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Machine learning for global trade analysis: a hybrid clustering approach using DBSCAN, elbow, and SOM

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ABSTRACT

Global trade constitutes a highly complex and interdependent system influenced by diverse economic, geographic, and political factors. This study proposes a hybrid clustering framework that integrates density-based spatial clustering of applications with noise (DBSCAN), elbow, and self-organizing maps (SOM) methods to uncover latent structures in international trade patterns. Utilizing averaged trade data from 25 countries spanning the period from 2013 to 2023, the framework identifies distinct clusters based on export-import characteristics. The DBSCAN is employed to detect dense trade hubs and outlier behaviors, the elbow method determines the optimal number of clusters, and SOM facilitates the visualization of non-linear, high-dimensional trade relationships. The analysis reveals three prominent trade clusters: Global Trade Leaders, Emerging Trade Powers, and Niche Exporters, each reflecting varying degrees of trade diversification and dependency. These empirical findings align with established economic theories, including the Heckscher Ohlin model and dependency theory, and provide actionable insights for policymakers seeking to enhance trade competitiveness and regional integration strategies.

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1. INTRODUCTION

Global trade has increasingly been recognized as a complex, multifaceted phenomenon with profound implications for the economic landscapes of nations [1]. Conventional methods of trade analysis, frequently focused on financial indicators and bilateral trade models, may fail to capture the intricate and dynamic nature of international trade flows. Recent advancements in data availability and analytical techniques, particularly through clustering methods, and present new avenues for comprehending these dynamics by enabling the grouping of countries based on similarities in their export and import profiles [2].

Prior analyses have underscored the value of sophisticated methodologies in enhancing the predictive power and interpretive capabilities of trade studies. Robust regression approaches by Niftiyev [3] and time series analyses by Alzahrani and Salah [4] illustrate the efficacy of employing advanced analytical techniques in international trade contexts. These studies underscore the need to move beyond traditional econometric models to gain a deeper understanding of trade dynamics. Additionally, qualitative methodologies and text-based analyses, as demonstrated in [5], [6], provide valuable complementary insights, particularly in evaluating the impacts of geopolitical events such as the 2022 escalation of the Russia-Ukraine war. Integrating these alternative approaches can significantly enrich econometric and statistical evaluations.

Clustering techniques, as a subset of unsupervised machine learning, facilitate the identification of latent groupings within trade data, potentially unveiling hidden structures and relationships that elude traditional models. For instance, research has demonstrated that trade networks can exhibit notable structural characteristics with the capacity to influence trade flows significantly. The virtual water trade networks analyzed by Xing and Chen [7] provide a relevant example, illustrating how trade patterns can substantially affect the distribution of water resources across nations. Herzberger *et al.* [8] similarly underscore the importance of trade relationships, emphasizing that interactions across various trade systems may either enhance or counterbalance trade flows, thereby complicating efforts to understand the multifaceted nature of global trade dynamics.

Moreover, applying machine learning methodologies in trade forecasting has proven advantageous in refining predictive accuracy. Jošić and Žmuk [9] argue that machine learning algorithms offer crucial insights for policymakers and researchers by enhancing the precision of bilateral trade flow predictions. Gopinath *et al*. [10] corroborate these findings, demonstrating that machine learning techniques hold particular efficacy in forecasting agricultural trade, yielding superior long-term fits when compared to traditional econometric models. Thus, integrating advanced analytical frameworks into trade analysis contributes to a more nuanced understanding of global trade patterns.

The clustering of countries based on trade profiles additionally provides essential insights into the economic interdependencies that characterize contemporary trade relationships. While the gravity model of trade, an extensively employed tool in trade flow analysis, suggests that economic size and geographic distance are critical determinants of bilateral trade [11], Rasoulinezhad and Jabalameli [11] contend that the complex integration patterns among Brazil, Russia, India, and China (BRICS) countries underscore the need for analytical approaches that extend beyond traditional models. This assertion suggests that clustering methodologies can reveal deeper insights into the economic linkages and patterns of trade integration among countries, aspects that are often obscured in conventional analyses. By incorporating machine learning techniques and recognizing the intricate nature of trade flows, researchers can better understand global trade dynamics, thereby equipping policymakers and stakeholders with insights into the economic development and sustainability implications of trade patterns.

