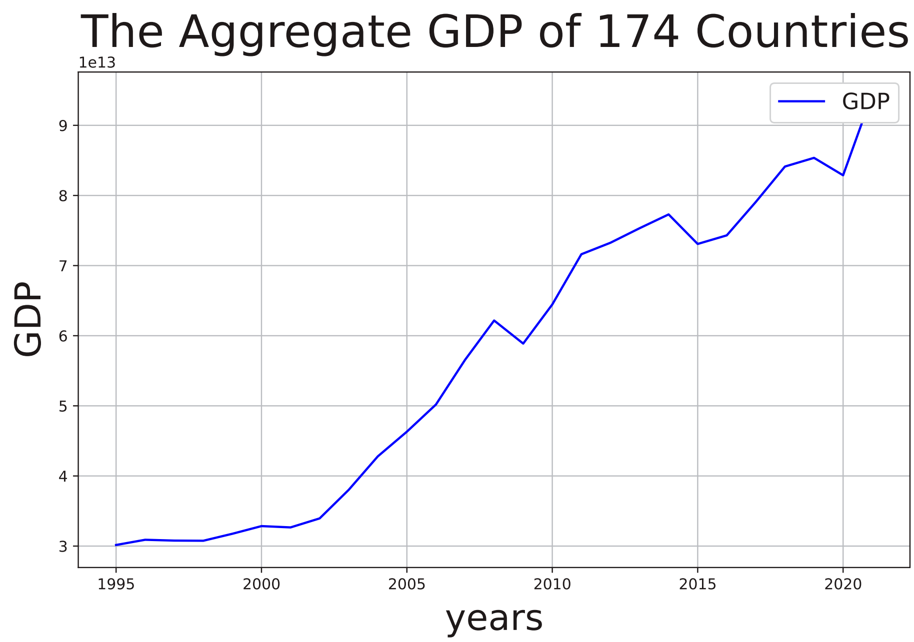

FIGURE 8
The time series plot of the aggregate GDP of 174 countries from 1995 to 2021. It can be observed that the global economic trend over these 27 years is generally characterized by an initial takeoff, followed by rapid development, and eventually a slowdown.

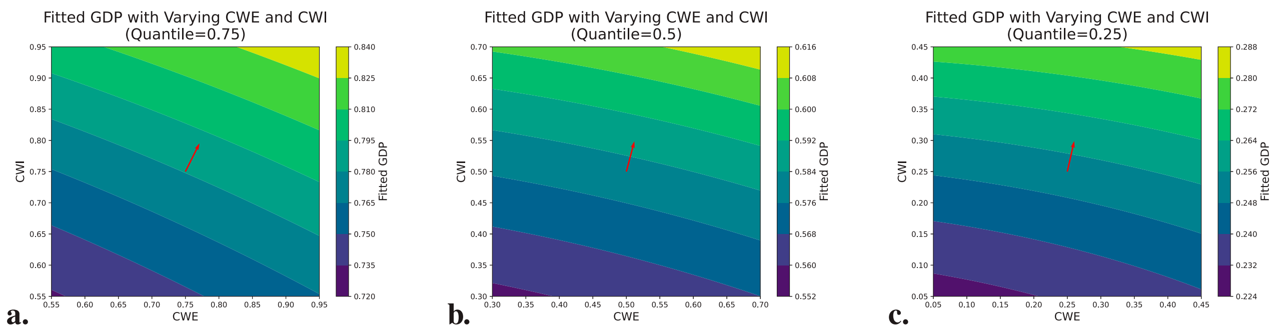

FIGURE 9
Contour plots of GDP responses to CWE and CWI at different economic stages. **(a–c)** Respectively represent the contour plots of GDP against CWE and CWI under high, medium, and low economic states. The red arrows indicate the optimal gradient direction for the current economic state. For high, medium, and low economic states, the corresponding growth ratios of CWE to CWI for the optimal gradient directions are 1:2, 1:4, and 1:5, respectively. Since CWE, CWI, and GDP were all standardized on a 0–1 scale during the modeling process, the growth ratio rather than absolute values should be used as the reference when applying the optimal gradient direction.

to the GDP value for the normalized CWI and CWE, in order to simulate the historical information of different economic stages in reality. While keeping the historical information fixed, we allowed the CWE and CWI of the current year to fluctuate within a range of ±0.2 based on the economic state of the previous year. This design aims to avoid excessive fluctuations in economic indicators between the current year and the previous year, thereby ensuring the validity and reliability of the simulation results.

