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Assessing the Belt and Road Initiative's Impact: A Multi-Regression Model Based on Economic Interaction

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Abstract: This study examines the impact of joining the Belt and Road Initiative (BRI) on the economies of ASEAN countries, focusing on the shipping industry's performance. Ten economic interaction indicators were analyzed using data from 2015–2022 and predicting future data for 2015–2030 through GM(1,1) and FOA-SVR models. The principal component regression (PCR) model, combined with the Analytic Hierarchy Process (AHP), assessed the correlation of these indicators with GDP and port container throughput (PCT). The findings reveal a strong correlation between economic interaction scores with China and economic and shipping performance, highlighting Chinese investment's significant impact on GDP and shipping connectivity's substantial influence on container throughput. This study provides a framework for quantifying organizational engagement levels and policy effectiveness.

Keywords: Belt and Road Initiative; economic interaction; economy and shipping performance; principal component regression

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1. Introduction

With the intensification of global trade friction, the trend of anti-globalization, and the sharp fluctuations in the container shipping market, establishing a stable and effective regional cooperation organization is vital [1]. After joining the organization, the effective performance of the organization's role is an issue that needs to be considered. Assessing the impact of joining a specific cooperation organization on participating countries' economies is essential.

While the global business sector is experiencing a trend of de-globalization, China is creating a new wave of connectivity in Europe, the Middle East, Africa, and Asia through the Belt and Road Initiative [2]. Proposed by President Xi Jinping of the People's Republic of China in 2013, the Belt and Road Initiative aims to expand trade routes along the ancient Silk Road, an ancient trade route that used to connect East and West. The initiative is part of China's strategy to realize openness, regional security, regional co-construction, and win–win cooperation [3,4].

The year 2023 is of particular significance as the tenth anniversary of the Belt and Road Initiative. In that year, more than 150 countries participated in the third Belt and Road Summit on International Cooperation, which signaled the widespread acceptance of the Belt and Road Initiative and reflected its central role in promoting international economic cooperation. During the forum, governments, local governments, and enterprises reached several cooperation outcomes, summarized into 89 projects covering five categories with 458 sub-projects [5]. These cooperative achievements reflect the depth and breadth of economic interactions between China and ASEAN countries and have far-reaching impacts on the shipping and logistics sectors.

In the past decade, trade and investment cooperation under the Belt and Road Initiative has played a positive role in promoting the sound development of the world economy [6].

Economic ties between China and ASEAN countries have strengthened through such cooperation, and trade has increased significantly. Under the Belt and Road Initiative framework, China and ASEAN countries have achieved remarkable cooperation results [4]. As of 2023, China has been ASEAN's largest trading partner for 14 consecutive years, and ASEAN has been China's top trading partner for 4 straight years. Under the Belt and Road framework, the China-initiated Asian Infrastructure Investment Bank (AIIB) and the New Development Bank (NDB), as opposed to the existing Western-dominated Bretton Woods system, have been widely welcomed by emerging economies, especially those along the Belt and Road routes [7,8].

The Belt and Road Initiative offers new opportunities for interaction between the Chinese economy and countries along the route, against the backdrop of a sluggish global shipping market. In the context of globalization, the Belt and Road Initiative, an important international cooperation project, has profoundly impacted the shipping and logistics industry. By actively promoting the construction of transport infrastructure, the initiative has effectively optimized maritime logistics corridors and significantly supported the economic growth and shipping performance of countries along the route. Specifically, by improving port facilities, enhancing transportation efficiency, and strengthening regional connectivity, the Belt and Road Initiative has helped to reduce logistics costs, increase the speed of cargo flow, and inject new vitality into the trade and economic development of countries along the route [9]. According to the World Bank's forecast, tens of millions of people are expected to be lifted out of poverty by 2030 when the transportation projects under the Belt and Road framework are fully implemented [10]. This projection not only demonstrates the potential of the Belt and Road Initiative to promote economic development and reduce poverty, but also reflects its long-term impact on the shipping and logistics industry. With improved transportation infrastructure, countries along the route can more effectively utilize their resources and advantages to participate in the global economy, thereby achieving sustained economic growth.

While these conclusions may seem tempting, not all countries endorsed the Belt and Road Initiative in its early stages, with some ASEAN countries expressing concerns, including the Philippines, Malaysia, and Myanmar, who were mainly concerned about the possible debt risks, environmental impacts, and geopolitical implications of the Belt and Road Initiative [11]. These countries aim to protect their national interests and regional stability, and to ensure the transparency and sustainability of the Belt and Road project, while remaining alert to the potential risks involved in cooperation with China, so as to preserve their sovereignty and realize sustainable development through collaboration [12,13]. The attitudes held by different countries towards this initiative affect the extent of their economic interaction with China, and indeed, positive attitudes have led to deeper involvement in Belt and Road cooperation, and to the enjoyment of maximizing the fruits of that cooperation.

In exploring the impact of economic interaction with China on the economic growth and shipping performance growth of ASEAN countries, previous studies have lacked a quantitative analysis of the relationships between indicators of economic interaction among member countries and their measurable outcomes. Currently, most studies take a geopolitical perspective and ignore the link between economic interaction and economic growth [14]. This research tendency may lead to a lack of understanding of how economic interactions specifically affect ASEAN countries' GDP and shipping performance. Nonetheless, some independent analysts have attempted to fill this gap. For example, the CIMB ASEAN Institute assessed the positive contribution of the Belt and Road program to the economic development of Southeast Asian countries in a report published in 2018 [15]. However, the report's assessment was mainly based on speculation and lacked specific data support, limiting its conclusions' credibility and usefulness. To more accurately understand the impact of China's economic interactions on the economic growth and shipping performance of ASEAN countries, this study assumes that economic interactions with China have a positive impact on ASEAN's economic and shipping growth, and through the collection and analysis of specific data including (but not limited to) indicators such as the trade volume, investment volume, and the shipping connectivity index, a quantitative analysis can provide a clearer view of how the economic interactions are transformed into economic growth and prosperity of the shipping industry [16].

In traditional quantitative impact studies of economic indicators, scholars often rely on specific econometric methods, such as ordinary least squares (OLS), to estimate the relationships between economic variables [17]. However, such methods may not adequately address the problem of multicollinearity in economic data and situations where assumptions about the normal distribution of data may be unrealistic [18]. This study adopts more advanced statistical and machine learning methods to overcome these limitations. First, this study employs principal component analysis (PCA) to deal with the problem of multicollinearity among economic variables. With PCA, highly correlated variables can be converted into a set of a smaller number of uncorrelated principal components, thus simplifying the model and avoiding instability in parameter estimation [19]. These principal components capture most of the variability of the original variables while reducing the model's complexity. Next, to further validate the model's robustness, this study utilizes various statistical methods for testing. These methods can provide more robust estimates of outliers and non-normally distributed data. In addition, given the uncertainty of the international political and economic environment, this study also employs machine learning techniques to forecast future data [20]. By training machine learning models, historical data are utilized to predict future trends in economic indicators. This approach improves forecasting accuracy and applies the complete dataset to the principal component regression model, which enhances the model's adaptability to changes in the complex international environment.

This study is divided into three steps: (1) identifying the indicator system by combining existing studies and official data released by the Belt and Road Initiative (BRI), and collecting the data for the multicollinearity test; (2) developing an empirical model for the participating countries of ASEAN; and (3) analyzing the changes in a specific country under the economic interaction indices to validate the model's conclusions.

The rest of this study is organized as follows: Section 2 describes the literature review, including studies related to the Belt and Road Initiative (BRI) in the countries along the route, as well as studies on economic interaction indices related to economic performance and shipping performance. Section 3 is the methodology section, which focuses on the tools used in this study, including the Support Vector Machine (SVM), principal component regression (PCR) technique, and Analytic Hierarchy Process (AHP). Section 4 discusses the results and findings of the developed models. Finally, Section 5 conducts a case study to verify the applicability of our proposed model, and Section 6 summarizes the conclusions and suggests future research directions.

2. Literature Review

Since its introduction, the Belt and Road Initiative has had a far-reaching impact on a global scale. Studies on the initiative can be broadly categorized into two levels: the political level, and the economic level. In the early stages of the Belt and Road Initiative, most studies focused on the political level [11–16]. However, with the gradual progress of the Belt and Road Initiative and its results, the proportion of studies on the economic dimension has increased significantly in the countries along the route. At the economic level, studies can be divided into regional and national economies based on their scope. At the regional economic level, existing studies have examined the overall economic impact of several regions in Asia and Europe, including South Asia [21–23], Central Asia [24–26], and Southeast Asia [7,27,28]. On the other hand, the studies on the economic levels of specific countries are centered around several countries central to the Belt and Road Initiative, such as India, Russia, and Singapore [29].

According to the object of study, there is macroeconomics and microeconomics. From the perspective of research objects, existing research presenting combined analysis on the macroeconomic level and the microeconomic level is relatively scarce; most of the existing literature is either a separate analysis of the macroeconomy or a separate analysis of the microeconomy, and there is almost no literature in consideration of the macroeconomy and then exploring the microeconomy. Macroeconomic research includes analysis of GDP, international trade, and investment flows, and these three areas are often inextricably linked. International trade stimulates investment flows, and investment flows counteract international trade to promote economic growth [30–34], so international studies are usually interested in this part. Microeconomic research explores different industries and business entities, involving specific industry development [35,36], enterprise performance [37,38], and other aspects.

Furthermore, academics have analyzed the factors affecting the economy under the Belt and Road Initiative. Regarding indicator selection, for the economic impact of the Belt and Road Initiative on the countries along the route, academics usually consider connectivity indicators, among which transportation connectivity has been a key focus. Chen and Li [31] assessed the overall impact of China's investment in the transportation infrastructure of the co-built countries on the regional economy, employing a computable general equilibrium (CGE) model. Kevin et al. [39] analyzed the impact of China's logistics transportation infrastructure construction on China's economy. They proposed extending the model to developing countries in the Belt and Road Initiative. Chao Wang et al. empirically investigated the impact of railroad and road transportation infrastructure on the economic growth of the relevant countries by analyzing cross-country panel data from 2007 to 2016, using static and dynamic spatial models [40]. Vinokurov and Tsukarev assessed and analyzed the prospects of seven trans-Eurasian land transport corridors, identifying the most economically promising ones for the EAEU [41]. There are many studies on BRI maritime connectivity around container transportation, port networks, liner networks, etc. Still, the primary beneficiaries are focused on shipping companies [36], while there are few specialized studies on its promotion of economic growth in the co-built countries. Only Liang and Liu have empirically suggested that improved port infrastructure connectivity can improve logistics performance and co-state economic development [42]. Other factors affecting the economy of the CCA that have been addressed in related studies include China's exports (EXP), China's imports (IMP), financial development (FDP), political stability (POL), corruption (COR), foreign direct investment (FDI) inflows, population growth rate (PGT), current account balance (CAB), and inflation (CPI), as suggested by scholars such as Iqbal [28]. Foo et al. [43] added to this by adding indicators of influencing factors such as common language, land borders, and distance. Ashraf et al. [20] used the indicators of both the quality of policy regimes and the openness of the economy.