Given this backdrop, the primary research questions this study seeks to address is: How can clustering techniques, specifically a hybrid framework involving density-based spatial clustering of applications with noise (DBSCAN), elbow, and self-organizing maps (SOM) methods, elucidate distinct patterns and actionable insights from global trade data? The objectives of this research include comprehensively analyzing global trade patterns, investigating factors that contribute to cluster formations, such as geographic proximity, industrial specialization, and economic development levels, and providing policymakers with actionable insights regarding potential trade partnerships, diversification strategies, and sector-specific collaboration opportunities. By systematically employing hybrid clustering methods, this study significantly enhances analytical precision and interpretive clarity, contributing both theoretically and practically to the field of international trade analysis.

2. RELATED WORKS

The analysis of global export-import strategies through data-driven segmentation is greatly enhanced by computational approaches, particularly clustering techniques applied to trade patterns. Clustering facilitates the identification of distinct trade communities and patterns, providing essential insights for strategic decision-making in international trade. A foundational element in understanding global trade dynamics lies in recognizing its complex network structure, which underscores these systems' interdependencies and potential vulnerabilities. The application of complex network theory has substantively advanced the analysis of trade networks, uncovering their structural characteristics and evolutionary dynamics. For instance, Cho *et al*. [12] argue that traditional measures of trade openness may overlook the intricate dependencies embedded within trade networks, noting that a focus on trade volume alone inadequately reflects a country's susceptibility to external shocks. Their findings reveal that trade openness, in isolation, was statistically insignificant, indicating that an analysis of network topology is crucial for accurately assessing a country’s resilience within the global market.

In agricultural trade, the evolution of trade networks further exemplifies these interdependencies. Qiang *et al*. [13] for instance, apply complex network theory to examine the global agricultural trade network, identifying power-law distributions that highlight the fundamental drivers of trade dynamics. Similarly, Li *et al.* [14] exploration of the global rice trade network demonstrates how factors such as centrality and structural gaps impact food security, further emphasizing the intricate interconnections that characterize food trade systems. Collectively, these studies illustrate that trade networks operate as complex systems characterized by varied degrees of connectivity and interdependence rather than as straightforward linear connections.

Recent global events, particularly the COVID-19 pandemic, have further complicated the topology of trade networks, underscoring their adaptability and resilience to external shocks. Zhao and Huang [15] comparative study of the international coal trade network, analyzed pre- and post-pandemic, highlights significant shifts in network structure, showcasing the adaptability of trade networks under stress. Such adaptability, intrinsic to complex systems, results from interactions between nodes (countries) and links (trade relationships), producing emergent behaviors that are not readily predictable based on individual components alone. This complexity is further evident in the trade of specific commodities. Wang *et al*. [16] for instance, illustrate how the evolution of the global soybean trade network is shaped by factors such as trade volume and partner relationships, thereby creating a dense web of interdependencies. Similarly, Niu *et al*. [17] characterize the global crude oil trade network by its core-periphery structure, where dominant countries exert substantial influence over trade flows, resulting in asymmetrical trade relationships and dependencies. Such imbalances highlight critical vulnerabilities within trade networks that can impact global trade stability.

The intricate topology of trade networks benefits significantly from advanced analytical methods, such as multilayer network analysis, which Dupas *et al*. [18] suggest can elucidate community structures and densely clustered trading groups. This method offers a deeper comprehension of the interconnections and dependencies underpinning global trade [18]. By mapping these intricate relationships, researchers can better trace the evolution of trade patterns over time. Furthermore, external shocks such as food price volatility or global crises like the COVID-19 pandemic substantially influence trade dynamics. Torreggiani *et al.* [19] for example, discuss how food price shocks reshape export barriers and import tariffs, consequently altering global trade flows. Similarly, the COVID-19 pandemic has exposed supply chain vulnerabilities, highlighting the necessity of resilience in trade strategy development. As demonstrated by Tu *et al.* [20], analytical techniques that allow for temporal and spatial clustering are instrumental in identifying dynamic communities within trade networks, facilitating better adaptation to such external shocks.

