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Research Article

Integrating Artificial Neural Networks into the Gravity Model: Analyzing Apparel Export from Belt and Road Asian Countries to the United States

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Abstract

Launched by China in 2013, the Belt and Road Initiative (BRI) aims to enhance trade connectivity between Asia and the global market while fostering mutually beneficial economic cooperation among participant countries. While previous research has highlighted the positive effects of the BRI on trade between China and its partner nations along the Belt and Road (B&R), there is limited understanding of its impact on trade among B&R countries themselves. This study seeks to fill this gap by examining bilateral apparel trade patterns, specifically focusing on clothing exports from China and 21 Asian B&R countries/cities to the United States (US).

To analyze these trade flows, we employed a refined gravity trade model augmented with the Logistics Performance Index (LPI) and utilized an Artificial Neural Network (ANN) framework. Additionally, an Extra Trees Regression (ETR) analysis was conducted to explore the factors influencing apparel export values to the US. Data spanning from 2008 to 2024 across the 22 countries/cities were analyzed.

The findings indicate that the BRI trade corridor significantly impacts apparel exports from China and other developing B&R Asian countries to the US. Notably, the ANN results indicate that incorporating the LPI feature does not enhance model performance. Furthermore, our results demonstrate that the ANN offers superior predictive accuracy compared to traditional regression models, with ETR serving as a valuable complementary tool to enhance the ANN analysis. Future research can expand on this work by exploring the application of ANN and ETR in new contexts to examine the BRI trade flow from other countries in the Far East and broader regions.

Keywords: Belt and Road Initiative; Gravity Trade Model; Panel Data Regression; Artificial Neural Network; Extra Trees Regression analysis

Introduction

Launched in 2013 by the People's Republic of China (PRC), the BRI aims to enhance trade and economic integration across Asia, Europe, and Africa. In 2014, Chinese leader Xi Jinping announced the establishment of the Silk Road Fund, a US$40 billion development initiative. As of January 2023, 151 countries had joined the BRI, representing nearly 75% of the global population and accounting for over half of the world's GDP (Nedopil, 2022 [1]; Giorgio, 2023 [2]). However, the initiative has received limited support from the United States, the largest economy and the second-largest clothing importer globally. Geopolitical risks, particularly concerning India, have also emerged, as Indian officials have consistently opposed the China-led BRI for various geopolitical reasons (Hindustan Times, 2016, 2020) [3].

One of the objectives of this study is to predict future clothing export patterns from selected locations using a limited data set. A timely analysis is essential to establish a more accurate forecast of the BRI's impact on the textiles and clothing (T&C) sector for 2023. A time-series analysis revealed a mix of rising and falling trends, indicating the need for more advanced machine learning algorithms to address these limitations and better investigate global trade flows under the BRI.

In the clothing industry, China plays a pivotal role in shaping global production and export patterns. Major modifications to the BRI by China, as the leading supplier, will significantly influence clothing supply sources and global trade flows. Conversely, shifts in GDP and U.S. trade policies will also impact the clothing supply chain. Previous studies, including Ho, et al. (2020) [4], have identified a positive correlation between the BRI and economic and infrastructural development among China and its partner nations along the B&R. However, the effects on apparel trade among member countries and those with minimal BRI support have largely been overlooked. This study aims to address this research gap.

Literature review

This literature review examines the T&C industries at the country level within the BRI. It also explores the U.S. clothing sector's connections with nations that have publicly opposed the BRI, specifically Japan, Australia, and India. The review also assesses existing literature on traditional gravity models, contrasting them with ANN and ETR for international trade estimations. The review contains two parts: 1. The BRI, International Trade, and T&C industries, and 2. The Gravity Trade Model, ANN, and ETR.

The BRI, International Trade, and T&C industries: According to Johnson LA (2018) [5], the BRI broadly emphasizes cooperation in five areas: (a) coordinating development policies; (b) forging infrastructure and facilities networks; (c) strengthening investment and trade relations; (d) enhancing financial cooperation; and (e) deepening social and cultural exchanges. He highlights the BRI's emphasis on aligning development policies, enhancing investment and trade relations, and strengthening social and cultural ties. The BRI's primary objective is to foster regional economic development through cooperation and shared prosperity between China and participating countries. The initiative encompasses five priority areas: policy dialogue, infrastructure connectivity, unimpeded trade, financial support, and people-to-people exchanges. Keane and Velde (2008) [6] underscore the significance of the T&C industries in generating income, jobs, and foreign currency, thereby contributing to sustained economic growth. With the BRI implementation in full swing since 2015 (Ye (2020)) [7], and as an ongoing endeavor, the BRI will continue shaping the global trade of different commodities and products including T&C (Ho et al. (2020)) [4].