Regarding the datasets used in empirical studies of the Belt and Road Initiative (BRI), the existing studies have data up to 2021, and the vast majority of them cover only up to 2016 [28,40,43,44]. Iqbal et al. used data from 2009 to 2016 to assess the impact of the Belt and Road Initiative on economic growth in countries along the route in Asia [28]. Wang et al. collected cross-country panel data from 2007 to 2016 to explore the impact of transportation infrastructure on economic growth in the countries of China's Belt and Road Initiative (BRI) [40]. Foo et al.'s study, which covers the period 2000 to 2016, explores the impact of the Belt and Road Initiative on international trade growth between ASEAN countries and China [43].

Meanwhile, in terms of research methodology, despite the richness of methods used in the existing literature, it concentrates on qualitative studies and static models. It ignores the characteristics of multicollinearity among economic variables. Yu explored the infrastructure investment opportunities provided by the BRI for Southeast Asian countries and its potential to promote regional economic integration through a qualitative analysis. Studies such as that of Iqbal [28] use panel data regression models that may have individual heterogeneity problems, leading to biased model estimates. Ashraf et al. [21] and Wang et al. [40] used a spatial econometrics approach, whose treatment of spatial correlation is overly complex and has a high dependence on model setup and assumptions, leading to sensitivity and difficulty in interpreting the results. Foo et al. [43] used an extended gravity model, which assumes that trade costs and preferences are fixed, ignoring the dynamics of these factors and other potential complexities. Sun et al. [44] used the propensity score matching double-difference (PSM-DID) approach, which requires strong assumptions to ensure the quality of the match and the validity of the causal inference, and is sensitive to the bias of the unobserved variables. Yang et al. [45] used the GTAP model, which relies on many assumptions and parameter calibration that may not accurately reflect the actual economic situation. Only a few studies have considered the problem of multicollinearity of independent variables. Chen et al. [46] extracted information about 16 secondary indicators of the five significant links by principal component analysis (PCA). However, after performing a principal component analysis, Chen et al. [46] used the Fixed-Effects Model (FEM) to analyze the contribution of connectivity to economic growth, ignoring the time-invariant case.

To summarize, the data selected by the existing research fail to fully consider the international political and economic changes since COVID-19 and do not form a system of indicators for the relevant influencing factors. The research methodology less often considers the problem of independent variables' multicollinearity. Therefore, this study proposes the concept of economic interaction indicators based on the influencing factors explored in existing studies, forming the relevant indicators into an economic interaction indicator system. At the same time, weights are assigned to each influencing factor in the indicator system through hierarchical analysis. Existing data are collected, and future data are predicted through machine learning and optimization algorithms to fully consider the complex changes in the international political and economic environment. Principal component regression analysis is applied to the complete dataset by combining actual and predicted data.

3. Research Methodology

3.1. Model Development Framework

This study aims to explore the quantitative impact of shipping performance and interaction indicators with China's economy on the economies and shipping sectors of ASEAN countries. Hence, it adopts the empirical model from multiple regression analysis, which explains the effects of economic interaction-related independent variables on different Y variables (PCT and GDP), as represented by Equation (1):

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + \varepsilon_i; i = 1, 2, \cdots, n \quad (1)$$

where y_i denotes the dependent variables, including PCT and GDP, while the independent variables, represented as $x_{i1}, x_{i2}, \cdots, x_{ik}$, encompass 11 indicators related to the interactions with China's economy and shipping performance.

Future data are predicted to enhance the dataset. Due to the significant impact of COVID-19 on the international economic environment, independent variable data are only available up to 2022, while dependent variable data are updated to 2023, which is insufficient to support conclusions. Therefore, this study predicts future data for relevant independent variables (influencing factors) up to 2030. Considering the instability of economic data, the Grey Model GM(1,1) is used for forecasting these factors. Then, the Support Vector Machine (SVM) model is employed to predict future dependent variable data. During this process, the Fruit Fly Optimization Algorithm (FOA) is used to optimize the parameters of the SVM model to enhance the accuracy of the prediction model.

Additionally, we diagnose multicollinearity among independent variables, as economic data indicators often exhibit high correlations. We construct a principal component regression (PCR) model and apply the complete dataset to principal component analysis (PCA) to extract critical components. Then, we build the PCR model. Finally, we revert the regression model to the original independent variable dimensions and update it with AHP weights. The updated model reflects the quantitative impact of independent variables on dependent variables, showing the influence of each indicator on the economy and shipping.

The framework for the development of the regression model consists of three stages:

1. Establish an indicator system, and weights are assigned to the indicators using the Analytic Hierarchy Process (AHP), followed by a consistency check;
2. Combine the GM(1,1) and FOA-SVR models to predict future data and complete the dataset;
3. Examine the correlation among independent variables and construct the principal component regression (PCR) model, and then update the coefficients of the independent variables using AHP weights.

3.2. Data Collection

This study incorporates economic interaction indicators from the existing literature [31,36,39–43], collecting ten officially released datasets from UNCTAD, the Belt and Road Portal, and the World Bank. The datasets include two dependent variables and eight independent variables. The data for the dependent variables are complete. Initially, the data for the five independent variable indicators, obtained directly, underwent preprocessing. This included handling any missing data points. The missing data were interpolated using an improved Long Short-Term Memory (LSTM) model. This enhanced LSTM model incorporates a self-attention layer, allowing it to capture the cross-sectional linkages between different countries simultaneously. By doing so, the model can better understand the relationships and dependencies across the dataset, leading to more accurate predictions of the missing values. This interpolation process was implemented using Python's TensorFlow library (Python 3.12 version), which facilitated the creation and training of the improved LSTM model for practical data completion. Additionally, three calculated indicators were added as independent variables. These include the distance to China (DIS), measured using a formula, and two policy indicators assigned values based on their status.

In this study, the economic center cities of the participating countries were chosen as benchmarks for assessing the distance to China's financial center, Shanghai. This method accurately estimates the actual economic exchange distance between China and each ASEAN country. The great-circle distance between two points was calculated using the haversine formula, represented as Equation (2):

$$\mathrm{DIS_{fi}} = 2\mathrm{r}\cdot\arcsin\left(\sqrt{\sin^2\left(\frac{|\phi_f-\phi_i|}{2}\frac{\pi}{180}\right)+\cos\left(\phi_f\frac{\pi}{180}\right)\cos\left(\phi_i\frac{\pi}{180}\right)\sin^2\left(\frac{|\phi\lambda_f-\lambda_i|}{2}\frac{\pi}{180}\right)}\right) \tag{2}$$

where r represents the average radius of the Earth; λ_f is the longitude of the fixed point (in decimal degrees); ϕ_f is the latitude of the fixed point, Shanghai (in decimal degrees), with a value of $31^\circ 13' 43''$; λ_i is the longitude of the i-th point (in decimal degrees), taking the negative value if not in the Eastern Hemisphere; and ϕ_i is the latitude of the i-th point (in decimal degrees), taking the negative value if not in the Northern Hemisphere.

Additionally, the RECP and FTA policy indicators are assigned values. If the RCEP of country i becomes effective in year m, then from year m onwards the RCEP indicator for country i is assigned a value of 1; otherwise, it is 0. The FTA indicator follows the same logic. If country i signs a bilateral free trade agreement with China from year n onwards, the FTA indicator for country i is assigned a value of 1. FTA refers to the bilateral free trade agreement between two countries, not between China and the entire ASEAN.

This results in a refined dataset that effectively represents the shipping capabilities of ASEAN countries. Table 1 provides a summary of all of the variables that are used in this study. These indicators were selected after combining relevant studies and BRI features [47], and the rationale for choosing each indicator was as follows:

- POP: Population is traditionally a critical indicator of a country's market potential, and it is a direct source of labor and market demand that directly affects economic activity and port cargo throughput.

- CDS: The investment stock reflects China's long-term capital investment in the country, and high levels of Chinese investment are usually accompanied by infrastructure development and economic development, which, in turn, increases the country's GDP and port cargo throughput.
- CNI: Direct investment is an essential indicator of China's economic activity in the country, and an increase in the volume of direct investment usually leads to economic growth, boosting GDP and cargo throughput at ports.
- CNU: The literature suggests that this indicator may negatively correlate with the dependent variable. China's use of foreign capital from the Commonwealth of Nations may have weakened the financing of the development of the domestic economies of the Commonwealth of Nations, and it may have created a shortage of investment, affecting the growth and innovation of domestic industries; moreover, the misallocation of Commonwealth of Nations funds may have dampened the potential of the home economy, as infrastructure and industrial development funds are used for outward investment, further exacerbating the slowdown of the Commonwealth of Nations' domestic economies.
- EFC and IFC: These are two indicators of imports and exports, and an increase in imports and exports means that more goods are being transported through the ports, increasing the ports' container throughput and also boosting the country's GDP growth.
- CRV: Chinese-registered vessels in the country show China's involvement in the country's shipping industry and, side by side, the country's shipping capacity. More registered ships means more cargo transportation and port activity, directly increasing container throughput at ports and positively affecting economic activity.
- CLC: Shipping connectivity reflects the density and efficiency of the shipping network between the country and China, and its enhancement contributes to more efficient trade and increased trade volumes, which, in turn, boost port container throughput and GDP.
- DIS: Geographical distance is essential to transportation costs and time. Closer proximity can help to reduce transportation costs and increase trade, thereby boosting port container throughput and economic activity levels.
- RCEP: Regional free trade agreements are designed to reduce trade barriers and promote economic cooperation among member countries. The implementation of RCEP has helped to increase the volume of trade, enhance economic growth, and increase the volume of container throughput at ports.
- FTA: The signing of a bilateral FTA aims to reduce trade barriers between the two countries and boost bilateral trade. This will increase the volume of bilateral trade, increase container throughput at ports, and contribute to GDP growth.