The digital transformation of the global economy has introduced new complexities in trade dynamics. The rise of digital markets has enhanced trade efficiency and competitiveness, necessitating a reassessment of traditional trade models [21]. E-commerce, for instance, reduces transaction costs and fosters new forms of market engagement, thereby reshaping the international trade landscape [22]. Integrating digital tools in trade analysis further refines segmentation strategies, enabling firms to target export initiatives more effectively by leveraging real-time data and market intelligence. Applying clustering techniques to analyze global export-import strategies offers a robust framework for navigating the complexities of international trade. By employing advanced network analysis, accounting for the impacts of external shocks, and integrating digital transformations, stakeholders are positioned to formulate more effective and resilient trade strategies in response to an evolving global landscape.

This research aims to construct a comprehensive, adaptable, and practical framework for segmenting global trade patterns. Through innovative clustering and network analysis, this study advances theoretical understanding. It provides actionable insights for policymakers and businesses, equipping them with data-driven strategies for fostering resilient and adaptive trade practices.

3. METHOD

This study employs several clustering algorithms to identify patterns in global trade data. This section describes the research approach used to provide an overview of how the study was conducted and what data were collected.

3.1. Data collection

This study analyzed trade data from 25 countries collected from the United Nations Comtrade and World Bank repositories. The dataset spans the period from 2013 to 2023. For each country, export and import values, trade volume, gross domestic product (GDP), number of trade partners, market distance, and tariff rates were averaged over the 10-year period to ensure consistency and to reflect long-term trade patterns suitable for clustering analysis.

3.2. Clustering techniques

Clustering is an unsupervised learning technique used to group data points into clusters based on similarity or specific criteria. Various clustering techniques are suitable for different types of data and research objectives.

3.2.1. Density-based spatial clustering of applications with noise

The DBSCAN clustering algorithm is an unattended algorithm based on its ability to define clusters without predefined class labels [23]. The DBSCAN clustering provides a robust and flexible approach to segmenting global trade networks. By identifying core clusters and outliers, DBSCAN enables a nuanced understanding of trade communities, capturing irregularities that traditional clustering methods might miss. This helps policymakers and businesses to identify key trade relationships, resilient and vulnerable markets, and emerging trade opportunities within a dynamic global trade landscape. The following are the mathematical formulas used at each stage of the DBSCAN algorithm:

i) Define parameters
eps (ε): Maximum radius of the neighborhood.
min_samples: Minimum number of points required to form a dense region.

ii) Find the neighbourhood of a point using (1):

$$N(p) = \{q \in D \mid distance\ (p, q) \leq \varepsilon\} \tag{1}$$

where $N(p)$ is the neighborhood of p.d is the dataset.

iii) Computing the distance (p,q) using (2):

$$Distance\ (p, q) = \sqrt{\sum_{i=1}^{d}(pi - qi)^2} \tag{2}$$

where d is the number of dimensions, pi and qi are the coordinates of p and q.

iv) Determining the label of a point p depends on its classification using (3):

$$Cluster\ (p) = \begin{cases} k, & if\ p\ belongs\ to\ cluster\ C_k \\ -1, & if\ p\ is\ noise\ (outlier), \end{cases} \tag{3}$$

3.2.2. Elbow method

Cluster analysis often faces challenges in determining the optimal number of clusters. Creating too many clusters can result in a minimal decrease in total cluster variants [24]. The stages of the elbow method in the clustering process are as follows:

i) Build the initial centroid and centroids randomly.

ii) Allocate all objects using Euclidean distance (4), as follows:

$$d(i, k) = \sqrt{\sum_{j=1}^{m}\left(X_{ij} - C_{kj}\right)^2} \tag{4}$$

where *d(i,k)* describes distance i- data to centroid, X_{ij} related index j- data, and C_{kj} is variable for center *cluster j-* index.

iii) Recalculate cluster membership using (5):

$$C_{kj} = \frac{\sum_{j=1}^{m} Y_{hj}}{p};\ Y_{hj} = X_{ij} \in cluster \tag{4}$$

where m is the number of data members, and p is the amount of data for a particular centroid.

iv) Calculate the centroid until finished: the elbow method is one of the methods used to determine the optimal amount in clustering analysis [25]. Evaluating the quality of clustering with elbow is carried out using (6) with the following stages:

$$SSE = \sum_{k-1}^{k}\sum_{xi \epsilon Sk}\left|\left|Xi = Ck\right|\right|^2 \tag{6}$$

where Xi is the attribute value i-data, Ck is the center cluster i- data.