The study of Huang (2016) [8] suggests that the BRI certainly has the potential of turning the underdeveloped B&R region into a new vibrant economic pillar. The study of Tian, Yu & Zhang (2016) [9] also confirms with the results of Huang (2016) [8], pointing out that the BRI further creates new markets for China's exports and outward foreign direct investment (FDI). Similarly, Huang (2016) [8] emphasizes that BRI plays a significant role in policy dialogue, unimpeded trade, financial support and people-to-people exchange, "much more comprehensive" than infrastructure development.

BRI benefits greatly not only China but also the developing countries that can enhance from FDI. The findings are shown in Tian, Yu & Zhang (2016) [9]. Dumor K, et al. (2022) [10] examined the impact of BRI from the trade and migration perspectives. Their model assessed 65 countries from 2000 through 2018. The findings indicate that migration has a significant impact on the flow of bilateral trade. Beverelli, et al. (2018) [11] investigated the effect of institutions on international trade flows and development using the gravity model. Their estimation is positive, significant and economically relevant. The impact is particularly strong for imports of the poor countries from the rich countries in their sample of 63 countries over the period 1996-2006.

Le, et al. (2019) [12] found out the perceived impacts on the garment and textile industry of Vietnam from the BRI, using both desk review and in-depth interviews with 54 leaders and high-ranked officials from public and private sectors in 2017. The potential challenges and opportunities of the BRI were also examined. Respondents agreed that the initiative could foster textile export and the development of infrastructure. Further, the huge challenge was found to be the poor competitiveness of Vietnamese textile firms on the international commercial playground.

Le, et al. (2019) [12] further pointed out that the BRI would significantly impact on the regional textile and apparel businesses. The important BRI contribution is the development of supply chains. In the context of Vietnamese textile industry, the supply chains connecting manufacturers with materials suppliers as garment manufacturers, who set up good supply chains, can do Free on Board, Original Design Manufacturing, and Own Brand Manufacturing business. It is found that establishing supply chains is the key for garment manufacturers in Vietnam to change from Cutting and Sewing business to Free on Board, and Original Design Manufacturing models that meet international buyer's requirements. Finally, their study highlights that the connectivity, which contributes the development of global value chains, is one of the pillars of the BRI.

Lau, et al. (2020) [13] employed the gravity model to investigate how the growth of China's T&C exports was dominating the exports of other Asian developing countries over the 1990–2015 period. It was found that that there was a negative impact of China's emergence on T&C exports on other Asian developing countries. However, China's BRI warrants further research to suggest that once the Initiative goes into full force, collaborative opportunities are available between China and other Asian developing counties. Celine and Christropher (2008) [14] used a panel gravity equation to assess the impact of internal infrastructure and landlockedness on Central Asian trade on 167 countries from 1992 through 2004. They found an improvement in the exports and imports by 2.4% and 3.1% respectively.

It is known that landlocked countries have high transport costs. Analysis of bilateral trade data by Limao and Venables (2001) [15] confirmed the importance of infrastructure, suggesting that poor infrastructure accounts for about 40% of the trade costs, and it could be as high as 60% if trade partners were landlocked. In concordance with previous research, they found that infrastructure problems largely explained the relatively low levels of African trade. More importantly, from their study, improving infrastructure from the 75th to the 50th percentile increases trade by 50%.

Lu, et al. (2018) [16] developed an econometric model to quantify the impact of improving transport connectivity on aggregate multilateral trade between areas covered by the BRI and the rest of the world. They found that multi-modal transport infrastructure and connectivity was key to boosting international trade and economic growth. In estimating the impact of trade-cost reducing measures, on supply chain trade and welfare from 2002 to 2011, Tristan Kohl (2019) [17] found that infrastructural improvements would yield asymmetric benefits to China, Russia and Southeast Asian countries.

Port performance of 18 port terminals in Malaysia was examined by Mohd Rozar, et al. (2023) [18]. Their hierarchical cluster analysis, based on the performance metrics, found that Westport and Northport of Klang Port had the best performance. The study of Yang and Yip (2019) [19] provides valuable suggestions to improve efficiency for container ports along the "Maritime Silk Road." Their Malmquist index method is able to identify the scale efficiency, pure technical efficiency and technological efficiency of the 23 Asian container ports.

The Gravity Trade Model, ANN, and ETR: This section begins with a brief overview of the structural gravity model, illustrating its effectiveness in analyzing the impact of policy on bilateral trade. It then discusses the application of neural networks and ETR in conjunction with the gravity model, followed by a comparison of predictions generated by these approaches.