Table 1. Summary of variables.

Description	Code	Type of Variables	Source
Container Throughput	PCT	Dependent (Y)	UNCTAD
GDP	GDP	Dependent (Y)	IMF
Population	POP	Independent (X_1)	World Bank
FDI Stock from CN	EI_{CDS}	Independent (X_2)	CNBS
Net FDI from CN	EI_{CNI}	Independent (X_3)	CNBS
Investments used by CN	EI_{CNU}	Independent (X_4)	CNBS
Export Value to CN	EI_{EFC}	Independent (X_5)	CNBS
Import Value from CN	EI_{IFC}	Independent (X_6)	CNBS
Vessels Registered by CN	EI_{CRV}	Independent (X_7)	UNCTAD
Container Liner with CN	EI_{CLC}	Independent (X_8)	UNCTAD
Distance to CN	EI_{DIS}	Independent (X_9)	
RCEP Implementation sts	EI_{RCEP}	Independent (X_{10})	
Bilateral FTA Signing sts	EI_{FTA}	Independent (X_{11})	

3.3. Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a structured technique for complex decision-making, introduced by Thomas L. Saaty [48]. It involves modeling problems in a hierarchical structure with goals, criteria, and alternatives.

Define the problem and structure it hierarchically, with the goal at the top, criteria at the intermediate level, and alternatives at the bottom. Construct pairwise comparison matrices for the elements at each level relative to a component above them. This results in a matrix $A = [a_i]$, where a_{ij} represents the relative importance of element i to element j. The pairwise comparisons use a 1–9 scale of relative importance.

Calculate the priority vector $w = [w_1, w_2, \cdots w_n,]^T$ for each matrix by normalizing the geometric mean of each row; the calculation process is shown in Equation (3):

$$w_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}} \tag{3}$$

The consistency index (CI) is calculated by Equation (4), and the consistency ratio (CR) is calculated by Equation (5), to check the acceptability:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{4}$$

$$CR = \frac{CI}{RI} \tag{5}$$

where λ_{max} is the maximum eigenvalue of the comparison matrix, n is the number of elements, and *RI* is the random index. A CR value less than 0.1 indicates acceptable consistency.

Aggregate the weight vectors to determine an overall score for each alternative. This is done by combining each criterion's weights with the alternatives' scores.

3.4. Data Prediction Model

3.4.1. GM(1,1) for Predicting Dependent Variables

The Grey Model GM(1,1) is a forecasting technique used in situations with limited or uncertain information [49]. This study uses the GM(1,1) model to predict future data for the independent variables. The construction of the GM(1,1) model begins with initializing the data sequence. Start with the original data sequence $X^{(0)}$, represented as $X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right\}$. It is essential that the data sequence is non-negative.

Next, perform the AGO to generate the accumulated sequence $X^{(1)}$. This sequence is represented as $X^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(k)\right\}$, where $x^{(1)}(k)$ is defined as $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$ for $k = 1, 2, \cdots, n$.

The accumulated sequence $X^{(1)}$ is expressed as a first-order attention equation, which is a core step in GM(1,1), expressed as $\frac{dX^{(1)}}{dt} + aX^{(1)} = b$, where a is the development coefficient and b is the grey input. To estimate the parameters a and b, use the least squares method. Construct the data matrix B and the data vector Y_N as shown in Equations (6) and (7), respectively:

$$B = \begin{bmatrix} -\frac{1}{2}\left(x^{(1)}(1) + x^{(1)}(2)\right) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left(x^{(1)}(n-1) + x^{(1)}(n)\right) & 1 \end{bmatrix} \tag{6}$$

$$Y_N = \begin{bmatrix} (x^{(0)}(2) \\ \vdots \\ (x^{(0)}(n) \end{bmatrix} \tag{7}$$

Solve for $\hat{a}$ and $\hat{b}$ using the equation $\hat{\beta} = \left(B^T B\right)^{-1} B^T Y_N$, where $\hat{\beta} = \left[\hat{a}, \hat{b}\right]^T$.The time response function of GM(1,1) is given by $x^{(1)}(k+1) = (x^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a}$. To restore the predicted values $\hat{x}^{(0)}(k+1)$ from the accumulated sequence, use the IAGO. This is done by calculating $\hat{x}^{(0)}(k+1) = x^{(1)}(k+1) - x^{(1)}(k)$. This process ensures that the GM(1,1) model effectively forecasts future data for the independent variables.

3.4.2. FOA-SVR for Predicting Dependent Variables

The FOA-SVR model combines the Fruit Fly Optimization Algorithm (FOA) with Support Vector Regression (SVR) to enhance predictive accuracy. Support Vector Regression (SVR) is a powerful regression technique that seeks to find a function $f(x)$ that has an epsilon deviation from the actual observed values for all training data while also being as flat as possible [50,51]. The basic form of Support Vector Regression (SVR) can be represented as Equation (8):

$$f(x) = \langle \omega, x \rangle + b \tag{8}$$

where $f(x)$ is the linear regression function, x is the input variable, ω is the weight vector, b is the bias term, and $\langle \cdot, \cdot \rangle$ denotes the dot product.

The mean squared error is commonly used as the loss function in standard linear regression. However, SVR uses the ε-intensitive loss function, defined as Equation (9):

$$L_\epsilon(y, f(x)) = \max(0, |y - f(x)| - \epsilon) \tag{9}$$

which means that the loss is zero when the difference between the predicted value $f(x)$ and the actual value y is less than or equal to ε. Loss is calculated only when the error exceeds ε.

The objective of SVR optimization includes minimizing the norm of the weight vector (to ensure model simplicity and avoid overfitting) while reducing the total error of the training samples. This can be formulated as Equation (10):

$$\min_{\omega, b, \xi, \hat{\xi}} \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{n} (\xi_i + \hat{\xi}_i) \tag{10}$$

subject to $y_i - \langle \omega, x_i \rangle - b \le \epsilon + \xi_i$ and $\langle \omega, x_i \rangle + b - y_i \le \epsilon + \hat{\xi}_i$, where $\xi_i, \hat{\xi}_i \ge 0$, and C is the penalty parameter.

The Fruit Fly Optimization Algorithm (FOA) is used to optimize the SVR parameters, specifically C, ϵ, and kernel parameters. Initially, the positions of the fruit fly swarm in the parameter space are randomly initialized, setting the initial parameters C, ϵ, and kernel parameters.

During the olfactory search, calculate the distance of each fruit fly i from the origin and estimate the smell concentration S_i at each position using Equation (11):

$$\begin{cases} D_i = \sqrt{X_i^2 + Y_i^2} \\ S_i = \frac{1}{D_i} \end{cases} \tag{11}$$

Evaluate the smell concentration using a fitness function, typically the SVR model's prediction accuracy or error. In the vision search phase, identify the fruit fly with the best smell concentration S_{best}, and update the positions of the fruit flies based on the best position using Equation (12):

$$\begin{cases} x_{new} = x_{best} + \text{rand}(\ ) \\ y_{new} = y_{best} + \text{rand}(\ ) \end{cases} \tag{12}$$

The olfactory and vision search process is iterated until convergence or a maximum number of iterations is reached.

3.5. Principal Component Regression (PCR)

Principal component regression (PCR) is a technique that combines principal component analysis (PCA) with linear regression. It addresses multicollinearity issues in regression models by transforming the predictors into a set of orthogonal components [52].

The predictors X are standardized to have a mean of zero and a standard deviation of one. Let X be the $n \times p$ matrix of predictors, where n is the number of observations and p is the number of predictors. PCA is performed on the standardized predictors X. Compute the covariance matrix $\sum = \frac{1}{n}X^TX$.

Calculate the eigenvalues λ_i and eigenvectors v_i of the covariance matrix $\sum$. The eigenvectors are the principal components, forming an orthogonal basis for the data. Form the matrix of principal components P:

$$P = XV \tag{13}$$

where V is the $p \times p$ matrix of eigenvectors.

Select the first k principal components that explain a significant amount of the variance in the data. Let P_k be the $n \times k$ matrix of the first k principal components.

Perform linear regression of the response variable Y on the selected principal components P_k. The regression model is

$$Y = P_k\beta + \epsilon \tag{14}$$

where β is a $k \times 1$ vector of regression coefficients, and epsilon is the error term.

To interpret the regression coefficients in terms of the original predictors, transform the principal component regression coefficients back to the original predictor space:

$$\hat{\beta} = V_k\beta \tag{15}$$

where V_k is the $p \times k$ matrix of the first k eigenvectors.

4. Results and Findings

Since China's introduction of the Belt and Road Initiative (BRI), most Southeast Asian countries have paid great attention and taken the lead in responding to it [52]. After ten years of construction, the Belt and Road Initiative has made remarkable achievements in Southeast Asia, with China deepening its economic and trade relations with Southeast Asian countries, further improving connectivity, realizing innovations in international production capacity cooperation, and transforming its industrial layout towards high-quality development. China and ASEAN are each other's largest trading partners, with China being ASEAN's top trading partner for 14 consecutive years and ASEAN being China's top trading partner for 4 straight years. Economic ties and interdependence between China and ASEAN are rather close. China's economic engagement and international influence in the Southeast Asian region have grown considerably since the early 1990s through the framework of the ASEAN–China Dialogue Relationship. This performance stems from the natural function of China's historical ties and geographic proximity to the ASEAN region. It is the result of decades of Chinese investment in building regional relations. Whether bilaterally with ASEAN member states or multilaterally through ASEAN and ASEAN-led regional structures, ASEAN countries have been the site of particularly intense Chinese investment and geopolitical activity. Therefore, this study focuses on the ASEAN region. In this study, the latest officially released data on the independent variable for the nine ASEAN countries for 2015–2022 and the dependent variable for 2015–2023, i.e., the nine coastal countries (excluding Laos, which is a landlocked country), were collected as the dataset and, to better take into account the changes in the international economic environment, a forecast was made for up to 2030, whereby the actual updated data and the forecasted data were merged to form the complete dataset.