3.2.3. Self-organizing maps

The SOM method addresses the limitation of traditional methods, which cannot directly explain the mining results for high-dimensional data, by maintaining the relationship between data transactions [26]. SOM clustering offers a powerful approach to exploring and visualizing the complexity of global trade networks [27]. By revealing latent structures and clusters within export-import data, SOM can facilitate a deeper understanding of trade interdependencies, identify resilient trade communities, and support the development of data-driven, adaptable strategies that are attuned to the dynamic nature of global trade. The stages of the SOM method are as follows [28]:

i) Initiation neuron each y1, y3, ..., yn, then determining the initial weight.
ii) Find the shortest distance using Euclidean distance using (7) as follows:

$$D_j = \sum_j (W_{ij} - X_j \tag{7}$$

iii) Update weight W_{ij} using (8) as follows:

$$W_{ij}(new) = W_{ij}(old) + \alpha(X_i - W_{ij}(old)) \tag{8}$$

iv) Calculate the centroid using (9):

$$V_{kj} = \frac{\sum_{i=1}^{n}((\mu ik))^{W} * X_{ij}}{\sum_{ij}^{n}(\mu ik)^{W}} \tag{9}$$

v) Calculate the value of membership degrees using (10):

$$Q_j = \sum_{k=1}^{c} \mu ik \tag{10}$$

vi) Determine the win cluster:
SOM comprises neurons arranged in an orderly, low-dimensional grid [29], interconnected to define map topology through input data into an orderly array of dimensional nodes.

3.2.4. Hybrid density-based spatial clustering of applications with noise, elbow, and self-organizing maps

This study introduces a hybrid clustering methodology that combines DBSCAN, elbow, and SOM methods to segment global export-import trade strategies with precision and scalability. The DBSCAN effectively identifies clusters based on density, making it suitable for detecting core trading hubs and peripheral markets. The elbow method provides robust cluster validation. The SOM is particularly adept at visualizing high-dimensional, non-linear trade data, offering interpretative ease for complex datasets, as discussed comprehensively by Niftiyev and Ibadoghlu [30]. By harnessing computational techniques, the research analyses large-scale trade pattern datasets, unveiling clusters of countries with similar trade behaviors. The DBSCAN facilitates density-based clustering to identify key trade hubs and outliers, while the elbow method determines the optimal number of clusters, ensuring robust and data-driven segmentation. The SOM further enhances the analysis by capturing complex, non-linear relationships in high-dimensional trade data. The resulting segmentation provides actionable insights into trade strategy typologies, empowering policymakers and businesses to craft informed and competitive strategies [31]. The detailed process flow of the proposed methodology is depicted in Figure 1.