Trade positively affects income levels and economic growth by enabling countries to specialize in sectors where they have comparative advantages, utilize resources efficiently, and offer consumers better products at lower prices (Bernhofen & Brown, (2005) [20]; Bühler, et al. (2011) [21]; Wacziarg & Horn Welch, 2008) [22]. The gravity model, initially proposed by Isard (1954) [23], provides a robust framework for empirical research, allowing for the examination of various factors, including institutional and policy changes on trade dynamics. For instance, Tristan Kohl (2019) [24] utilized a structural gravity equation to assess the BRI's impact on supply chains across 64 economies from 2002 to 2011. It is found that infrastructure investments yield asymmetric benefits for China, Russia, and Southeast Asian nations.

The gravity model is both flexible and intuitive, positing that bilateral trade increases with the economic sizes of the exporter and importer while decreasing with trade costs (van Bergeijk & Brakman, (2010) [25]; Head & Mayer (2014) [26]. Varian (2014) [27] proposed machine learning techniques, such as decision trees and neural networks, as effective tools for modeling complex relationships within large data sets. He emphasized the potential of these methods to enhance economic analysis.

$$\ln Y_{ijt} = \beta_0 + \beta_1 \ln DIST_{ij} + \beta_2 CNTG_{ij} + \beta_3\, LANG_{ij} + \beta_4\, CLNY_{ij} + \beta_5 RAT_{ij} + \pi_{it} + X_{jt} + \epsilon_{ijt}$$

Varian (2014) [27] suggested machine learning techniques such as decision trees, support vector machines, neural nets, deep learning, etc. might allow for more effective ways to model complex relationships with the sheer size of data. He believed that these methods had a lot to offer and should be more widely known and used by economists. Finally, he expected that collaboration between computer science and econometricians would also be productive in the future.

Kanrak, et al. (2023) [28] applied a complex network approach to analyze shipping networks among 239 voyages serviced by 14 international cruise lines in the Caribbean. It is revealed that while some ports in emission control areas play significant roles, many ports outside these areas are more critical in the network due to regulatory barriers.

Neural networks, structured similarly to brain neurons, estimate and analyze relationships between variables in large data sets. Comprising an input layer, hidden layers, and an output layer, each neuron receives inputs and provides outputs, with connections represented by weights that are adjusted during the training process. This process involves forward propagation, whereby input data is processed to generate output, and backpropagation updates weights to minimize prediction errors.

Dumor and Yao (2019) [29] analyzed the BRI's impact using bilateral trade export data from 1990 to 2017 and found that ANN outperformed traditional gravity models in predictive power. Similarly, Wohl and Kennedy (2018) [30] examined international trade data between the U.S. and its major partners, concluding that ANN with country-year fixed effects demonstrated higher accuracy compared to the gravity model. It was particularly evident in Root Mean Square Errors (RMSEs).

Vemuri and Munim (2023) [31] employed univariate models, including ARIMA and seasonal autoregressive neural networks (SAR-NN), to forecast container freight seasonality patterns for six Southeast Asian routes. It was found that ARIMA performed better for one-week forecasts, while SAR-NN excelled for four-week forecasts on select routes.

In comparing trip distribution predictions, Tillema, et al. (2006) [32] and Pourebrahim, et al. (2018) [33] found that ANN outperformed gravity models with limited data, while gravity models excelled with larger datasets. Elif (2014) [34] investigated bilateral trade flows among 15 EU countries from 1964 to 2003. It was revealed that ANN explained greater variations in bilateral exports compared to gravity models, particularly in forecasting performance, where ANNs exhibited lower Mean Square Error (MSE).

Ho, et al. (2020) [4] conducted panel regression and ANN analysis to explore bilateral clothing trade imports between the U.S. and 14 B&R countries in Asia from 1998 to 2018. Their findings indicated a positive impact of the BRI on clothing exports, with ANN demonstrating superior predictive power, achieving an RMSE of 0.1824 with 10 hidden neurons.

As an alternative to ANN, the ETR algorithm combines predictions from multiple decision trees for classification and regression tasks. By selecting random subsets of features and training decision trees accordingly, ETR reduces bias and variance, enhancing predictive accuracy.

Most previous studies and policy research working papers focus on measuring the impact of China's B&R initiative using panel data analysis and the ANN. Some use a method for approximating the international trade with a gravity equation. However, limited research has been conducted to apply the extended gravity model and the ETR model to study their advantages and applications, which are the focus of this study designed to fill the research gap.

This paper approaches the analysis of bilateral trade data from a machine learning (ML) perspective, employing several ML methods to uncover patterns and insights. Among the various ML techniques, ANN were chosen for several compelling reasons:

1. Handling non-linear relationships: ANN is particularly effective in capturing complex and non-linear relationships within data, which are often present in international trade flows. Traditional econometric models may struggle to account for these complexities, whereas ANN can model them more accurately.
2. High predictive power: Previous studies, such as those by Dumor and Yao (2019) [29] and Wohl and Kennedy (2018) [30], have demonstrated the superior predictive power of ANN over traditional gravity models. This makes ANN a suitable choice for forecasting trade patterns and understanding the underlying factors influencing trade flows.
3. Flexibility and adaptability: ANN can be easily adapted to different data sets and problem domains. Its flexibility allows for the incorporation of various features and the ability to learn from large data sets, making it a robust tool for trade analysis.
4. Empirical validation: Empirical evidence from studies like Ho, et al. (2020) [4] shows that ANN outperforms traditional regression models in predicting bilateral trade flows, particularly in the context of the BRI. This empirical validation supports the choice of ANN for this study.