Through simulation experiments, we aim to provide references for optimizing import and export strategies for countries at different stages of economic development, in order to facilitate their economic improvement. The research results show that the lower the economic state, the greater the role of imports relative to exports in driving the economy. However, for countries in a higher economic position, imports still play a more significant role than exports. Details can be seen in Figure 9. This finding reveals the differences in import and export strategies across different stages of economic development.

4 Conclusion

In this paper, we systematically investigate and compare the roles that CWE and CWI play in economic growth. Simultaneously, by employing a LSTM neural network for modeling, a universal model applicable to all countries was developed. Based on this model, simulation experiments were conducted to further explore the underlying mechanisms through which the CWI and CWE affect GDP. In order to reflect abstract concepts such as technological content and scarcity in import and export values, we employ non-linear dynamics methods to calculate product complexity indicators and verify their effectiveness. Furthermore, we study cases where countries are net exporters but actually net Complexity-Weighted importers, and vice versa, net importers but actually net Complexity-Weighted exporters, further confirming that CWI and CWE can effectively capture complicated factors such as technology.

During the in-depth study, we noticed a notable phenomenon: unlike the linear correlation coefficient of NE to GDP, which is not an obvious distribution pattern, the linear correlation coefficient between NCWE indicator that takes into account abstract factors like technology–and GDP generally shows a strong negative correlation. By further analyzing the linear correlation of CWI and CWE with GDP, as well as their impact coefficients on GDP in a multiple linear ridge regression model, we arrived at a significant conclusion: compared to exports, imports that encompass abstract factors such as technology have a more pronounced effect on economic growth. This discovery underscores the importance of not only paying attention to export performance but also valuing the quality and technological content of imports when considering economic activities Rodrik [21].

Considering the significant differences in the linear regression coefficients of CWI and CWE on GDP across different countries, we leveraged the memory characteristics of LSTM neural networks to construct a regression model applicable to various countries. Through fixed historical information simulation experiments with the fitted LSTM model, we have further validated the following critical conclusion: Regardless of a country's economic stage, CWI consistently play a more significant role in driving economic growth than CWE. Moreover, the lower the economic stage, the more pronounced the relative impact of CWI compared to CWE. This finding provides important insights for policymakers when formulating import and export strategies, enabling them to precisely adjust trade policies based on the nation's level of economic development to achieve sustainable economic growth.

In short, the core innovations of this paper are mainly reflected in two aspects. First, it breaks through the traditional analytical framework of economic growth driven by trade volume. By constructing the CWE and CWI indicators, it incorporates abstract factors such as product technology content and trade scarcity into the evaluation system of the relationship between trade and GDP growth. Finally, it reveals the key phenomenon that "after considering the above factors, the driving effect of imports on GDP is significantly greater than that of exports". This conclusion is not only initially verified by comparing the differences in correlation coefficients between "NE and GDP" and "NCWE and GDP" among various countries, but also quantitatively supported by the comparison of ridge regression coefficients of CWE and CWI on GDP in a multi-country sample. Second, aiming at the heterogeneity of the relationship between trade complexity and GDP in different countries, this paper conducts simulation analysis by constructing a general model. It further clarifies the differential characteristics of the mechanism by which CWE and CWI affect GDP at different stages of economic development, providing a more universal analytical tool for countries to formulate differentiated import and export strategies.

Overall, the findings of this paper have certain reference value for national macroeconomic decision-making. They suggest that policymakers should place greater emphasis on the import side, increase import value, enhance the quality of imported products, and introduce more technology to promote domestic economic development. At the same time, the export side should not be neglected; it is important to not only increase export value but also to strengthen the competitiveness of export products.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YiZ: Writing – review and editing, Writing – original draft, Methodology, Conceptualization, Investigation, Data curation, Visualization. YaZ: Writing – review and editing. NF: Writing – review and editing. XS: Writing – review and editing. SP: Writing – review and editing. LY: Writing – review and editing. JL: Writing – review and editing. RW: Writing – review and editing. YK: Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A

1 Specific pathway of the LSTM network

The network pathway of the LSTM is illustrated in Figure A1.