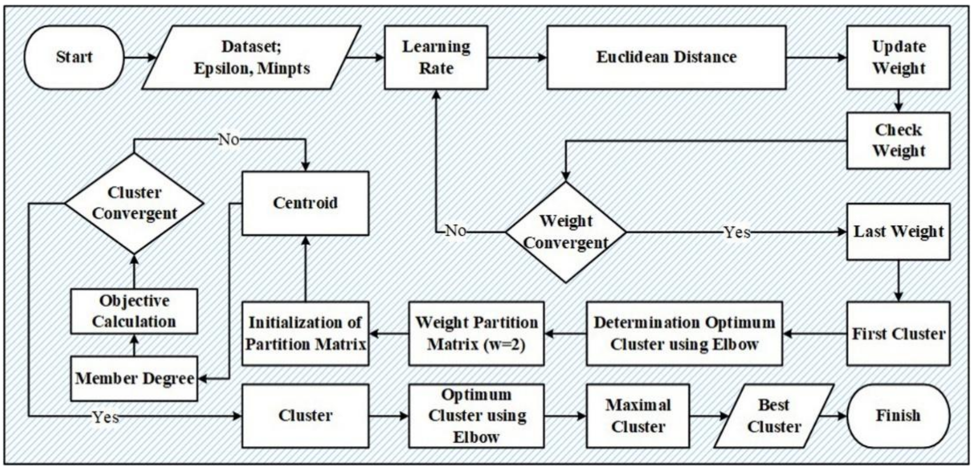


Figure 1. Proposed hybrid DBSCAN, elbow, and SOM

The explanation based on the illustration in Figure 1 is as follows:

i) Input
Datasets are the data to be grouped, while the Epsilon, MinPts, and LearningRate parameters are used for iteration control and weight updates.

ii) Initialization
Initialized partition matrix to initially group data.

iii) Iteration for cluster convergence:
- Centroid cluster counted.
- The degree of data membership to the cluster is calculated.
- Objective functions are evaluated to check if the cluster is convergent.

iv) Iteration for weight convergence:
- The Euclidean distance is calculated for each data.
- Weights are updated with the pace of learning.
- The process continues until the weights reach a convergent value.

v) Determination of optimal cluster with elbow method:
- Calculate intra-cluster variation for different numbers of clusters.
- Identify elbow points to determine the optimal number of clusters.

vi) Validation and output:
- The best clusters are selected based on maximum performance.
- Data is assigned to the best cluster.
- The end result is the optimal cluster.

This systematic method is ideal for datasets where both optimal cluster distribution and scalability are critical, making it a powerful tool for data analysis and pattern recognition tasks.

4. RESULTS AND DISCUSSION

This section describes how to use hybrid DBSCAN, elbow and SOM, where each step is correlated until the process functions as a whole. Multiple subsections feature discussion about this study.

4.1. Determining of criteria weight

Recent advances in DBSCAN have led to the development of hybrid algorithms that combine DBSCAN with other techniques to improve clustering performance [32]. Therefore, this study involves the role of the DBSCAN method in determining the weight of the collected dimensions, as shown in Table 1. Based on Table 1, neuron weights are formed using the scale function on DBSCAN. As is known, the scaling criteria value in DBSCAN can be used as input to the SOM method to group data and update the weight of neurons so that it can produce representative cluster results [33]. The results of the scale value formation for each criterion are shown in Table 2.

Based on the results in Table 2, it is known that the scaling function in the DBSCAN algorithm adjusts the distance between data in datasets with features with different scales. It is given example calculation of the mean and standard deviation of the export criteria:

Export_value =[250, 350, 100, 250, 450, 250, 200, 100, 70, 300, 200, 150, 40, 200, 60, 150, 150, 150, 150, 250, 50, 100, 250, 80, 300]

Export_mean $= \frac{25\ 250+350+100+\cdots+300}{25} = \frac{5310}{25} = 212.4$

Standard_deviation $= \sqrt{\frac{(250-212.4)^2+(350-212.4)^2+\cdots+(300-212.4)^2}{25}} = \frac{55964}{25} = 2238.56 = \sqrt{2238.56} = 47.3$

After getting the standard deviation value, the scale export value in Argentina (250) is calculated as follows:

Scale_export $= \frac{250-212.4}{47.3} = 0.66$

4.2. Analyze global trade patterns hybrid DBSCAN, elbow, and self organizing maps

The elbow and SOM hybrid approach leverages the power of both the elbow method for optimal grouping and a self-alignable map to visualize high-dimensional data [28], [34]. This study utilizes the role of the elbow method in determining the optimum cluster value (K) as a guideline for cluster formation. The results of the elbow calculation involving the data in Table 2 are shown in Figure 2.