4.1. Data Forecasting

Using the GM(1,1) model, the independent variable data for 2023–2030 were predicted. Then, the Fruit Fly Optimization Algorithm–Support Vector Machine (FOA-SVR) model was applied, using odd-year data as the test set and even-year data as the training set, to predict the dependent variable data.

In the SVR model, the penalty parameter (C) and gamma (γ) are critical hyperparameters. The penalty parameter C controls the trade-off between achieving a low error on the training data and minimizing the model complexity. It determines the weight of the regularization term in the loss function, thus influencing the margin size of the Support Vector Machine. Gamma (γ), conversely, defines the influence range of a single training example. It is a parameter for the RBF (Radial Basis Function) kernel and controls the flexibility of the decision boundary. A low gamma value indicates a larger influence radius for each support vector, making the model more generalized. Conversely, a high gamma value means that each support vector has a smaller influence radius, making the decision boundary more sensitive to the training data, which could result in overfitting.

Table 2 shows the optimal parameters for the PCT and GDP models, along with the mean squared error and the coefficient of determination.

Table 2. FOA-SVR model training results.

	C	γ	**MSE**	r^2
PCT	100.0	0.001	0.002975	0.991507
GDP	87.337959	0.001	0.030559	0.984568

The learning curves were drawn as shown in Figure 1. Both models exhibited high predictive accuracy and low error; hence, the optimal model was applied to predict the dependent variable data for 2024–2030. The prediction curves are shown in Figure 2. The actual and predicted data were combined to form a complete dataset for 2015–2030.

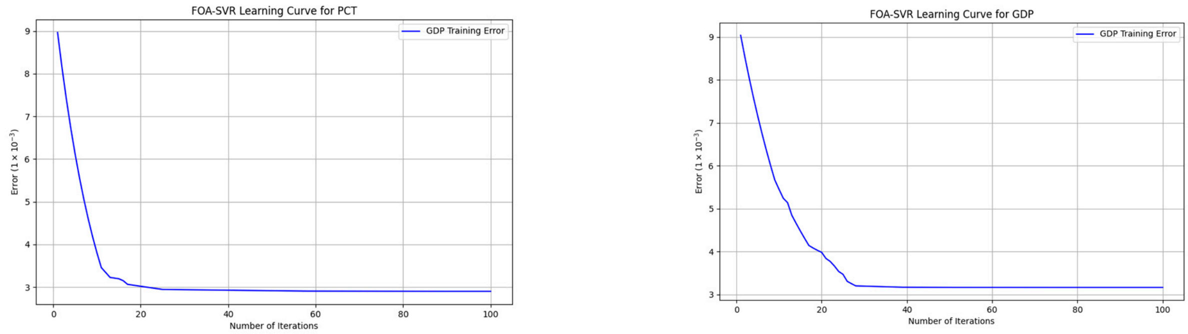
After combining the predicted data, the descriptive statistics of the variables (except DIS, RCEP, and FTA) were as shown in Table 3, where the respective variables differed significantly in their magnitudes. Therefore, the data of the independent variables should be standardized. To better reflect the quantitative impact of each independent variable increasing by one unit on the dependent variable, the independent variables were standardized on a scale of 1–9, using the formula shown in Equation (16):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \times (9 - 1) + 1 \tag{16}$$

where x is the original value of the independent variable.

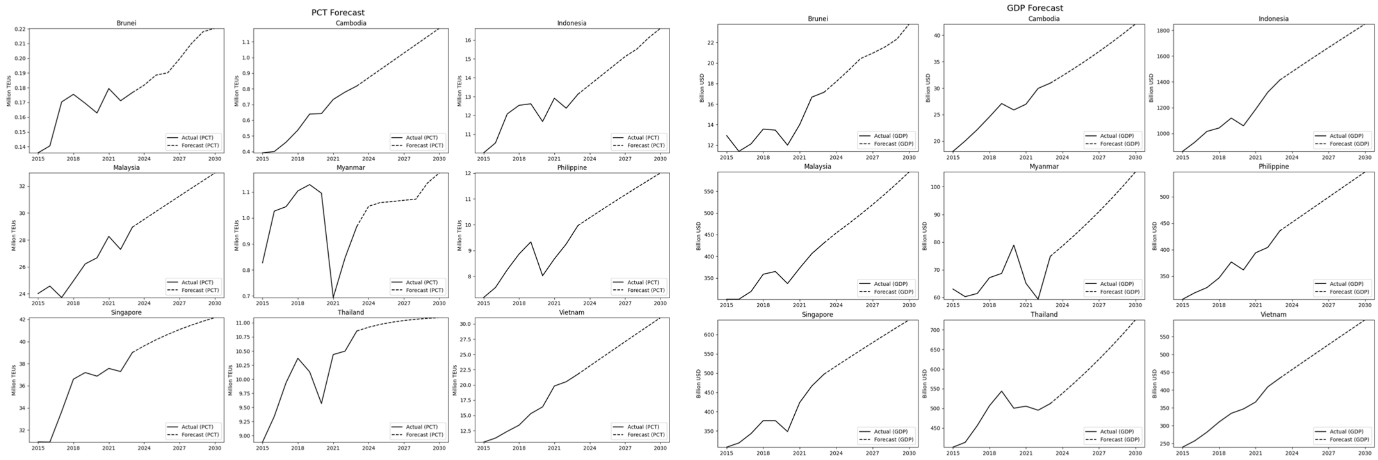
Table 3. Descriptive statistics.

	PCT	**GDP**	**POP**	**CDS**	**CNI**	**CNU**	**EFC**	**IFC**	**CRV**	**CLC**
Count	144	144	144	144	144	144	144	144	144	144
Mean	13,606,073	41,750,248	74,516,097	739,339	164,858	1,151,957	1,941,852	2,289,933	305	0
Std	12,773,408	40,453,830	80,703,640	1,205,052	211,610	6,874,805	2,360,507	2,876,012	1041	0
Min	135,804	1,140,100	421,437	30,428	2885	−201	65	12,720	0	0
25%	1,055,750	6,460,500	16,162,119	175,211	71,031	815	113,231	377,598	0	0
50%	10,894,212	37,683,000	54,363,419	340,852	98,049	5585	1,096,192	845,985	0	0
75%	24,118,997	53,844,400	98,186,856	697,741	140,401	93,050	2,782,915	4,081,820	0	0
Max	42,164,115	184,821,600	286,594,495	7,344,991	1,045,248	69,496,935	10,983,860	14,387,570	7430	1



(**a**) (**b**)

Figure 1. FOA-SVR learning curves: (**a**) FOA-SVR learning curve for PCT; (**b**) FOA-SVR learning curve for GDP.



(**a**) (**b**)

Figure 2. Prediction curves of the FOA-SVR model: (**a**) prediction curve for PCT; (**b**) prediction curve for GDP.

4.2. AHP Analysis

To evaluate the importance of each independent variable to the two dependent variables, a 1–9 scale was employed for pairwise comparisons, forming a judgment matrix. Based on these comparisons, the weights of the independent variables for both PCT and GDP were calculated. Consistency checks were rigorously performed to ensure the reliability and validity of the judgments. The estimated weights of the independent variables for the PCT and GDP systems are displayed in Table 4, providing a clear quantitative assessment of their relative significance.

Table 4. Weights calculated by AHP.

	CDS	CNI	CNU	EFC	IFC	CRV	CLC	DIS
PCT	0.0542	0.1077	0.0251	0.1296	0.122	0.0969	0.1491	0.0282
GDP	0.0382	0.1088	0.096	0.1038	0.1152	0.0573	0.0949	0.048

The calculated maximum eigenvalue λ_{max} for GDP was 10.84, with a consistency index (CI) of 0.093 and a consistency ratio (CR) of 0.063. For PCT, the calculated maximum eigenvalue λ_{max} was 10.42, with a consistency index (CI) of 0.047 and a consistency ratio (CR) of 0.031. Therefore, the weights for both indicator systems are acceptable.

4.3. Correlation Study

To check for multicollinearity among the independent variables, a heat map of correlation coefficients was plotted, as shown in Figure 3, and scatterplots of each dependent and independent variable were plotted, as shown in Figure 4. In Figure 3, darker colors represent stronger correlations between indicators, with stronger correlations observed between CDS and CRV, CDS and CNI, and IFC and EFC. This is also confirmed by the scatterplots in Figure 4, which show a more convergent distribution within the two groups CDS and CNI, as well as EFC and IFC. In particular, the scatterplots for all four independent variables—GDP and CDS, CNI, EFC, and IFC—show more consistent distributions.

