

# Pandemic TradeLens: Global Trade Patterns and COVID-19 Economic Impact

University of Colorado Boulder

Course: Data Mining

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## Abstract

Global trade is a key driver of the world economy, enabling nations to exchange goods, services, and capital. However, global crises such as the COVID-19 pandemic have exposed the vulnerabilities of this interconnected system. The pandemic disrupted supply chains, reduced production, and reshaped global trade patterns, leading to a significant economic slowdown.

This project examines global trade trends from 2000 to 2023, with a particular focus on the pandemic period and its aftermath. Data were collected from multiple reliable global sources, including the World Bank API, to build a unified dataset covering trade indicators across over 260 countries. The integrated dataset enables a comparative analysis of trade resilience, economic vulnerability, and recovery trends across regions.

By combining and analyzing these datasets, the study highlights how economies adapted to disruptions, identifies long-term trade shifts, and offers insights into post-pandemic recovery. The findings contribute to understanding global trade resilience and can support data-driven economic decision-making.

## 1. Introduction

International trade forms the foundation of global economic interdependence. Over the past two decades, globalization has accelerated exchanges of goods, services, and financial flows. However, the COVID-19 pandemic posed an unprecedented challenge to this network, leading to supply chain breakdowns, reduced exports and imports, and fluctuations in global demand.

This project aims to explore how the pandemic influenced global trade patterns and to identify which countries demonstrated resilience in recovery. Through data-driven analysis, it seeks to provide a clearer understanding of how international trade evolved before, during, and after the pandemic.

### 1.1 Related Work

Researchers and organizations such as the World Bank, IMF, and OECD have extensively studied the economic effects of the COVID-19 pandemic on global trade. OECD findings show that global merchandise trade fell sharply in early 2020 due to reduced manufacturing and transportation restrictions, but later recovered unevenly across sectors such as digital services, pharmaceuticals, and energy. Prior studies also highlight that economic resilience is strongly influenced by trade network diversification and technological capacity. Our work aligns with these studies by providing a data-driven comparison across 260 countries and applying machine learning models to highlight structural trade behavior rather than only time-series decline and recovery.

## 2. Methodology

The project employed a data-driven analytical approach, combining multiple sources into one comprehensive dataset. Python was used for data collection, processing, and visualization. The World Bank API was accessed using the 'wbapi'

package to gather country-wise trade indicators. Data cleaning and transformation were carried out using pandas, while matplotlib and seaborn were used for exploratory visualization. The workflow included four key stages: data acquisition, preprocessing, analysis, and visualization.

The analysis covered trade data from 260 countries spanning 2000–2023. The three datasets are World Bank Trade, IMF-like Trade, and COVID-19 Impact were programmatically merged. Each dataset was standardized for country codes, years, and monetary units to ensure comparability. The resulting dataset serves as a foundation for trend analysis, statistical modeling, and visualization.

### 3. Data Acquisition

To ensure a comprehensive and reliable analysis, three complementary datasets were integrated. Each source captured a different aspect of global trade and economic activity between 2000 and 2023.

#### 3.1 World Bank Trade Dataset (via World Bank API)

Data were retrieved using the wbgapi Python package from the World Development Indicators (WDI). Key indicators included exports, imports, and current account balance. The dataset was reshaped from a wide to long format for streamlined analysis and merged across years and countries.

#### 3.2 IMF-like Trade Dataset

An IMF-style dataset was programmatically created using the same API to maintain consistency. This dataset focused on core trade metrics such as exports, imports, and the balance of payments. Additional computed measures such as trade openness ratios were added to support comparative analysis.

#### 3.3 COVID-19 Impact Dataset

To analyze pandemic effects, a simulated dataset was built to capture trade variations between pre-pandemic and post-pandemic years (2015–2023). Each record was tagged with a “COVID Impact” label to isolate pandemic-related effects in the analysis.