Table 1. Dataset for each criterion on trade patterns

No	Country	Export ($ Billion)	Import ($ Billion)	Trade partner Count	GDP ($ Billion)	Distance markets (Km)	Trade volume ($ Billion)	Tariff rate (%)
1	Argentina	250	300	80	600	7000	550	8.0
2	Australia	350	400	90	1500	6000	750	5.5
3	Bangladesh	100	150	50	200	5500	250	8.0
4	Brazil	250	300	100	2000	7000	550	10
5	Canada	450	500	150	1800	4500	950	5.0
6	Chile	250	200	80	300	7000	450	5.0
7	Colombia	200	250	70	400	5500	450	7.0
8	Egypt	100	150	60	300	6500	250	8.5
9	Ethiopia	70	100	30	120	8000	170	11.0
10	India	300	400	130	3000	3500	700	7.5
11	Indonesia	200	250	70	1100	5000	450	7.0
12	Kenya	150	200	60	300	5000	350	8.0
13	Libya	40	60	20	70	7000	100	11.5
14	Malaysia	200	250	80	400	4000	450	6.0
15	Mozambique	60	90	30	100	9000	150	10.5
16	Nigeria	150	200	70	400	8000	350	9.0
17	Pakistan	150	200	60	300	4500	350	9.0
18	Peru	150	200	60	250	6000	350	7.5
19	Philippines	150	200	70	350	5000	350	7.0
20	South Africa	250	300	80	400	6000	550	7.5
21	Sudan	50	70	20	80	8500	120	12.0
22	Tanzania	100	150	50	200	6000	250	9.0
23	Thailand	250	300	90	500	4500	550	6.5
24	Uganda	80	120	40	150	7000	200	10.0
25	Vietnam	300	250	100	500	3500	550	5.5

Table 2. Results of scale value formation

No	Country	Export	Import	Trade partner count	GDP	Distance markets	Trade volume	Tariff rate
1	Argentina	*0.66*	0.72	0.34	-0.02	0.69	0.70	-0.03
2	Australia	1.65	1.67	0.67	1.25	0.01	1.68	-1.31
3	Bangladesh	-0.84	-0.70	-0.64	-0.58	-0.32	-0.77	-0.03
4	Brazil	0.66	0.72	1.00	1.96	0.69	0.7	0.99
5	Canada	2.65	2.62	2.63	1.68	-1.00	2.66	-1.57
6	Chile	0.66	-0.22	0.34	-0.44	0.69	0.21	-1.57
7	Colombia	0.16	0.25	0.01	-0.30	-0.32	0.21	-0.54
8	Egypt	-0.84	-0.70	-0.31	-0.44	0.35	-0.77	0.23
9	Ethiopia	-1.13	-1.17	-1.30	-0.70	1.36	-1.17	1.51
10	India	1.15	1.67	1.98	3.38	-1.67	1.43	-0.29
11	Indonesia	0.16	0.25	0.01	0.69	-0.66	0.21	-0.54
12	Kenya	-0.34	-0.22	-0.31	-0.44	-0.66	-0.28	-0.03
13	Libya	-1.43	-1.55	-1.62	-0.77	0.69	-1.51	1.76
14	Malaysia	0.16	0.25	0.34	-0.3	-1.33	0.21	-1.06
15	Mozambique	-1.23	-1.27	-1.30	-0.73	2.03	-1.26	1.25
16	Nigeria	-0.34	-0.22	0.01	-0.3	1.36	-0.28	0.48
17	Pakistan	-0.34	-0.22	-0.31	-0.44	-1.00	-0.28	0.48
18	Peru	-0.34	-0.22	-0.31	-0.51	-0.66	-0.28	-0.29
19	Philippines	-0.34	-0.22	0.01	-0.37	0.01	-0.28	-0.54
..	..	..	..	..	..	..	..	..
25	Vietnam	1.15	0.25	1.00	-0.16	-1.67	0.7	-1.31