While the primary focus of this paper is on exploring various ML methods, the inclusion of ANN is justified by its ability to handle complex relationships, its high predictive power, and its empirical success in similar studies. The use of ANN does not imply that other variables, such as the Logistics Performance Index (LPI) are trivial in explaining trade flow. Instead, it highlights the potential of advanced ML techniques to provide deeper insights and more accurate predictions in the analysis of international trade.

The objectives of this study are to:

1. Predict future trade patterns of clothing exports from China to the U.S. and 21 B&R Asian countries/cities.
2. Compare the predictive power of the gravity trade model using panel data regression, ANN, and ETR in U.S. clothing imports.
3. Estimate the value of clothing exports to the U.S. from China and four Asian developing countries.

Following this introduction with a literature review focusing on the BRI, gravity model, ANN, and ETR in relation to clothing trade. Section 2 details the research methodology, sample, and data set. Section 3 discusses the results and findings, including panel data regression, ANN, and ETR outcomes. Finally, Section 4 concludes the study.

Research Methodology, Sample and Data Set

Specifications of extended gravity model

According to Beverelli, et al. (2018) [35], structural gravity model (GM) can be derived from a very wide class of micro-economic foundations:

$$X_{ij} = T_{ij} Y_i E_j \pi_i P_j \quad \text{----------} (1)$$

$$\pi_i = X_j T_{ij} E_j P_j \quad \text{----------} (2)$$

$$P_j = X_i T_{ij} Y_i \pi_i \quad \text{----------} (3)$$

where:

- X_{ij} are bilateral trade flows from exporting country i to importing country j.
- T_{ij} denotes any determinants of trade between countries i and j, including bilateral trade barriers, such as geographic distance and regional trade agreements, as well as country-specific trade-related drivers, such as institutions.
- Y_i denotes the total national output / GDP of country i.
- E_j is the import expenditure in country j.
- Π_i and P_j in equations (2) and (3) respectively denote the

structural outward and inward multilateral trade resistance terms (MRTs).

Regarding the last two variables, $P_j = X_i T_{ij} Y_i \pi_i$ Anderson and van Wincoop (2003) [36] noted that they represent multilateral resistance due to the relative trade costs but not absolute costs. They also argued that GM suffers from omitted variables bias and that comparative statics analysis is not well founded. They therefore developed a method that (i) consistently and efficiently estimates a theoretical gravity equation and (ii) correctly calculates the comparative statics of trade frictions. The results of their method indicate that the McCallum borders reduce trade between industrialized countries by a moderate 20-50%. Noticeably, Anderson and van Wincoop's [36] finding is a huge challenge of the traditional belief that the commonly used the Gravity Model has a strong theoretical basis because trade and institutions are determinants of income and growth.

According to Whol and Kennedy (2018) [30], the gravity model can take the following form:

$$InY_{ijt} = \beta_0 + \beta_1 \ln\mathrm{DIST}_{ij} + \beta_2 \ln GDP_{it} + \beta_3 \ln\mathrm{GDP}_{jt} + \beta_4 CNTG_{ij} + \beta_5 LANG_{ij} + \beta_6 CLNY_{ij} + \beta_7 RAT_{ij} + \varepsilon_{ijt} \quad \text{-------(4)}$$

or the following form with the exporter's and importer's fixed effects:

$$InY_{ijt} = \beta_0 + \beta_1 \ln\mathrm{DIST}_{ij} + \beta_2 \ln GDP_{it} + \beta_3 \ln\mathrm{GDP}_{jt} + \beta_4 CNTG_{ij} + \beta_5 LANG_{ij} + \beta_6 CLNY_{ij} + \beta_7 RAT_{ij} + \pi_{it} + X_{jt} + \varepsilon_{ijt} \quad \text{---------(5)}$$

or with exporter-year and importer-year fixed effects:

$$InY_{ijt} = \beta_0 + \beta_1 \ln\mathrm{DIST}_{ij} + \beta_2 CNT_{ij} + \beta_3 LANG_{ij} + \beta_4 CLNY_{ij} + \beta_5 RAT_{ij} + \pi_{it} + X_{jt} + \varepsilon_{ijt} \quad \text{---------(6)}$$

This last equation relaxes the assumption that country-specific factors are constant over time. The exporting and importing countries' GDP are absorbed by the country-year dummies and are therefore dropped.