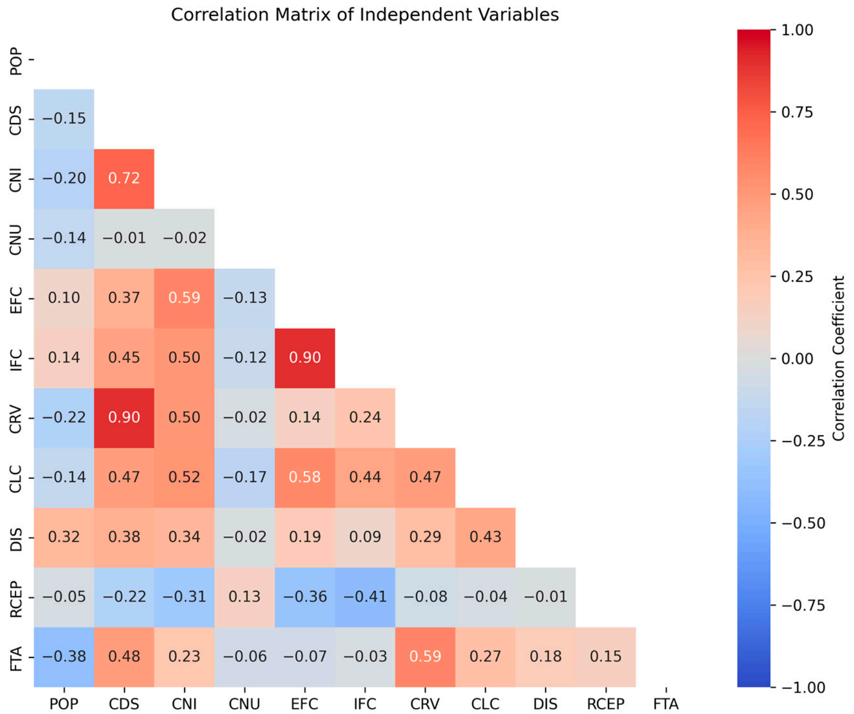
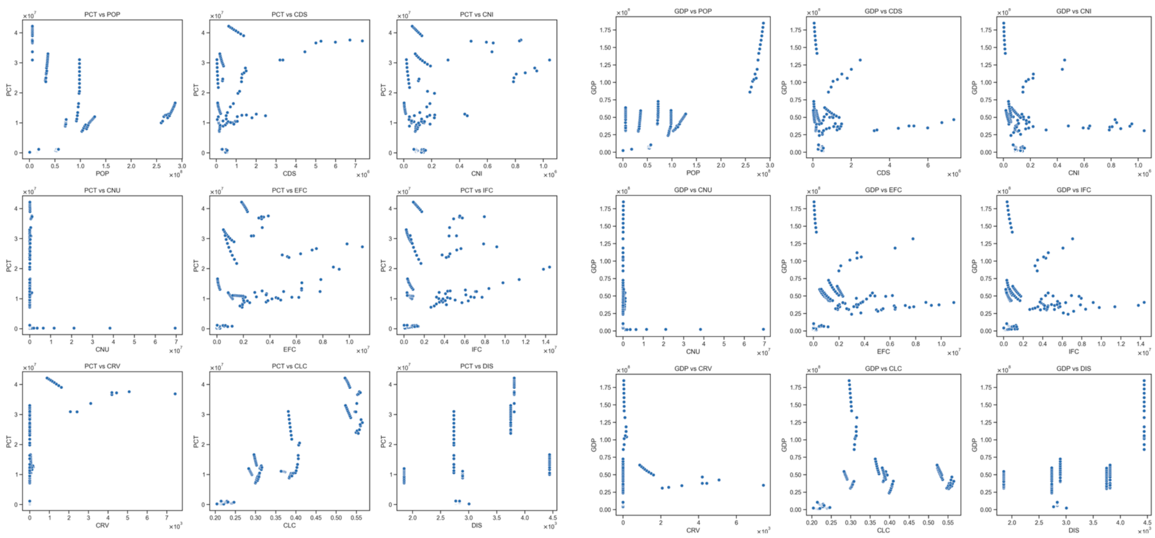


Figure 3. Correlation coefficients of independent variables.



(**a**) (**b**)

Figure 4. Scatterplots of dependent variables vs. independent variables: (**a**) scatterplot of PCT vs. independent variables; (**b**) scatterplot of GDP vs. independent variables.

To further determine multicollinearity among the independent variables, the variance inflation factor (VIF) was calculated using Equation (17). The variance inflation factor (VIF) is an essential metric for assessing multicollinearity in regression models [53].

$$\mathrm{VIF}_{x_i'} = \frac{1}{1 - R_i^2} \tag{17}$$

whewhere R_i^2 is the coefficient of determination obtained by regressing x_i' on the remaining independent variables.

A higher VIF value indicates greater collinearity, meaning that other independent variables can linearly predict an independent variable. Generally, the interpretation of VIF is as follows:

- $\mathrm{VIF} = 1$: no multicollinearity at all;
- $1 < \mathrm{VIF} < 5$: mild multicollinearity, acceptable;
- $5 < \mathrm{VIF} < 10$: moderate multicollinearity, needs caution;
- $\mathrm{VIF} > 10$: severe multicollinearity, requires corrective measures.

The VIF calculation results are shown in Table 5, indicating severe multicollinearity among the variables.

Table 5. VIF results.

	POP	CDS	CNI	CNU	EFC	IFC	CRV	CLC	DIS	RCEP	FTA
VIF	3.764	23.033	7.168	1.185	15.759	12.184	12.851	28.552	29.159	3.25	2.437

The matrix of correlation coefficients in the heat map visualizes the high correlation between the independent variables. Multiple scatterplots show a linear trend in the distribution of points between pairs of independent variables, which indicates the existence of linear dependence between the independent variables, further confirming the correlation. The computation of VIF values quantifies the degree of multicollinearity between the independent variables. In summary, it can be concluded that there is multicollinearity between the independent variables in the dataset. Therefore, this study applied the principal component regression (PCR) model presented in Section 4.4.

4.4. Principal Component Regression Model Development

4.4.1. PCA

We conducted a principal component analysis (PCA) on the independent variables, resulting in the eigenanalysis of the correlation matrix, as shown in Table 6. Table 7 reflects the loadings of the independent variables on each principal component. According to Table 6, the cumulative explanatory power of the first four principal components reaches 86.1%, which is more than 85%, indicating that they can represent the primary information of the data. Extracting these four principal components effectively retains essential patterns and trends in the data while discarding noise and redundant information.

Table 6. Eigenanalysis of the correlation matrix.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
Eigenvalues	18.117	15.086	8.453	5.228	2.876	2.084	1.239	0.701	0.498	0.136	0.053
Proportion of Variance	0.333	0.277	0.155	0.096	0.053	0.038	0.023	0.013	0.009	0.002	0.001
Cumulative Proportion	0.333	0.61	0.765	0.861	0.914	0.952	0.975	0.987	0.997	0.999	1

Table 7. Loadings of the independent variables on the principal components.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
POP	0.172	0.559	−0.893	−1.219	0.799	−0.273	0.320	−0.181	0.151	−0.004	−0.002
CDS	0.554	0.871	6.5×10^{-5}	−0.130	0.123	0.565	0.496	0.192	−0.106	−0.038	−0.160
CNI	1.884	0.833	−0.199	0.257	−0.069	0.843	0.058	−0.560	0.131	0.074	0.038
CNU	−0.129	−0.049	0.051	0.044	−0.106	0.281	−0.080	0.335	0.627	−0.001	−0.003
EFC	1.086	0.437	−0.131	0.630	0.609	0.128	−0.448	−0.002	−0.013	−0.256	3.7×10^{-4}
IFC	1.031	0.325	0.087	0.459	0.841	0.165	−0.206	0.317	−0.115	0.230	0.028
CRV	0.265	0.799	0.127	0.137	0.028	0.237	0.588	0.262	−0.083	−0.095	0.157
CLC	0.914	1.879	0.150	0.788	−0.438	−0.765	0.263	−0.046	0.110	0.035	−0.016
DIS	−0.915	0.397	1.608	0.843	−0.768	0.279	−0.431	0.167	−0.118	0.010	0.012
RCEP	0.582	0.911	0.601	1.418	0.216	0.233	−0.007	−0.003	−0.034	0.003	0.001
FTA	−0.328	2.591	0.669	−0.831	0.547	−0.289	−0.193	−0.085	0.073	0.002	−0.004

The same conclusion can be drawn based on Figure 5. There is a distinct elbow point at the fourth principal component in Figure 5, where the eigenvalue curve shifts from a sharp decline to a flat decline. The elbow point is a standard criterion for determining the number of principal components to be retained, indicating that the principal components before the elbow point are essential in explaining the main variance of the data, while those after the elbow point contribute less to the variance of the data. Starting with the fourth principal component, the eigenvalues gradually approach zero, indicating that these principal components explain very little of the variance in the data and may be noise.

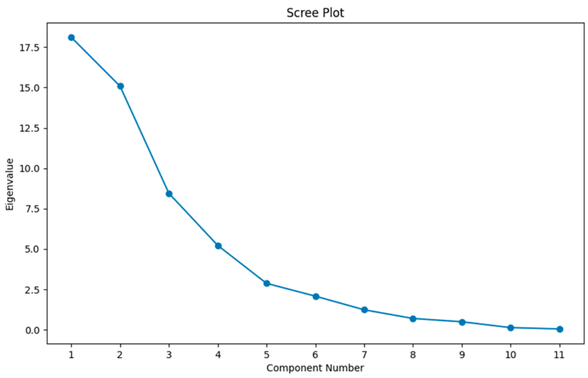


Figure 5. Scree plot of principal component eigenvalues.

4.4.2. PCR

We performed principal component analysis on the original independent variables to determine the top four principal components to be selected to develop a regression model consisting of the new independent variables based on the cumulative explanatory power and eigenvalue elbow-point characteristics of each principal component. The principal component regression model constructed is shown below.

$$PCT = \gamma_1 Z_1 + \gamma_2 Z_2 + \gamma_3 Z_3 + \gamma_4 Z_4 + \varepsilon \quad (18)$$

$$GDP = \gamma_1 Z_1 + \gamma_2 Z_2 + \gamma_3 Z_3 + \gamma_4 Z_4 + \varepsilon \quad (19)$$

The solution of gammacan is presented in Tables 8 and 9.

Regression analysis was executed for the PCT and GDP models, and the results are displayed in Tables 8 and 9, respectively. In the regression analysis, the T-Value and *p*-Value are two key indicators. The T-value reflects the significance of the effect of the independent variable on the dependent variable. The larger the absolute value of the T-value, the more significant the impact of the independent variable on the dependent variable, and the stronger the model's explanatory power. The *p*-value measures the credibility of the hypothesis that there is no linear relationship between the independent and dependent variables. Generally, a *p*-value greater than 0.005 is usually considered to be statistically insignificant, which means that there is not enough evidence to reject the null hypothesis that there is no significant linear relationship between the independent and dependent variables. According to Tables 8 and 9, the first four principal components should be retained in the PCT model. In the GDP model, PC3 and PC4 have a T-value of 0 and a *p*-value that is much more insignificant than 0.05. Therefore, only the first two principal components were retained in the final GDP model. Table 10 reflects the updated explanatory power of the obtained PCs.

Table 8. Analysis of variance for the PCT regression model.

Term	Coef ($\hat{\gamma}$)	SE Coef	T-Value	*p*-Value	VIF
Const	13,606,073	528,067	26	0.0000	1
Z_1	427,456	124,496	3	0.0008	1
Z_2	2,380,791	136,433	17	0.0000	1
Z_3	−1,963,704	182,267	−11	0.0000	1
Z_4	720,685	231,759	3	0.0023	1

Note: $R^2 = 76.08\%$, and $\text{adj} - R^2 = 75.39\%$.

Table 9. Analysis of variance for the GDP regression model.