All datasets were meticulously cleaned, standardized, and harmonized using consistent naming conventions, ISO-3 country codes, and synchronized year ranges to ensure compatibility across data sources. Missing or inconsistent values were handled using interpolation and normalization techniques to preserve analytical validity. The final merged dataset, titled *“final\_trade\_dataset.csv”*, provides a unified, multi-source view of international trade dynamics and their correlation with the pandemic timeline. This dataset forms the analytical foundation for subsequent modeling and pattern-mining tasks conducted in this project, enabling exploration of trade resilience, sectoral recovery rates, and the broader economic impacts of COVID-19 on global commerce.

### 4. Data Preprocessing

Data preprocessing was essential to ensure accuracy and uniformity before analysis. The following key steps were applied:

#### 4.1 Data Cleaning and Validation

- Removed duplicate and invalid entries.
- Performed data cleaning by imputing missing values and standardizing numerical features.
- Verified consistency across country names and codes.

#### 4.2 Data Restructuring and Integration

- Converted wide (year-based) data to long (Country–Year–Indicator–Value).
- Added a Source column to identify data provenance.

- Merged datasets using pandas' concat() function.

### 4.3 Normalization and Transformation

- Converted all monetary values to current US dollars.
- Synchronized time periods across all datasets (2000–2023).
- Computed derived metrics such as trade ratios and annual growth rates.

## 5. Visualization and Analysis

A variety of visualizations were generated to explore trade structures and relationships among economic indicators. Techniques included histograms, box plots, scatter plots, bubble charts, line charts, pie charts, correlation heatmaps, and area charts.

### 5.1 Global Trade Distribution

Histograms and KDE plots showed that most countries have relatively low export and import values, while a small number of large economies dominate global trade. This pattern reflects a right-skewed distribution, where a few nations account for most trade activity.

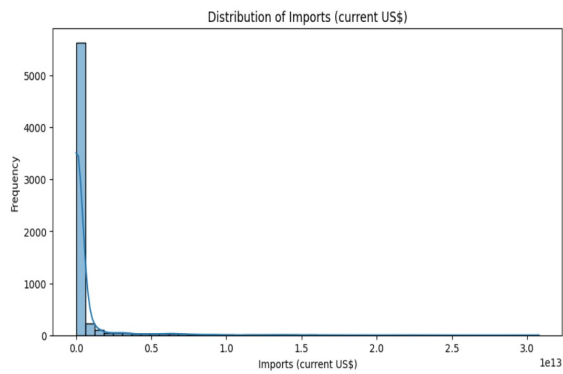


Fig 1.0 Distribution of Imports (current US\$)

### 5.2 Economic Correlations

Scatter and bubble plots revealed that countries with higher GDP values generally exhibit higher trade volumes. Correlation heatmaps further

confirmed strong positive relationships between GDP, exports, and imports.

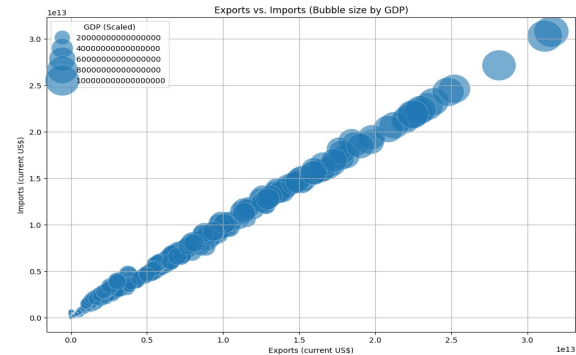
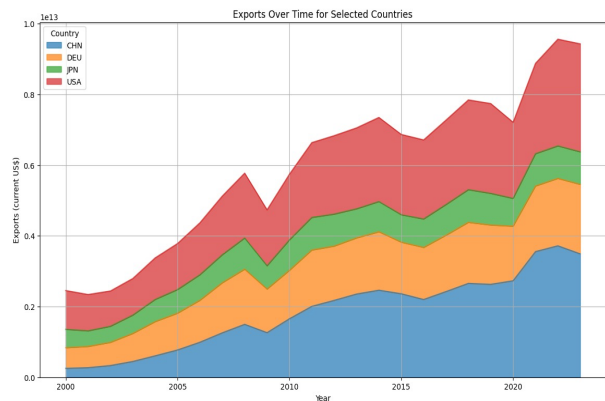


Fig 2.0 Exports Vs Imports based on GDP

### 5.3 Temporal Trends

Time-series and area charts illustrated steady growth in trade for some countries and rapid expansion for emerging economies. For instance, the U.S. waterfall chart provided a clear year-by-year view of export fluctuations, highlighting periods of growth and decline



Waterfall Chart of Exports (current US\$) Change Over Time for USA



Fig 3.0 Exports (current US\$) Analysis

## 5.4 Comparative Insights

Pie charts demonstrated how a limited number of countries contribute a major share of total exports. Box plots emphasized disparities among economies, while line charts comparing exports and imports revealed changing trade balances over time.