To investigate the factors influencing the value of clothing exports to the U.S., we conduct an ETR analysis using panel data from the Scikit Learn Ensemble library. The ETR is chosen for its advantages, including robustness against overfitting, effective handling of missing values, computational efficiency, and variance reduction.

This study employs an extended gravity model to estimate the value of U.S. clothing imports from 22 countries and cities between 2008 and 2024. The locations analyzed are as follows:

1. Hong Kong
2. Shanghai, China
3. Dhaka, Bangladesh
4. Lumut, Brunei
5. Sihanoukville, Cambodia
6. Tanah Merah, Indonesia
7. Le Mon, Laos
8. Telok Anson, Malaysia
9. Sittwe, Myanmar
10. Calcutta, Nepal
11. Port Qasim, Pakistan
12. Pagbilao, Philippines
13. Singapore, Singapore
14. Colombo, Sri Lanka
15. Bangkok, Thailand
16. Quy Nhon, Vietnam
17. Himekawa, Japan
18. Kakinada, India
19. Silloth, United Kingdom
20. Thevenard, Australia
21. Mazatlan, Mexico
22. South Korea

These 22 locations were selected for analysis due to their emerging markets in the Asia-Pacific region. The data obtained from these sources is regarded as valid and reliable for analytical purposes. It should be noted that one of the study goals is to estimate the value of clothing exports to the U.S. from China and four Asian developing countries. These countries include India, which is not a BRI signatory country (Dasgupta, 2018) [37]. But it is one of the leading borrowers from the Asian Infrastructure Investment Bank. The official Indian narrative of the BRI is not positive. Moving beyond this one-sided view, it would be helpful to explore the BRI's effect on India's clothing exports if India would become a B&R country (Ho et al. (2020)) [4].

Data Pre-processing

Before constructing the ETR model, the dataset undergoes pre-processing to ensure its suitability for analysis. Continuous variables — Simport, GDP, Xrate, and D — are first log-transformed and then standardized to achieve a mean of zero and a standard deviation of one. No transformations are applied to the categorical variables: Landlock, WTO, and BRI.

The original dataset contains 330 observations. However, 15 rows are removed due to the absence of the LPI for Brunei. Additionally, all observations from 2022 (21 records) are retained for model validation. A review of the data set confirms that there are no missing values requiring imputation or interpolation, resulting in a final training data set of 294 records. An appropriate imputation strategy, such as mean imputation or interpolation, is predetermined based on the nature of any missing data. As LPI data is unavailable for Lumut, Brunei, those records are excluded. Conversely, all data from 2022 are utilized for validation purposes.

Model development

Following data pre-processing, the data set is divided into training and testing subsets, with 80% allocated for training and 20% for testing. The development of the ETR model proceeds through six stages:

Stage 1- Model Initialization: An instance of the ETR class from Scikit-learn is created using default hyperparameters. The baseline model's results serve as a foundation for subsequent hyperparameter optimization.

Stage 2- Hyperparameter Optimization: This stage aims to identify the optimal hyperparameters for the ETR model. Randomized search is performed using the Randomized Search CV method, which efficiently explores the best combinations of hyperparameters for the model.

Stage 3- Model Training: During this phase, the model is trained while simultaneously searching for the best set of parameters. Various hyperparameter combinations are evaluated using cross-validation, with Randomized Search CV fitting the ETRr model to assess performance based on different configurations. The number of hyperparameter combinations tested is determined by the n_iter parameter.

Stage 4- Model Evaluation: The performance of the trained ETR model is assessed on the testing dataset using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) score.

Stage 5- Feature Importance: With the best model identified, feature importance is analyzed to determine which variables contribute most to model performance, informing potential feature engineering strategies for improvement.

Stage 6- Feature Selection: Based on the feature importance analysis, the least important features are identified and removed to enhance model performance.

Proposed Artificial Neural Network (ANN) Structure

The neural network model employs a Sequential architecture and the Adam optimizer for training. This model consists of a linear stack of layers, featuring four dense layers with ReLU activation functions and one output layer without an activation function.

The network is trained using MSE as the loss function, which is appropriate for regression tasks. To ensure compatibility with the Scikit-learn library, the model is wrapped and subjected to hyperparameter optimization using Grid Search CV. This process automates the tuning of hyperparameters, including the learning rate, beta_1, beta_2, epsilon, and the decay rate of the Adam optimizer.

The model is trained for 200 epochs with a batch size of 10. Its performance is evaluated using the RMSE on the test set. The architecture includes five hidden layers, with the number of neurons in each layer determined through empirical trial and error:

Input Layer

Dense Layer (64 neurons, 'ReLU' activation)

Dense Layer (64 neurons, 'ReLU' activation)

Dense Layer (128 neurons, 'ReLU' activation)

Dense Layer (128 neurons, 'ReLU' activation)

Dense Layer (64 neurons, 'ReLU' activation)

Dense Layer (32 neurons, 'ReLU' activation)

Output Layer (1 neuron)

Results and Discussion

Results of extra trees regression model

For feature importance analysis, the results from Tables 2 (without LPI) and 3 (with LPI) are provided below.