Term	Coef ($\hat{\gamma}$)	SE Coef	T-Value	*p*-Value	VIF
Const	41,750,248	1,437,389	29	0.0000	1
Z_1	10,584,783	496,127	21	0.0000	1
Z_2	8,745,600	630,845	14	0.0000	1
Z_3	13,433	338,875	0	0.9684	1
Z_4	171,793	371,369	0	0.6444	1

Note: $R^2 = 82.33\%$, and $\text{adj} - R^2 = 81.82\%$.

Table 10. Updated explanatory power of principal components for the model.

Term	Proportion of Variance	PCT	GDP
Z_1	0.3326	0.3864	0.5457
Z_2	0.2770	0.3218	0.4543
Z_3	0.1552	0.1803	
Z_4	0.0960	0.1115	

The adjusted models do not include the intercept term, because the coefficient of determination takes into account the number of variables in the model to avoid a spurious increase in R^2 due to the addition of variables. According to Tables 8 and 9, the $\text{adj} - R^2$ of determination of the two models are still high, indicating that the models have explained the variability of the dependent variable well and that the explanatory power of the models may be sufficient even without the intercept term. The residual plots for PCT and GDP in Figure 6 show that the residual values increase as the predicted values increase, which suggests that the models have some systematic error in dealing with high predicted values. However, the proportions of residuals relative to predicted values are small, indicating that both models are more accurate in their predictions overall. Conclusively, the multiple regression models of the PCT and GDP of the participating ASEAN countries under the BRI are shown in Equations (20) and (21), as follows:

$$\text{PCT} = 427456Z_1 + 288387Z_2 - 1963704Z_3 + 720685Z_4 \tag{20}$$

$$\text{GDP} = 10584783Z_1 + 8745600Z_2 \tag{21}$$

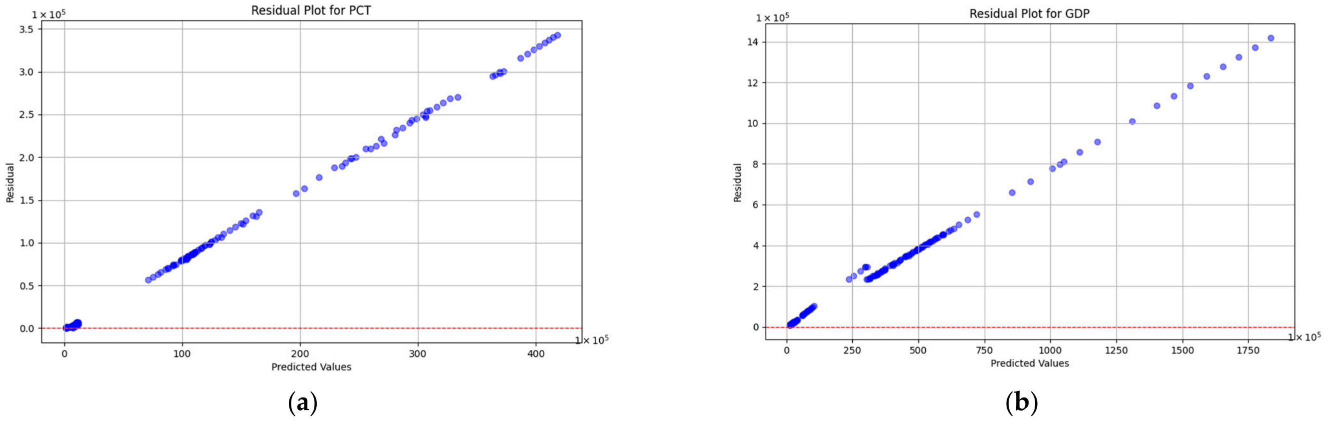


Figure 6. Residual plots: (**a**) residual plot of PCT; (**b**) residual plot of GDP.

Figure 7 illustrates the loadings of the respective variables on the first two principal components. In particular, the red line represents the loadings associated with the EI indicator. The loadings are the projection coefficients of the original variables on the principal components, which reflect the variables' relative importance in the principal components' direction. A considerable absolute value of the loadings means that the variable's contribution in forming the principal component is more significant.

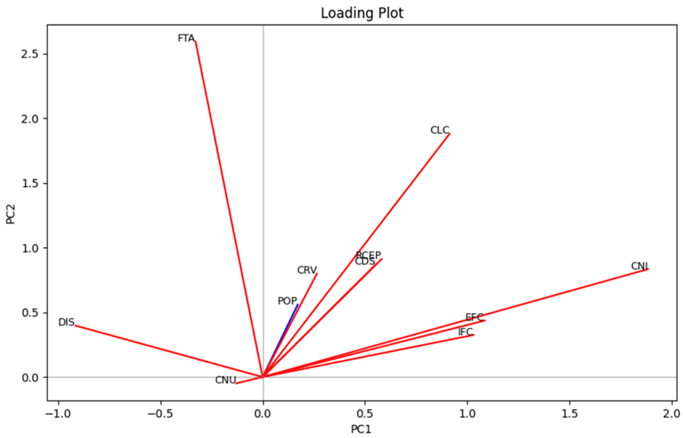


Figure 7. Loading plot.

In the first two principal components, the line of the traditional indicator POP is shorter, which means that the POP indicator plays a minor role in explaining the variability of the first two principal components. Therefore, the POP indicator was not temporarily disregarded in the latter study. The loadings of the ten economic interaction indicators were then normalized as shown in Table 11, using a method that makes the normalized loadings sum to 1. For each original independent variable, we multiplied the principal component coefficients by the standardized loadings of each variable on the principal components and then summed these products to obtain the principal component regression model in the original variable dimensions.

To further optimize the two regression models (PCT and GDP), the independent variable coefficients obtained through the Analytic Hierarchy Process (AHP) were integrated. The results of the AHP weights are summarized in Table 4. These weights were applied to adjust the regression coefficients in the principal component regression model, a process captured in Equations (22) and (23). Table 12 provides a comparative analysis of the regression coefficients before and after applying the AHP weights to adjust the regression coefficients. This adjustment improves the predictive power of the model and enhances the interpretability and credibility of the model results.

Table 11. Standardized loadings of the independent variables on the first four principal components.

	PC1 Normalized	PC2 Normalized	PC3 Normalized	PC4 Normalized
CDS	0.111959454	0.096790011	2.20638×10^{-5}	−0.036060454
CNI	0.381078461	0.092669237	−0.067037375	0.071103945
CNU	−0.026121275	−0.005456924	0.01733799	0.012302057
EFC	0.219722501	0.048537249	−0.044266613	0.174341106
IFC	0.208625645	0.036114498	0.029355903	0.126979769
CRV	0.053693116	0.088848089	0.042790589	0.037852672
CLC	0.184797618	0.208892413	0.050513283	0.217824641
DIS	−0.185060031	0.044152016	0.542654766	0.233248298
RCEP	0.11764873	0.101332742	0.202937318	0.392148079
FTA	−0.06634422	0.28812067	0.225692076	−0.229740112

$$\begin{aligned} PCT = {} & 4862CDS + 17600CNI - 342CNU + 13370EFC + 7556IFC + 6283CRV \\ & + 28363CLC - 4802DIS + 7709RCEP + 16849FTA \end{aligned} \tag{22}$$

$$\begin{aligned} GDP = {} & 39437CDS + 279449CNI - 16569CNU + 151748EFC + 155336IFC + 38006CRV \\ & + 38006CRV + 180006CLC - 42881DIS + 179195RCEP + 131156FTA \end{aligned} \tag{23}$$

Table 12. Coefficient comparison.

Variables	PCT Model		GDP Model	
	Coefficient	**AHP-Coefficient**	**Coefficient**	**AHP-Coefficient**
CDS	89,735	4862	1,031,234	39,437
CNI	163,386	17,600	2,569,192	279,449
CNU	−13,645	−342	−172,550	−16,569
EFC	103,160	13,370	1,461,900	151,748
IFC	61,939	7556	1,348,446	155,336
CRV	64,825	6283	663,152	38,006
CLC	190,172	28,363	1,897,362	180,006
DIS	−170,119	−4802	−893,399	−42,881
RCEP	56,728	7709	1,082,144	179,195
FTA	111,395	16,849	761,676	131,156

5. Case Study

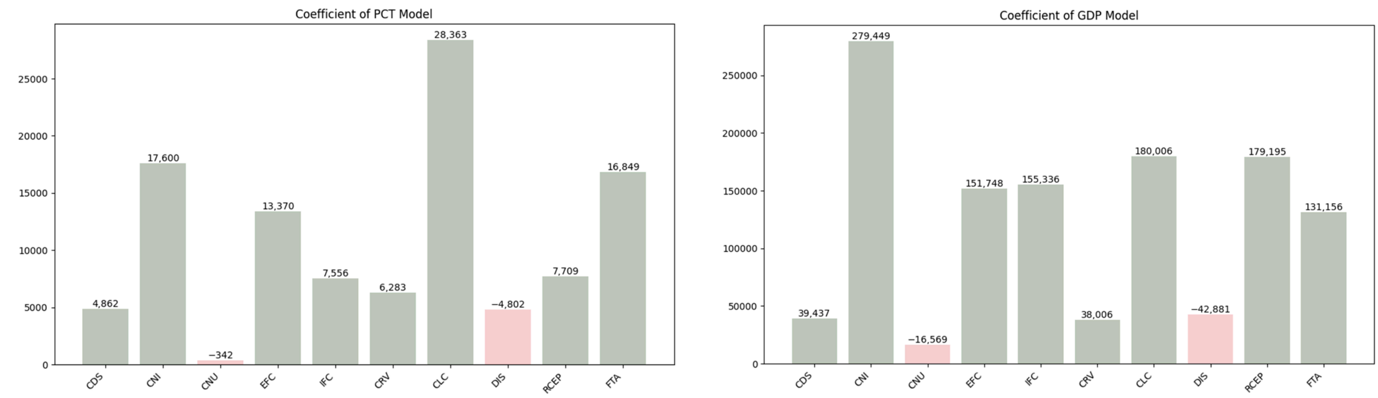
As a vital component of the national economy, the shipping industry holds a dominant position in international trade and transportation operations. The Southeast Asian region, where ASEAN is located, has strong maritime connections. The South China Sea–Pacific Ocean corridor is a crucial shipping route for China's foreign trade and a significant strategic cooperation belt, primarily involving Southeast Asia. Every year, there is an endless stream of ships traveling from Southeast Asia to and from the Middle East, South Asia, and East Asia, and some of these countries use the power of the sea to promote economic development. ASEAN's natural shipping advantages are critical in advancing the 21st Century Maritime Silk Road and One Belt, One Road strategies. Therefore, this study provides a case study of the region's performance to explore the impact of economic interaction indicators (EIIs) on the economy and shipping.