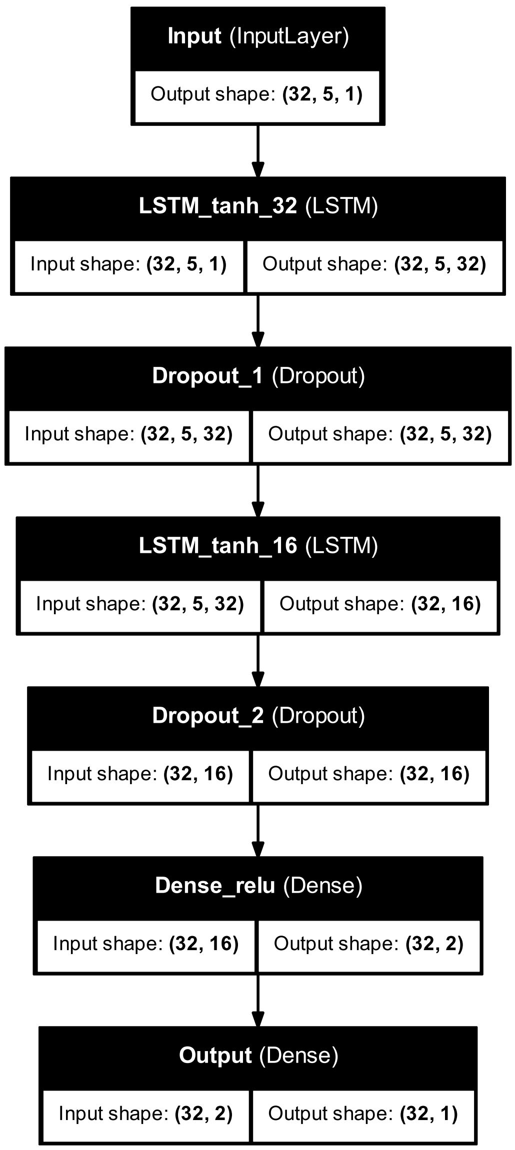

FIGURE A1
Each block represents a layer in the neural network. "Input shape" and "Output shape" indicate the matrix dimensions for that layer's input and output, respectively, where the first dimension denotes the number of samples processed in parallel. Each block represents a layer in the neural network. "Input shape" and "Output shape" indicate the matrix dimensions for that layer's input and output, respectively, where the first dimension denotes the number of samples processed in parallel.

TABLE A1 Descriptive statistics of ridge regression coefficients.

Ridge regression coefficient	Mean	Std	Median
CWE on GDP	0.23	0.17	0.28
CWI on GDP	0.48	0.12	0.48

TABLE A2 MSE comparison of different models.

Model	Training MSE	Testing MSE
LSTM	4.98×10^{-3}	4.86×10^{-3}
RNN	6.32×10^{-3}	5.71×10^{-3}
GRU	5.32×10^{-3}	5.34×10^{-3}

2 Significance test

As shown in Table A1, the mean and median of the ridge-regression coefficients for CWI are markedly higher than those for CWE. Meanwhile, in terms of standard deviation, the distribution of CWI is more concentrated than that of CWE. Overall, the ridge-regression coefficients for CWI are significantly larger than those for CWE.

3 Comparison of the effects of different recurrent neural

In the process of neural network modeling, we selected three types of recurrent neural networks for comparison, namely, Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and LSTM. All three recurrent neural networks demonstrated effective fitting of GDP for both CWI and CWE, without encountering overfitting issues, as illustrated in the Table A2. The comparison of multiple models in the example country is shown in Figure A2.

Ultimately, we selected the LSTM model, which demonstrated the best fitting performance, as the model for the article's modeling and simulation analysis.

4 The multiple ridge regression coefficients of CWE and CWI on GDP across 174 countries

The multiple ridge regression coefficients of CWE and CWI on GDP for the selected 174 countries and regions are detailed in Figure A3.

5 Details on the calculation of product complexity and country fitness

The product complexity and country fitness converge in approximately 20 iterations during the computational process, as shown in Figure A4.