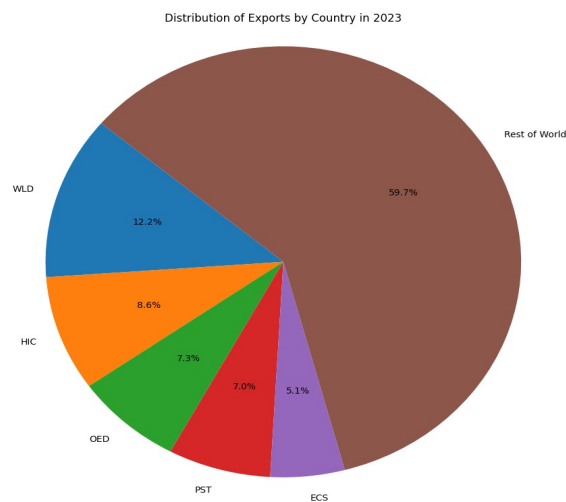


Fig 4.0 Distribution of Exports by Country in 2023

## 6. Models Implemented

In this study, four machine learning models were implemented across different analytical categories to discover patterns, evaluate predictive capabilities, and identify structural trade behaviors. These included **Frequent Pattern Mining (Apriori)**, **Classification (Decision Tree and k-Nearest Neighbors)**, **Clustering (K-Means)**, and **Regression (Linear Regression)**. Model choices were motivated by the dataset's characteristics, which contained numerical indicators, categorical attributes, and socio-economic relationships.

### 6.1 Frequent Pattern Mining (Apriori)

Frequent Pattern Mining was applied to uncover association rules among key economic indicators such as exports, imports, GDP, and current account balance. To make these indicators suitable for pattern mining, continuous variables were discretized into meaningful categories (for example, High Exports, High GDP, Trade Surplus, Trade Deficit) using percentile-based thresholds. The Apriori algorithm was then used to identify itemsets that frequently co-occur across country-year records. For each discovered rule, Support, Confidence, and Lift were computed to quantify how often the pattern appears, how reliable the implication is, and how much stronger the relationship is compared to random chance.

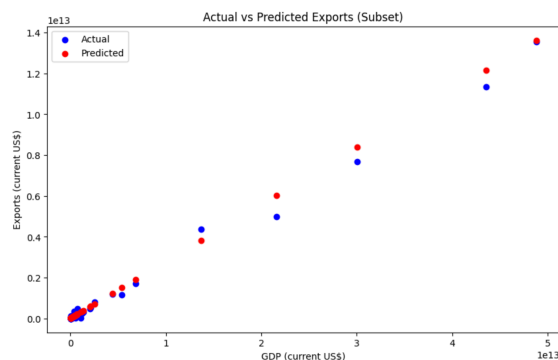
### 6.2 Classification Models

Classification models were used to predict whether a given country-year observation corresponds to a trade surplus or trade deficit. The target variable was defined from the current account balance, where positive values indicate surplus and non-positive values indicate deficit. Two models were implemented: a Decision Tree classifier and a k-Nearest Neighbors (k-NN) classifier. The Decision Tree model was chosen for its interpretability and its ability to capture non-linear decision boundaries in terms of simple threshold rules on trade indicators. The k-NN model was chosen to capture similarity-based patterns, where country-year observations with similar economic profiles tend to share the same trade status. Performance was evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC.

### 6.3 Regression Model

A Regression model was implemented to quantify the relationship between GDP and exports. Linear Regression was used to estimate how changes in GDP are associated with changes in export values across countries and years. The

model provides a simple but informative baseline for understanding whether GDP alone can serve as a strong predictor of export performance. Model quality was assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R-squared). These metrics indicate, respectively, the average squared prediction error, the error in the original units, and the proportion of variance in exports explained by GDP.