5.1. Correlation Coefficient Study of EI Indicators

Figure 8 presents the regression coefficients of the economic indicators in the PCT and GDP models as a bar chart. Green bars represent positive impacts, indicating that an increase in the economic indicator score leads to a corresponding increase in the dependent variable, while pink bars indicate negative impacts.

Figure 8 shows that CLC has the most considerable impact in the PCT model, indicating that improved shipping connectivity significantly boosts port container throughput. This finding aligns with theoretical expectations that better connectivity increases trade volumes and operational efficiency. Enhanced shipping connectivity reduces logistical barriers, improves supply chain integration, and fosters smoother international trade flows, thereby increasing port throughput. In addition, CNU and DIS show negative correlations in both the PCT and GDP models. For CNU, the negative correlation arises because increased foreign capital use by China reduces domestic economic opportunities, affecting port throughput and growth. Specifically, as more capital flows to China, domestic firms face increased competition and resource allocation issues, leading to lower-than-expected economic and port performance. For DIS, the negative correlation reflects the impact of distance from China on economic and port performance. Greater distance increases trade costs, logistical complexity, and uncertainty, adversely affecting container throughput and economic activity. Longer trade routes also encounter more tariff and non-tariff barriers, hindering bilateral economic interactions.

The results of the analysis show that economic interaction with China significantly impacts the GDP and PCT of co-building countries. Economic growth and port performance are enhanced through increased connectivity and capital investment. However, CNU and DIS negatively impact economic activity and port efficiency, which must be managed by quantifying foreign investments and seeking efficient transportation routes. Strategic economic interactions and infrastructure development are essential to promote sustainable economic growth and strengthen bilateral economic relations among co-bordering countries.



(**a**) (**b**)

Figure 8. EIIs' coefficients for the models: (**a**) coefficients of the PCT model; (**b**) coefficients of the GDP model.

5.2. Study of Changes in ASEAN's Overall EI with China

Figure 9 presents the standardized scores of five leading economic interaction indicators between ASEAN and China from 2015 to 2022. The scores for various indicators are summed for all ASEAN countries and then standardized on a scale of 1 to 9.

The general upward trend of the five critical economic interaction indicators between 2015 and 2022 is shown in Figure 9. However, of particular interest between 2019 and 2021 is the significant decline in the CLC indicator scores. This phenomenon is closely linked to the massive congestion in global ports during the epidemic, which weakened shipping connectivity. Nonetheless, import and export scores have maintained their high growth momentum. In particular, the IFC indicator shows that, in 2020, despite the ASEAN countries being hit by the epidemic, China benefited from effective epidemic prevention and control measures, and its production capacity recovered relatively quickly [54]. This contributed to a significant release of ASEAN countries' import demand for Chinese goods in 2020.

However, during the same period, China's investment score growth in Southeast Asia appears to have been relatively slow. This can be attributed to the volatile international political and economic environment, which has led to a slowdown in China's investment efforts in ASEAN countries. By 2021, the CNI indicator score achieved a significant improvement. This jump is related not only to the gradual recovery of global supply chains but also to China's proposal to build a Regional Comprehensive Economic Partnership

(RCEP), which can be viewed as an extension of the Belt and Road Initiative (BRI) to a certain extent, as most of the members of the RCEP are countries along the BRI routes. The RCEP proposed by China provides a new opportunity to strengthen economic interactions between China and ASEAN and promotes the further deepening of economic relations between the two sides.

To summarize, the trend of economic interaction indicators presented in Figure 8 reflects the epidemic's impact on the global economy. It demonstrates the resilience and potential of economic interaction between China and ASEAN countries. The signing and implementation of the RCEP opens up new prospects for economic cooperation between China and ASEAN countries and heralds the further development and prosperity of the economic relations between the two sides.

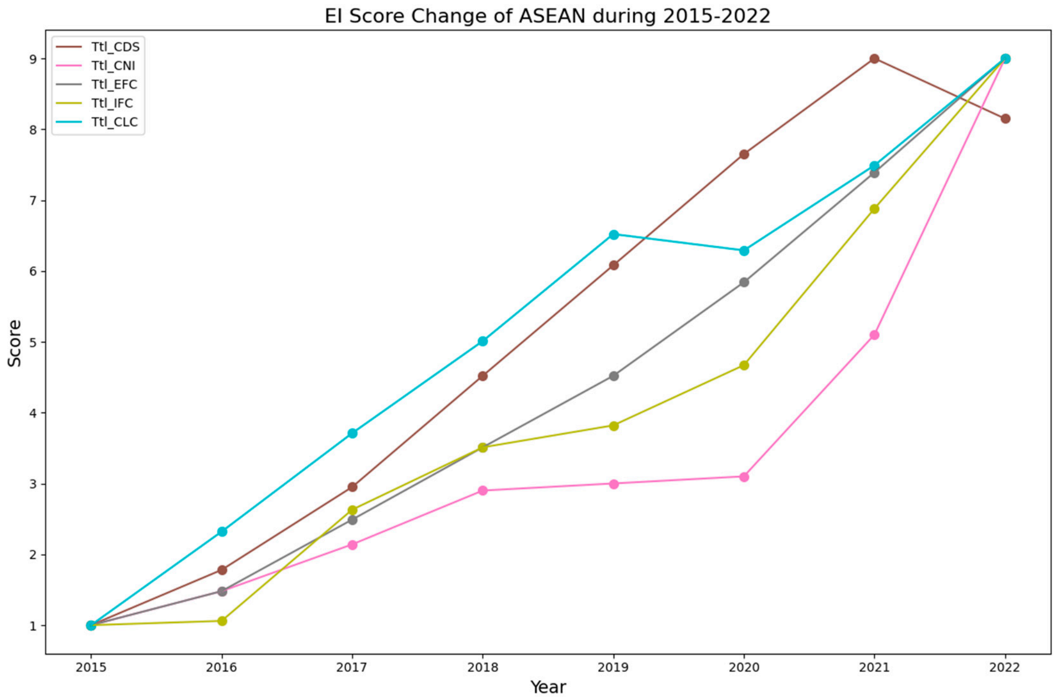


Figure 9. EI score change of ASEAN during 2015–2022.

5.3. Study of Four ASEAN Countries

Figure 10 shows the changes in countries' GDP and PCT scores between 2015 and 2022, and Figure 11 shows the changes in countries' scores for the six main EI indicators between 2015 and 2022. By combining Figures 10 and 11, it is possible to analyze in depth how the evolution of the EIIs affects the GDP and PCT of the ASEAN (Association of Southeast Asian Nations) countries.

Singapore is well ahead of other ASEAN countries in the scores related to China's investment in ASEAN, especially in CDS and CNU, which reflect Singapore's capital market flows with China. This leading position is closely related to Singapore's financial and trade center status in Southeast Asia. In addition, Singapore is the first ASEAN country to sign a bilateral free trade agreement (FTA) with China, and the two countries signed an FTA as early as 2008, allowing for a deeper level of economic interaction with China. Singapore's enthusiasm and active participation in the Belt and Road Initiative when China first proposed it was an important reason for China's substantial investment in the initiative in the early stages of its construction [55,56]. At the beginning of the Belt and Road Initiative, Singapore quickly became a key country for Chinese investment due to its strategic advantages. In 2017, China's net investment score in Singapore rose rapidly, while the container throughput of Singapore's ports also increased significantly. This trend suggests that Chinese investment in Singapore has boosted Singapore's economy and its position as a regional logistics hub.

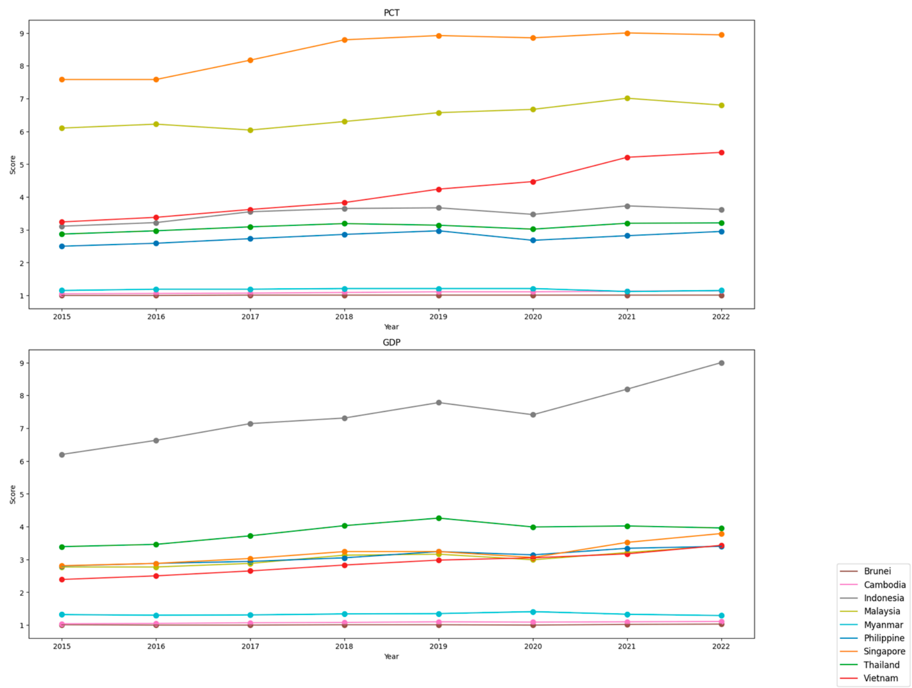


Figure 10. Dependent variables' score changes for ASEAN by country during 2015–2022.