The results presented in Tables 2 and 3 indicate that the "WTO" feature should be removed from the data set. This feature is the least important, and after eliminating five rows of observations, the entire "WTO" column consists solely of the value 1. During the initial analysis, it was noted that the "WTO" feature, which indicates a country's membership in the World Trade Organization (with a value of 1 for members), exhibited low importance. Upon further examination, it became clear that all countries except Laos are WTO members. The lack of variation in the "WTO" feature suggests it does not significantly contribute to the model's predictive power.

Since the "WTO" feature is effectively constant (with a value of 1) except for Laos, it is reasonable to classify it as unimportant for our model. Removing such features can enhance model performance by simplifying the model without sacrificing critical information. Consequently, the "WTO" feature will be excluded from the data set moving forward. This decision is supported by both its low importance in the initial analysis and its lack of variation across observations. After removing observations related to Laos from 2008 to 2012, the remaining entries all have "WTO" equal to 1. With these considerations, the "WTO" column is dropped, leading to a significant improvement in model performance; the RMSE with five features decreases from 0.1594 to 0.1292 (see Tables 5 and 6).

Table 1: Data sources.

Variables	Units	Data Sources
1. $Simport_{ijt}$	USD	The US Office of Textiles and Apparel (Category 1: Apparel)
2. $GDP_{it,}$	USD	The World Bank
3. GDP_{jt}	USD	The World Bank
4. $Exrate_{it}$	Local currency	The World Bank
5. D_{ij}	Kilometer	Sea Rates Website (www.searates.com)
6. $Landloc_{ki}$	0 or 1	World Atlas Website (www.worldatlas.com)
7. WTO_{it}	0 or 1	The World Trade Organization
8. BRI_{it}	0 or 1	Belt and Road Portal (eng.yidaiyilu.gov.cn)

Table 2: Feature Importance Analysis, without LPI.

Parameters	6-feature Importance	5-feature Importance	4-feature Importance
ln_distanceKM	0.3376	0.285	0.2636
Landlock	0.2095	0.2181	0.2212
l_nimport_export	0.2013	0.2067	0.2171
RealExChge	0.1389	0.1914	0.298
BRI_member	0.1019	0.0988	NA
WTO	0.0109	NA	NA

Table 3: Feature Importance Analysis, with LPI.

Parameters	7-feature Importance	6-feature Importance	5-feature Importance	4-feature Importance
LPI	0.2461	0.248	0.2542	0.2964
Landlock	0.2077	0.2102	0.2211	0.2267
ln_distanceKM	0.1581	0.168	0.183	NA
ln_import_export	0.1551	0.1519	0.1565	0.2446
RealExChge	0.1153	0.1132	0.1852	0.2324
BRI_member	0.1071	0.1087	NA	NA
WTO	0.0106	NA	NA	NA

Table 4: Summary of the RMSEs of the ANN.

	GridSearchCV	RandomizedSearchCV
Without LPI	0.7887	0.6614
With LPI	0.7686	1.0268

Table 5: Model performance of different number of features, without LPI.

	MSE	RMSE	R^2
6 Features	0.0118	0.1084	0.9979
6 Features Optimized*	0.0254	0.1594	0.9955
5 Features	0.0256	0.1599	0.9955
5 Features Optimized*	0.0167	0.1292	0.997
4 Features	0.0219	0.1481	0.9961
4 Features Optimized*	0.0322	0.1795	0.9943

Notes:

1. *Optimized by Random Search Optimization with 5-Fold CV.

2. Removing all 2022 data for validation and Brunei Data.

3. An RMSE of 0.1292 for “5 Features Optimized” is the least value of RMSE, which is one of the important performance indicators for the model.

Table 6: Model performance of different number of features, with LPI.

	MSE	RMSE	R^2
7 Features	0.0178	0.1334	0.9968
7 Features Optimized*	0.0342	0.185	0.9939
6 Features	0.0241	0.1554	0.9957
6 Features Optimized*	0.0452	0.2126	0.992
5 Features	0.0286	0.1692	0.9949
5 Features Optimized*	0.0518	0.2276	0.9908
4 Features	0.031	0.176	0.9945
4 Features Optimized*	0.064	0.253	0.9886

Notes:

1. *Optimized by Random Search Optimization with 5-Fold CV.

2. Removing all 2022 data for validation and Brunei Data.

Table 7: Estimated values of clothing exports to the US as in 2025.