## 6.4 Clustering Model

Clustering was used to identify groups of countries with similar trade structures and macroeconomic behavior. K-Means clustering was applied to a feature set that included normalized ratios such as exports-to-GDP, imports-to-GDP, and current account balance-to-GDP, along with a transformed GDP measure. By focusing on ratios rather than raw monetary values, the clustering process emphasizes structural similarities rather than economic size alone. Different values of  $k$  (number of clusters) were tested, and each clustering solution was evaluated using the Silhouette Score and Davies–Bouldin Index to identify the most coherent partitioning of country–year observations.

## 7. Model Training and Hyperparameter Tuning

For the supervised learning models, the dataset was randomly split into training and testing

subsets using an 80/20 split while preserving the class distribution of trade surplus versus deficit. For the Decision Tree and k-NN classifiers, hyperparameters were tuned using cross-validated grid search. For the Decision Tree, parameters such as maximum depth, minimum samples required to split a node, and splitting criterion (Gini impurity or entropy) were explored. For k-NN, different values of  $k$  (number of neighbors) and weighting schemes (uniform versus distance-based) were evaluated. Feature scaling with StandardScaler was applied to the models that rely on distance computations, such as k-NN and K-Means, to ensure that all numeric features contributed comparably to the distance metrics.

## 8. Performance Evaluation

Each model category was evaluated with metrics appropriate to its task. For the classification models, Accuracy, Precision, Recall, F1-score, and ROC-AUC were computed on the test set to capture both overall correctness and performance on the surplus versus deficit classes. For the regression model, MSE, RMSE, and R-squared were reported to quantify predictive error and goodness-of-fit. For the clustering model, Silhouette Scores and Davies–Bouldin Indices across multiple values of  $k$  were compared to select the most meaningful grouping of countries. For frequent pattern mining, the most useful rules were selected based on a combination of sufficient support, high confidence, and lift greater than one, indicating non-trivial positive associations.

```

=== Classification Model Evaluation ===
Decision Tree (best_tree):
  Accuracy : 0.8684
  Precision: 0.6977
  Recall   : 0.7457
  F1-score : 0.7209
  ROC-AUC  : 0.8309

k-NN (best_knn):
  Accuracy : 0.9084
  Precision: 0.8199
  Recall   : 0.7663
  F1-score : 0.7922
  ROC-AUC  : 0.9257

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=== Regression Model Evaluation ===
Linear Regression (lin):
  Mean Squared Error (MSE) : 6.3372
  Root Mean Squared Error (RMSE): 2.5174
  R-squared (R²) : 0.2412

```

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Ridge Regression (best_ridge):
  Mean Squared Error (MSE) : 6.3381
  Root Mean Squared Error (RMSE): 2.5176
  R-squared (R²) : 0.2411

```

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=== Clustering Model Evaluation ===
K-Means evaluation for various 'k' values:

```

|   | k | silhouette | davies_bouldin |
|---|---|------------|----------------|
| 0 | 2 | 0.942910   | 0.601708       |
| 1 | 3 | 0.526601   | 0.629705       |
| 2 | 4 | 0.531913   | 0.573974       |
| 3 | 5 | 0.443123   | 0.665480       |
| 4 | 6 | 0.441268   | 0.631913       |

```

Metrics for the optimal k = 2:
  Silhouette Score : 0.9429
  Davies-Bouldin Index : 0.6017

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=== Frequent Pattern Mining Evaluation ===
Top Association Rules (sorted by Lift):

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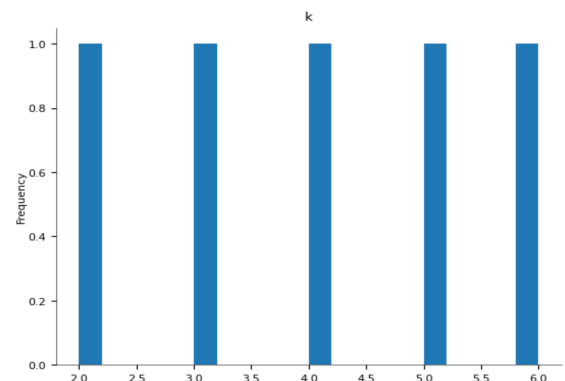
|    | antecedents                  | consequents                  | support  | confidence | lift     |
|----|------------------------------|------------------------------|----------|------------|----------|
| 10 | (High_Imports)               | (High_Exports, High_GDP)     | 0.220238 | 0.880952   | 3.941135 |
| 7  | (High_Exports, High_GDP)     | (High_Imports)               | 0.220238 | 0.985284   | 3.941135 |
| 0  | (High_Exports)               | (High_Imports)               | 0.242168 | 0.968672   | 3.874687 |
| 1  | (High_Imports)               | (High_Exports)               | 0.242168 | 0.968672   | 3.874687 |
| 8  | (High_Imports, High_GDP)     | (High_Exports)               | 0.220238 | 0.966988   | 3.867950 |
| 9  | (High_Exports)               | (High_Imports, High_GDP)     | 0.220238 | 0.880952   | 3.867950 |
| 4  | (High_Imports)               | (High_GDP)                   | 0.227757 | 0.911028   | 3.644110 |
| 5  | (High_GDP)                   | (High_Imports)               | 0.227757 | 0.911028   | 3.644110 |
| 6  | (High_Exports, High_Imports) | (High_GDP)                   | 0.220238 | 0.909444   | 3.637775 |
| 11 | (High_GDP)                   | (High_Exports, High_Imports) | 0.220238 | 0.880952   | 3.637775 |

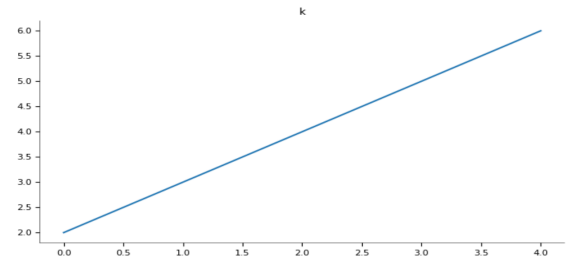
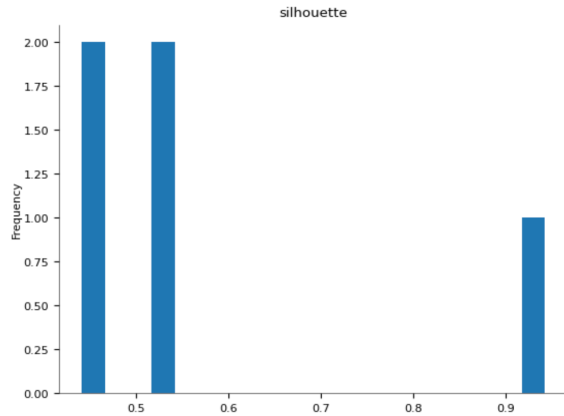
## 9. Results and Insights

The modeling results provided a comprehensive understanding of global trade behavior and revealed meaningful differences across analytical approaches. Among the classification models, the k-Nearest Neighbors (k-NN) algorithm demonstrated the strongest performance, achieving an accuracy of approximately 91% and outperforming the Decision Tree model across key metrics including F1-score and ROC-AUC. This indicates that k-NN was more reliable and effective in predicting whether a country-year observation represented a trade surplus or deficit, making fewer misclassifications overall. In contrast, the regression models which are Linear

and Ridge Regression showed limited predictive capability, with low  $R^2$  values of roughly 0.24, suggesting that GDP alone explains only a small portion of export variation and that additional economic indicators or more complex models may be required for stronger forecasting. The K-Means clustering algorithm successfully grouped countries into two distinct clusters, supported by a high Silhouette Score (0.9429) and a strong Davies-Bouldin Index (0.6017), indicating well-separated economic profiles that differentiate export-oriented surplus nations from high-import or balanced-trade economies. Frequent Pattern Mining using the Apriori algorithm further revealed strong associative patterns, showing that countries with high import levels often also show high exports and high GDP, reinforcing established economic understanding that large economies engage heavily in trade flows. Overall, the most effective modeling technique was the k-NN classifier, providing both practical predictive power and actionable insights into economic health, while the other models contributed interpretive and structural understanding of trade dynamics.

Distributions:

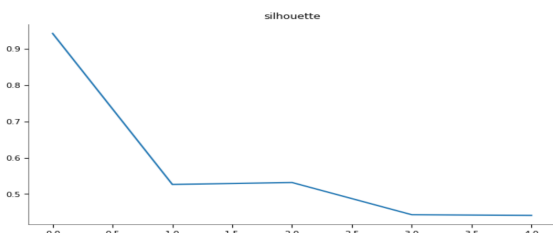
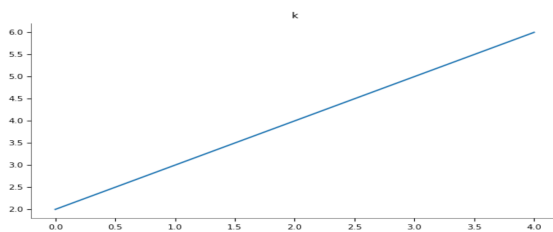