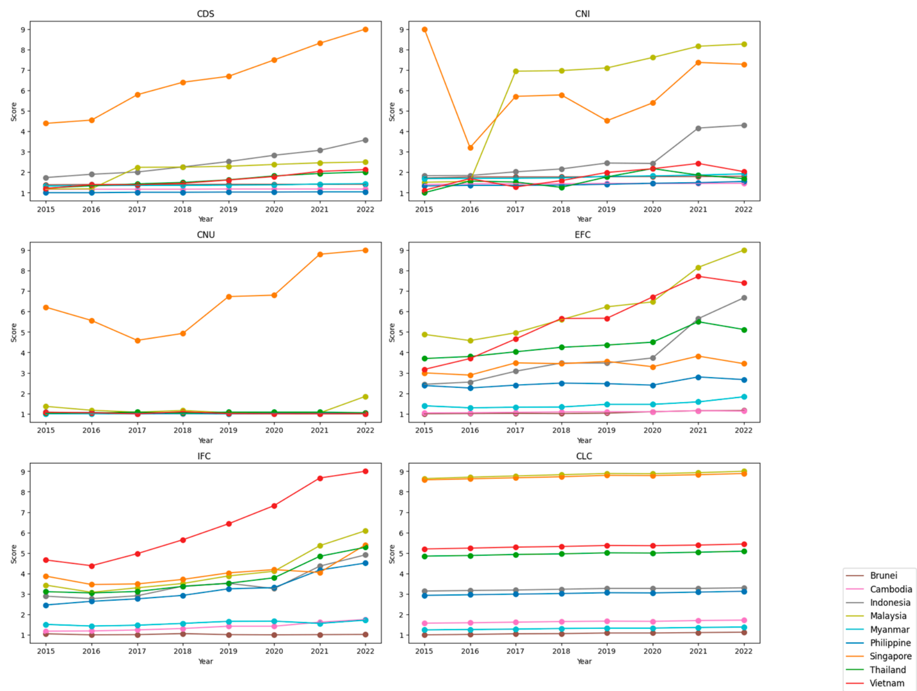


Figure 11. Independent variables' score changes for ASEAN by country during 2015–2022.

Chinese direct investment in Malaysia has increased significantly since 2016, with a rapid growth in interaction scores. This phenomenon can be attributed to the fact that following China's announcement of the Belt and Road Initiative (BRI) in 2013, the two countries have undertaken a series of cooperative projects in a variety of areas, including infrastructure, industrial parks, energy, and finance, and most of these projects were either agreed upon or commenced construction in 2016. This includes the signing of the East Coast Railway Project (ECRL), the Port of Huangjing in Malacca, and the official launch of the Kuantan Industrial Park. These projects mark the deepening of China–Malaysia cooperation and further enhance Malaysia's position in the global trade network.

Meanwhile, Malaysia's GDP score growth rate in 2016 was significantly higher than in 2015, which proves the positive impact of economic interaction with China on Malaysia's economic growth. According to the findings of this study, cooperation with China on economic interaction indicators has significantly contributed to the GDP growth of ASEAN countries. The rapid growth of Malaysia's GDP in 2016 was attributed to the in-depth cooperation between China and Malaysia in several areas [57]. Specifically analyzed, these cooperation projects brought direct economic benefits, promoted the modernization of Malaysia's infrastructure, and improved regional connectivity.

Vietnam's import and export scores with China have remained high among ASEAN countries for a long time, mainly attributed to the two countries' geographical proximity and their complementary strengths in several areas, which have led to frequent import and export trade between the two countries. In specific areas, Vietnam and China have significant complementarities in the manufacturing sector, especially in electronics manufacturing. Vietnam has excelled in taking on industrial transfers from China. For example, Dell Computer established an ODM (Original Design Manufacturing) plant in Vietnam, further contributing to the strong trade ties between the two countries. Notably, on the PCT (port container throughput) indicator, while other ASEAN countries' PCT scores declined or leveled off in 2020 due to the global impact of the novel coronavirus epidemic (COVID-19), Vietnam's PCT scores increased significantly. This phenomenon can be attributed to Vietnam's increasing position in the global supply chain, especially in the electronics sector. Global demand for electronics is set to increase significantly in 2020 due to surging global demand for telecommuting and teaching. As a substantial production base for electronic products, Vietnam's exports have risen sharply, driving growth in port container throughput.

As the largest economy among the ASEAN countries, Indonesia has a much larger economy than other countries. However, even under these circumstances, Indonesia maintained a high GDP growth rate in 2021, a particularly noteworthy phenomenon. At the same time, Indonesia's export and import growth rates with China were also significantly higher in 2021, with exports to China scoring the most significant growth. These data suggest that export and import activities with China can boost Indonesia's GDP growth to a certain extent. First, Indonesia's economic cooperation with China has deepened in recent years, and bilateral trade has continued to grow. In 2021, Indonesia and China significantly increased their total exports and imports, reflecting the strong ties between the two countries in the trade sector. In particular, Indonesia's exports to China scored the most significant growth, meaning that Indonesian goods have seen a substantial increase in demand in the Chinese market, boosting Indonesia's economic growth. Specifically, the Yavan high-speed rail project is the first vivid example of China's high-speed rail "going out", originally planned to open to traffic in 2021. However, due to the impact of the COVID-19 epidemic, the construction progress has been hindered, and the project has been delayed. China has increased its investment in Indonesia in 2021 to accelerate the project. This has not only helped boost the construction process of the Yavan high-speed rail project but also had a positive impact on Indonesia's economy. China's investment in Indonesia mainly focuses on infrastructure construction, manufacturing, energy, and other fields. These investment projects have improved Indonesia's infrastructure conditions, upgraded the hardware environment for economic development, and driven the development of related industries.

Overall, ASEAN shows significant growth in total imports and exports with China in 2021, with a concomitant increase in GDP. This growth is not only closely linked to the backdrop of the post-epidemic economic recovery, but also due to the signing of the Regional Comprehensive Economic Partnership (RCEP) between China and the ten ASEAN countries in 2020, as well as the official entry into force of the Regional Comprehensive Economic Partnership (RCEP) with six of the major countries in 2021. First, the economic recovery after the epidemic has laid a solid foundation for ASEAN–China trade growth. The gradual recovery of global supply chains and the rebound in market demand have revitalized trade activities between ASEAN and China. Countries have adopted economic stimulus measures to promote a rapid import and export trade recovery. Against this backdrop, ASEAN countries, as important trading partners, have witnessed a significant increase in trade with China. Trade with China has grown significantly. Secondly, trade between ASEAN and China has been further boosted by the signing and entry into force of the RCEP. The signing of this agreement marks the gradual elimination of tariff and non-tariff barriers in the region, the enhancement of the level of trade facilitation, and the optimization of the investment environment. The RCEP came into effect in one ASEAN country after another in 2021, making it easier and more efficient to trade in commodities and services between the ASEAN countries and China, significantly lowering the cost of trade for enterprises, and further stimulating the growth of bilateral trade.

6. Conclusions

6.1. Discussion and Implications

Economic, trade, and infrastructure cooperation between China and ASEAN countries has deepened with the continued promotion of the Belt and Road Initiative and the 21st Century Maritime Silk Road. This cooperation has evolved from simple commodity exchange to multi-level industrial cooperation and capital flows. Therefore, it is necessary to explore the factors affecting China–ASEAN bilateral trade, which can provide both sides with a more in-depth perspective on trade cooperation, enhance the smooth flow of commerce, and promote the shared prosperity of the regional economy. While the global economy has been hit by the double blow of anti-globalization trends and protectionist policies, the increase in international trade barriers has led to the impediment of the development of free trade. Meanwhile, global geopolitical tensions and the outbreak of the COVID-19 epidemic have brought additional uncertainties and challenges to economic cooperation between China and ASEAN countries. Under these threats, the stability and efficiency of the shipping industry, as the dominant force in international trade transportation, is essential. Incorporating the BRI perspective of economic and shipping interactions between participating countries and China into the considerations of the forecasting model allows for a more comprehensive assessment of flows and trends, thus providing more precise and powerful support for policymakers and business decisions.

Based on this, this study constructed a principal component regression model, which digs deeper and extracts the key factors affecting trade flows from the Belt and Road Initiative (BRI) economic interaction perspective. To enhance the applicability and foresight of the model, this study also forecasted future data by combining the dataset obtained from the prediction with the existing original dataset. A regression model capable of quantifying the impact of economic interaction indicators on GDP and PCT was constructed by performing principal component analysis on the independent variables in the dataset. In this process, the coefficients of the independent variables were carefully analyzed to obtain an accurate quantification of the impact of the economic interaction indicators.

This study highlights the critical roles of shipping connectivity and China's direct investment in ASEAN countries. CLC significantly boosts port container throughput (PCT), underscoring the importance of efficient maritime links in trade operations. CNI (China's direct investment) has the most substantial positive impact on GDP, reflecting the vital role of capital flows in economic growth. Conversely, CNU and DIS negatively affect GDP and PCT, likely due to increased trade barriers and logistical challenges. These insights emphasize the need for improved connectivity and strategic investments to enhance economic interaction and pursue better income under the Belt and Road Initiative.

6.2. Limitations and Future Research

After analyzing the impact of joining the Belt and Road Initiative on the economy, several potential directions for future research have been identified.

Firstly, although this study selected ten major economic indicators as independent variables, the economic effects of joining the initiative are multifaceted and extend beyond these indicators. Future research could incorporate a broader and more diversified set of independent variables, including social, political, and environmental factors, to comprehensively assess the Belt and Road Initiative's impact.

Secondly, this study primarily employed traditional statistical analysis methods and some machine learning techniques. While effective to a certain extent, the data's growing complexity and size necessitate the use of more advanced analytical tools and methods in future research. Incorporating cutting-edge technologies such as deep learning, reinforcement learning, and complex network analysis could enhance the models' predictive power and analytical depth. Additionally, utilizing more dynamic models in time-series analysis could better capture the time-varying characteristics of the data.

Thirdly, this study's research data span from 2015 to 2022, which includes the period of the COVID-19 pandemic. However, this timeframe may not fully capture the long-term impacts of the Belt and Road Initiative. Future studies should consider extending the time horizon and conducting longer longitudinal studies to observe long-term effects and policy implementation trends.

Lastly, due to limitations in data acquisition and quality control, this study may have issues with data accuracy and precision. Future research could enhance the reliability and validity of the findings by collaborating with more diverse data sources to obtain higher-quality and more comprehensive datasets.

In summary, future research should aim to incorporate more comprehensive independent variables, utilize advanced data analysis tools, extend the study period, and improve data quality to thoroughly assess the global economic impact of the Belt and Road Initiative.

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