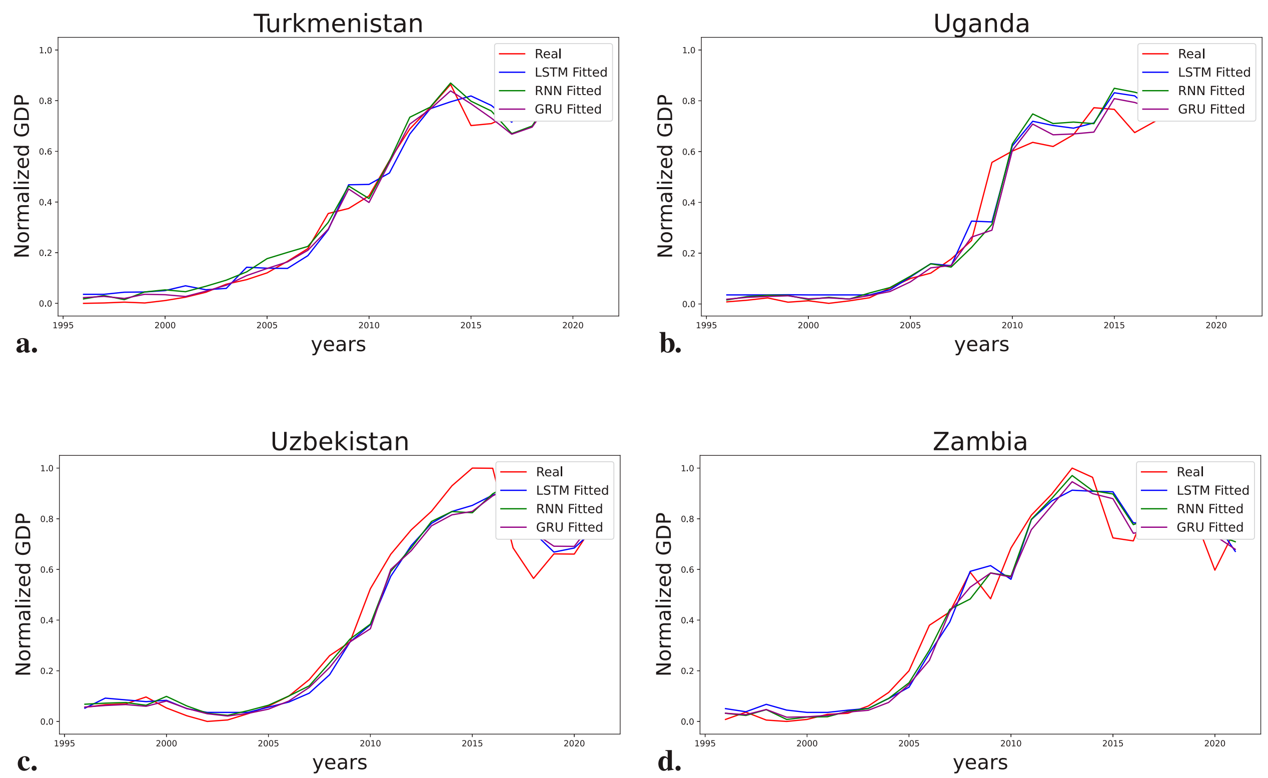

FIGURE A2
Comparison between actual values and fitted values for a few test set data. **(a–d)** The prediction generated by the LSTM, RNN and GRU models for four countries (Turkmenistan, Uganda, Uzbekistan, and Zambia). The red, blue, green, and purple curves represent the true value of the country's normalized GDP, the fitted value of the LSTM model, the fitted value of the RNN model, and the fitted value of the GRU model, respectively.