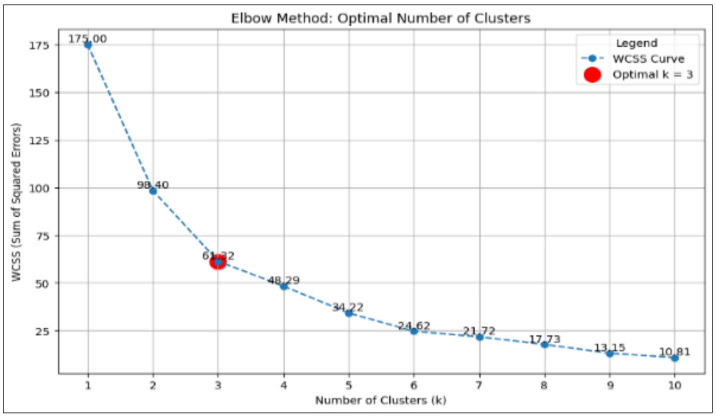


Figure 2. Result of elbow for determining optimum cluster

The sum of squared errors (SSE) is an important metric for evaluating the performance of SOM and assessing the quality of clustering by measuring the deviation of data points from the center of each cluster [35], [36]. Based on the illustration in Figure 2, it is known that the optimum value (K) is 3 with an SSE value of 61.32. The results of the calculation of the Each feature dataset represent all the criteria showing that the countries that are cluster-1 members consist of Argentina, Brazil, and Chile with centroid values=(0.66, 0.42, 0.56, 0.50, 0.69, 0.54, −0.03). For each country assigned to cluster-1, calculate the squared distance to the centroid C1, and it is following the explanation:

Argentina ($x1$) =0.66, 0.72, 0.34, −0.02, 0.69, 0.70, −0.03.
$\|x1-c1\|^2$ $=(0.66-0.66)^2+(0.72-0.42)^2+(0.34-0.56)^2+(-0.02-0.50)^2+(0.69-0.69)^2+(0.70-0.54)^2+(-0.03-(-0.03))^2=0.4344$.
Brazil ($x2$) =0.66, 0.72, 1.00, 1.96, 0.69, 0.70, 0.99.
$\|x2-c1\|^2$ $=(0.66-0.66)^2+(0.72-0.42)^2+(1.00-0.56)^2+(1.96-0.50)^2+(0.69-0.69)^2+(0.70-0.54)^2+(0.99-(-0.03))^2 = 3.5077$.
Chile ($x3$) =0.66, −0.22, 0.34, −0.44, 0.69, 0.21, −1.57.
$\|x3-c1\|^2$ $=(0.66-0.66)^2+(-0.22-0.42)^2+0.34-0.56)^2+(-0.44-0.50)^2+(0.69-0.69)^2+0.21-0.54)^2+(-1.57-(-0.03))^2=3.7915$.
SSE(C1) =0.4344+3.5077+3.7915=7.7336.
SSE(C2) =30.45.
SSE(C3) =23.1364.
SSE is finally determined=SSE(C1)+SSE(C2)+SSE(C3).
SSE =7.7336+30.45+23.1364=61.32.

The next stage determines the distribution of each country within the cluster area based on the centroid value using SOM. Previous research has stated that SOM and clustering require that data be normalized to ensure features contribute equally [37]. An example of the calculation of the standard value is given for feature1 (export) in the following way:

The values for C1 across all countries are:
[0.66, 1.65, −0.84, 0.66, 2.65, 0.66, 0.16, −0.84, −1.13, 1.15, 0.16, −0.34, −1.43, 0.16, −1.23, −0.34, −0.34, −0.34, −0.34, 0.66, −1.33, −0.84, 0.66, −1.03, 1.15].
Determining min and max values: $X_{min}= -1.43$, $X_{max}=2.65$.
Then, plugging into the normalization calculation:

Substitute the values $X' = \frac{2.65-(-1.43)}{0.66-(-1.43)}$.

Result X' $= \frac{2.65+1.43}{0.66+1.43} = \frac{4.08}{2.09} = 0.385$.

The calculation results are displayed in Table 3.