Countries	Export Values in 2025 (USD)
China	$76,731,641,798
Vietnam	$13,340,095,015
Indonesia	$8,697,052,394
Bangladesh	$3,803,851,716
India	$3,716,320,861

Additionally, this section notes that the introduction of the “LPI” feature does not enhance the performance of the model. It is important to emphasize that this finding pertains specifically to the ETR modeling and was identified during the feature engineering process. For the ETR, adding ‘LPI’ as a new feature does not yield an improvement in model performance.

Furthermore, removing the “BRI_member” feature alters the feature importance ranking. This change indicates that the “exchange rate” becomes a more significant predictor of trade flows when BRI membership is excluded. This sensitivity to feature inclusion or exclusion was observed during feature engineering. When the “BRI” feature is removed, the “exchange rate” feature ranks among the top three in importance, while “ln_distanceKM” emerges as the second most important feature, surpassing “BRI_member” (see Tables 2 and 3).

The study explores the potential of using the ETR model to predict U.S. export values. ETR models, based on decision trees, offer greater interpretability than deep learning approaches and are robust to outliers. This robustness arises because decision trees split data based on feature thresholds, making them less sensitive to extreme values. In contrast, deep learning models may be affected by outliers, which can degrade performance. Additionally, ETR models can handle missing values in input features without requiring imputation, whereas deep learning models typically necessitate imputation or other pre-training adjustments.

ETR models could complement deep learning models, such as ANN. As the dataset expands and includes more features, it is likely that the ANN will outperform the ETR due to its ability to learn complex and non-linear relationships. Therefore, incorporating ETR as a supplementary approach to ANN is recommended.

Results of the ANN and Comparison with the ETR

The results from the ANN indicate that incorporating the LPI feature does not enhance model performance. A comparison between the ANN and ETR methods reveals that the ANN demonstrates superior predictive power. However, the ETR can serve as a valuable supplement to the ANN, particularly in managing outliers and missing values. As shown in Table 4, the RMSEs for the Grid Search CV decrease, while those for RandomizedSearchCV increase.

Adding the LPI feature does not significantly affect model performance. Consequently, a refined version of the ETR is applied to the same data set. Table 5 below illustrate the extent of prediction deviations from the target, measured by the RMSE and the Coefficient of Determination (R^2).

The results indicate that the ETR method, even with default hyperparameters, performs better with fewer features. The best RMSE achieved in this study is 0.1292, equivalent to approximately 1.2379 billion USD (see Table 5 above).

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Notably, as shown in Table 5, the out-of-sample RMSE without the LPI feature is 0.1292, or 1.2379 billion USD. This is significantly lower than the out-of-sample RMSE of 0.1824 (or 2.29 billion USD) reported in Table 4 of Ho et al.'s (2020) [4] study. Given that the minimum RMSE is 0.1292, this model demonstrates superior performance in predicting trade volume (Table 6).

The Prophet library, developed by Facebook, is a robust tool for time-series forecasting, applied individually to each data location. The model is trained on historical data to generate forecasts for the next three years.

The results of the analysis are presented in Table 7 and Figure 1, which illustrate the historical and forecast data for five selected locations. It is important to note that the trends in future trade flows are mixed; while clothing exports from China are projected to rise, those from India and other countries are expected to decline over the next three years.