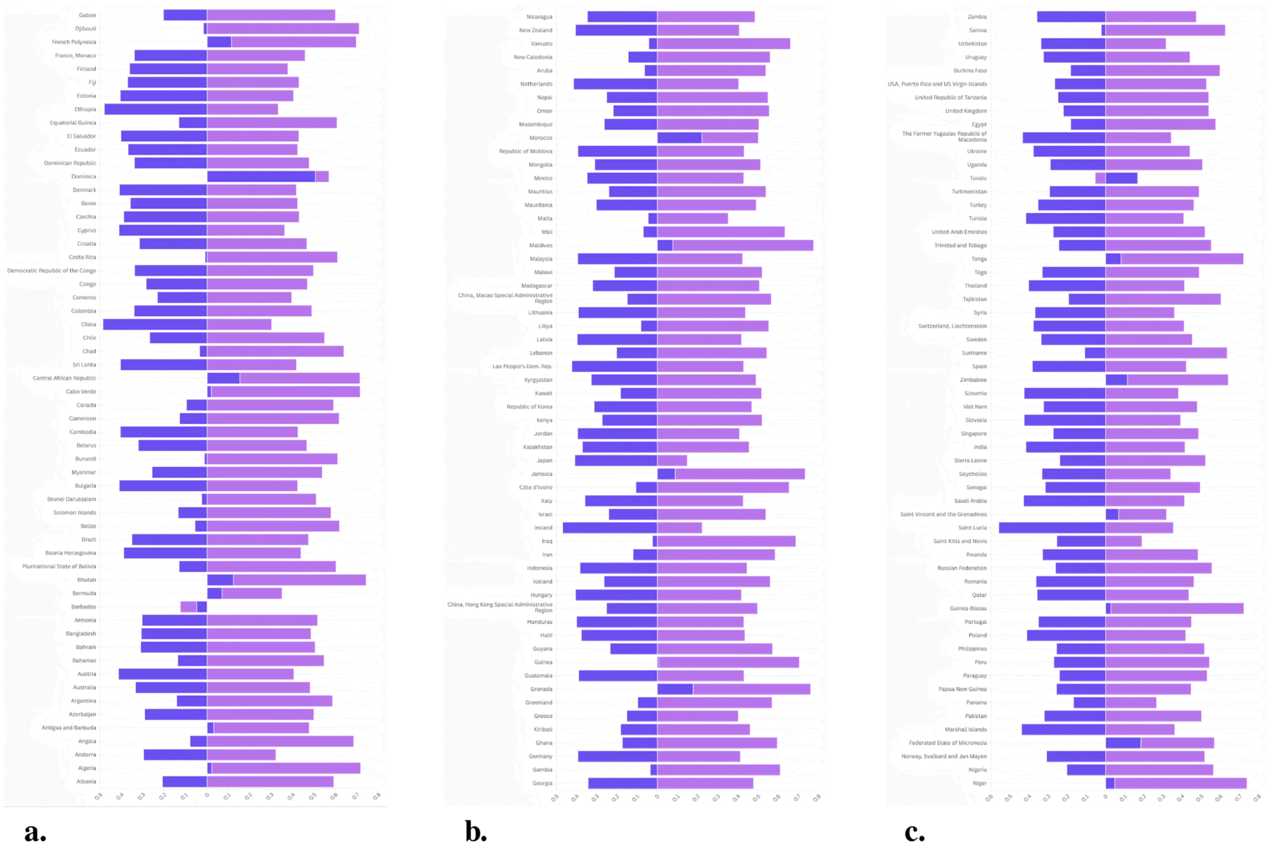

FIGURE A3
The ridge regression coefficient results of CWE and CWI for GDP. **(a–c)** Show the multiple ridge regression coefficients of CWE and CWI on GDP for 174 countries and regions. The left side is the linear regression coefficient of CWE on GDP, and the right side is the linear regression coefficient of CWI on GDP.

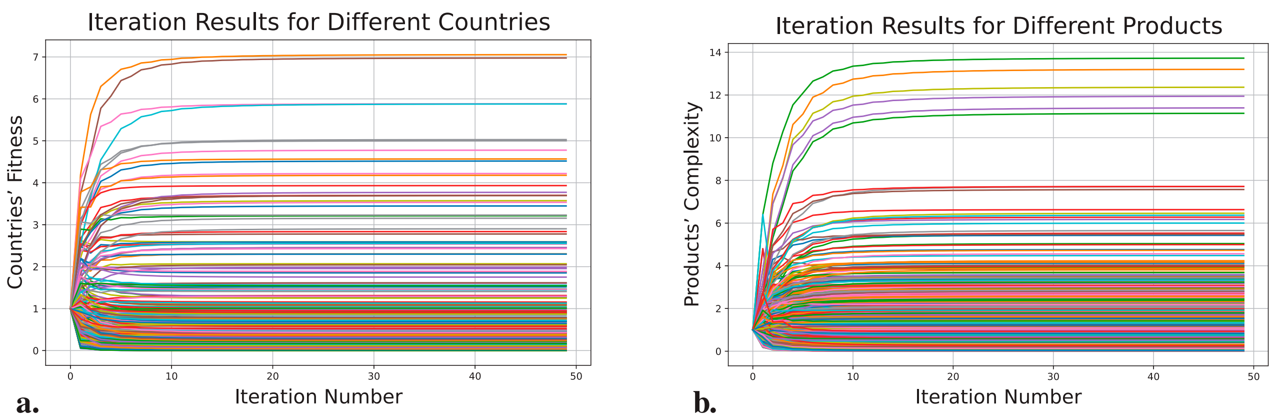

FIGURE A4
Iteration diagram of product complexity and country fitness. **(a)** Iterative calculation graph of country fitness. Curves of different colors represent different countries. **(b)** Iterative calculation graph of product complexity. Curves of different colors represent different products.