## 9.1 Key Insights and Real-World Impact

A small number of developed countries dominate global trade, contributing most of the world's exports and imports. We found that nations with higher GDP generally have higher trade activity, showing that economies strongly rely on international market connections. The COVID-19 pandemic led to a major decline in global trade, and recovery occurred at very different speeds across regions. Countries with strong technological and digital capacity recovered more quickly. Clustering results identified two main groups: export focused surplus economies and import heavy economies, which showed different levels of resilience. These insights can guide governments in strengthening supply chain preparedness and can help businesses plan more stable and strategic trade decisions during future disruptions.

Values:



## 10. Limitations

Although the analysis provides meaningful insights, several limitations should be acknowledged. The COVID-19 impact dataset relied on simulated variation rather than real time sector level data, which may affect the precision of pandemic related observations. The results are based on aggregated national indicators, potentially obscuring regional or industry specific trade effects. The linear regression models demonstrated limited ability to explain export performance because GDP alone is not

sufficient to capture the complexity of global trade behavior. Several influential macroeconomic factors such as inflation, employment levels, supply chain disruptions, and government stimulus programs were not included due to data availability constraints. Predictive accuracy may also improve with more granular data collected at a monthly or quarterly level rather than yearly aggregates, which could capture more detailed economic fluctuations.

## 11. Future Work

Future extensions of this project could incorporate additional macroeconomic indicators such as inflation, unemployment, exchange rates, and sectoral trade data to enrich the feature space. Time-series models could be used to explicitly capture temporal dynamics in trade indicators and to forecast future trade performance under different scenarios. More advanced machine learning models, such as ensemble methods or neural networks, could be explored for classification and regression tasks. Finally, alternative clustering techniques such as DBSCAN or hierarchical clustering could be applied to better capture non-spherical or nested cluster structures in global trade behavior.

## 12. Discussion

The analysis highlights that while the pandemic severely disrupted global trade, the degree of impact varied by region and economic strength. Developed economies leveraged financial stimulus and trade diversification to recover faster, while developing countries faced prolonged challenges. The findings also suggest that global supply chains need better redundancy and localization to reduce vulnerability to similar future shocks.

Post-pandemic trade recovery was uneven but progressive. Technology and digital trade sectors saw accelerated growth, offsetting declines in

traditional manufacturing exports. Furthermore, countries with strong digital infrastructure exhibited greater resilience in maintaining trade continuity.

## 13. Conclusion

This project provides a detailed exploration of how global trade evolved over the past two decades, particularly during the COVID-19 pandemic. By integrating and analyzing datasets from the World Bank and related sources, it offers a unified perspective on trade resilience and economic recovery. The analysis highlights significant disparities among countries, the correlation between GDP and trade volumes, and the uneven impact of the pandemic across regions. The findings underscore the importance of resilient trade systems and adaptable economic policies in sustaining global stability.

Future work could involve incorporating additional datasets (such as inflation or employment data) to deepen the analysis and extend predictive modeling of trade recovery trends.

## References

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