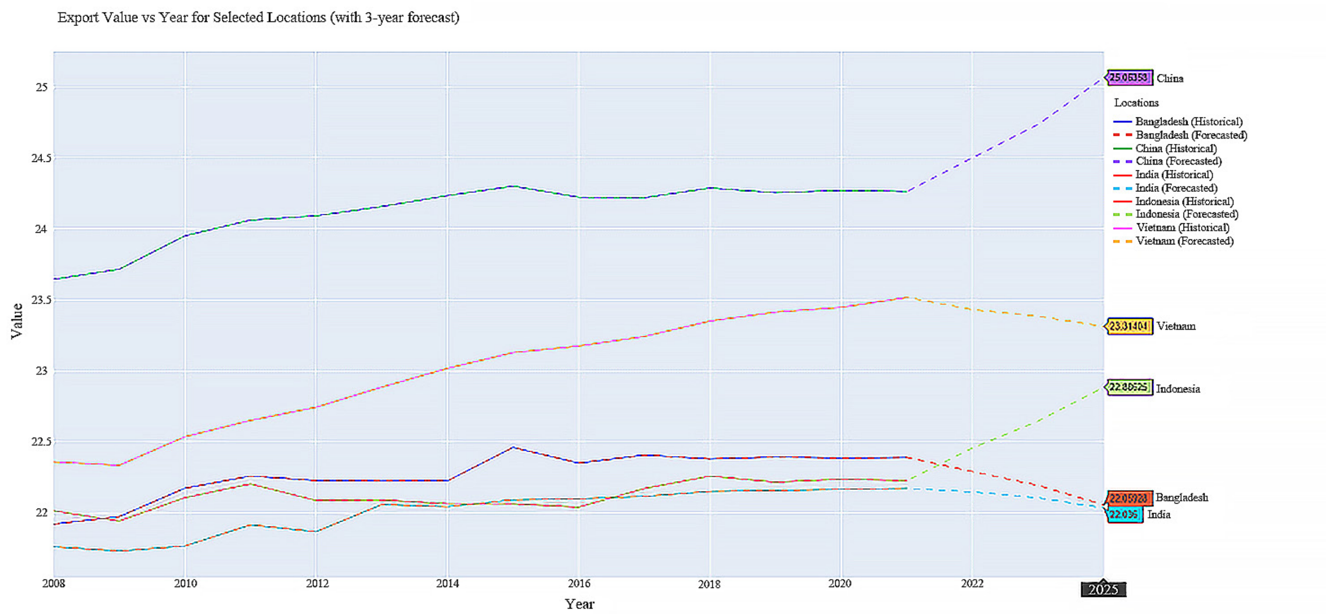

Figure 1: Current and Future Trade of Clothing Exports to the US.

Finally, the bilateral relationship in the gravity model takes the form of OLS estimators. In the study, ANN and ETR are incorporated into the gravity model. The models are a workhorse tool of international trade analysis. The study can be considered as a reasonable attempt at critical reflection, which is a crucial component of original research. We do not merely apply standard techniques but engages with the underlying data and explores the implications of these techniques for understanding trade flows and policy dynamics in the context of the BRI. The choice of method in the study somehow reflects the technical competence and ability to work with both traditional and advanced econometric techniques. One of the important findings is that machine learning has more explanatory power than the traditional gravity model.

Conclusions

International trade is vital for economic growth, heavily reliant on effective supply chains. BRI aims to enhance trade by investing in transport and logistics infrastructure. This study employs innovative ANN and ETR methods to analyze clothing export patterns from China and 21 BRI Asian countries to the U.S. between 2008 and 2022. The results indicate a positive impact of the BRI on clothing exports from the analyzed countries, reinforcing the notion that the BRI fosters international trade for developing nations along the B&R. Notably, the study also demonstrates improvements in bilateral trade between non-BRI countries, including the U.S., and China.

The research further compares ANN and ETR methodologies, particularly regarding their predictive capabilities. The findings suggest that ANN outperforms regression models in predicting international trade flows. Previous studies have recognized ANN as a viable alternative to panel data regression models, and this study adds that ANN can effectively capture and evaluate complex, non-linear relationships within the data set. Additionally, the ETR is deemed appropriate for analysis and estimation, serving as a valuable supplement to ANN, as it surpasses the extended gravity model in neural network analysis, as shown in Ho, et al. (2020) [4].

This study contributes to the literature on international trade and supply chains, emphasizing that government policies and investments, such as the BRI, can facilitate and promote international trade. First, the research highlights the BRI's influence on trade between BRI and non-BRI countries, in addition to trade between China and BRI member nations. Second, it establishes that ANN demonstrates greater predictive power than multiple linear regression of panel data , similarly to the findings of Dumor and Yao (2019) [29] and Wohl and Kennedy (2018) [30] and can be effectively combined with ETR for more reliable analytical outcomes.

While ANN provides superior predictive power relative to the traditional OLS with an ETR serving as a valuable supplementary tool to improve the ANN analysis, this paper does not break new ground in the design of an ANN or constructing gravity model data sets. Nonetheless, the ETR analysis performed in this paper utilizes updated panel data up to 2023 for updated outcomes.

Finally, future research should explore the application of ANN and ETR in new contexts. For instance, incorporating the effects of initiatives from other countries in the Far East and broader regions, such as Kazakhstan and Indonesia, could provide valuable insights. Additionally, emerging factors like climate change and artificial intelligence warrant consideration. Advancements in data analytics, including more sophisticated ensemble methods like AdaBoost, Gradient Boosting, and XGBoost, should also be investigated.

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Author Contributions

Conceptualization, Man-Hin Eve Chan and Tsz Leung Yip; methodology, Man-Hin Eve Chan, Tsz Leung Yip and Hong-Oanh Nguyen, formal analysis, Man-Hin Eve Chan and Tsz Leung Yip; investigation, Man-Hin Eve Chan; resources, Man-Hin Eve Chan and Yin Cheung Eugene Wong, data curation, Man-Hin Eve Chan; writing—original draft preparation, Man-Hin Eve Chan, writing—review and editing, Tsz Leung Yip and Hong-Oanh Nguyen supervisor, Man-Hin Eve Chan; funding acquisition, Man-Hin Eve Chan and Yin Cheung Eugene Wong. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest

The authors declare no competing interests.

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