Table 3. Result of normalization value for every feature

No	Country	Feature1	Feature 2	Feature3	Feature4	Feature5	Feature6	Feature7
1	Argentina	0.385	0.460	0.419	0.231	0.600	0.427	0.464
2	Australia	0.755	0.806	0.800	0.661	0.198	0.782	0.187
3	Bangladesh	0.199	0.254	0.290	0.072	0.400	0.229	0.476
4	Brazil	0.454	0.485	0.501	0.448	0.600	0.471	0.602
5	Canada	0.755	0.806	0.800	0.661	0.198	0.782	0.187
6	Chile	0.491	0.455	0.473	0.155	0.405	0.474	0.219
7	Colombia	0.353	0.392	0.370	0.187	0.383	0.374	0.353
8	Egypt	0.199	0.254	0.290	0.072	0.400	0.229	0.476
9	Ethiopia	0.065	0.081	0.081	0.025	0.826	0.074	0.823
..	..	..	..	..	..	..	..	..
25	Vietnam	0.471	0.488	0.511	0.140	0.142	0.474	0.166

Then, work on the training process to learn the data structure by mapping similar data points to the nearest neurons in the network so that countries with similar feature values are grouped in the same cluster. The optimal number of clusters is 3 in the SOM and DBSCAN, which is applied with a 3×3 grid produced in 9 nodes. Comparative studies have shown that DBSCAN and SOM can effectively be applied in clustering tasks [38]. The DBSCAN excels in density-based clustering, particularly in noisy environments, while SOM provides powerful visualization capabilities for high-dimensional data. The results are seen in Table 4.

Table 4. Result of the clustering based on node value

No	Country	Node1	Node2	Node3	Node4	Node5	Node6	Node7	Node8	Node9	Cluster
1	Argentina	0.572	0.332	0.611	0.418	0.888	0.39	0.202	0.339	0.991	2
2	Australia	0.688	0.627	0.625	0.438	0.423	0.813	0.776	0.751	1.599	1
3	Bangladesh	0.493	0.622	0.126	0.814	1.375	0.404	0.559	0.762	0.650	3
4	Brazil	0.912	0.763	0.914	0.660	0.834	0.741	0.565	0.286	1.165	1
5	Canada	1.136	1.182	1.685	0.968	0.475	1.380	1.362	1.285	2.198	1
6	Chile	0.560	0.362	0.670	0.556	1.055	0.492	0.527	0.732	1.110	2
7	Colombia	0.308	0.175	0.386	0.384	0.960	0.122	0.320	0.539	0.970	2
8	Egypt	0.771	0.635	0.174	0.826	1.378	0.426	0.475	0.668	0.518	3
9	Ethiopia	1.269	1.103	0.659	1.279	1.801	0.903	0.849	0.965	0.040	3
10	India	1.035	1.100	1.424	0.845	0.455	1.169	1.175	1.007	1.907	1
11	Indonesia	0.326	0.289	0.491	0.305	0.833	0.220	0.394	0.490	1.065	2
12	Kenya	0.482	0.442	0.179	0.612	1.165	0.229	0.441	0.635	0.813	2
13	Libya	1.338	1.215	0.711	1.387	1.910	0.992	0.994	1.105	0.264	3
14	Malaysia	0.141	0.348	0.583	0.431	0.915	0.384	0.615	0.771	1.224	3
15	Mozambique	1.361	1.171	0.769	1.354	1.875	0.991	0.913	1.036	0.181	3
16	Nigeria	0.861	0.637	0.456	0.804	1.311	0.512	0.355	0.517	0.556	2
17	Pakistan	0.559	0.555	0.266	0.686	1.200	0.350	0.523	0.665	0.824	3
18	Peru	0.450	0.416	0.210	0.600	1.160	0.225	0.458	0.668	0.850	2
19	Philippines	0.481	0.345	0.248	0.559	1.131	0.192	0.351	0.593	0.817	3
20	South Africa	0.381	0.186	0.567	0.312	0.837	0.303	0.287	0.454	1.063	2
21	Sudan	1.478	1.311	0.866	1.482	1.991	1.111	1.047	1.140	0.231	3
22	Tanzania	0.790	0.684	0.156	0.869	1.420	0.458	0.537	0.719	0.506	3
23	Thailand	0.113	0.258	0.676	0.253	0.724	0.404	0.541	0.655	1.278	2
24	Uganda	1.036	0.894	0.412	1.077	1.615	0.680	0.677	0.826	0.242	3
25	Vietnam	0.269	0.480	0.863	0.450	0.754	0.626	0.795	0.885	1.483	3

Based on the results of clustering using SOM, the cluster division is determined as follows:

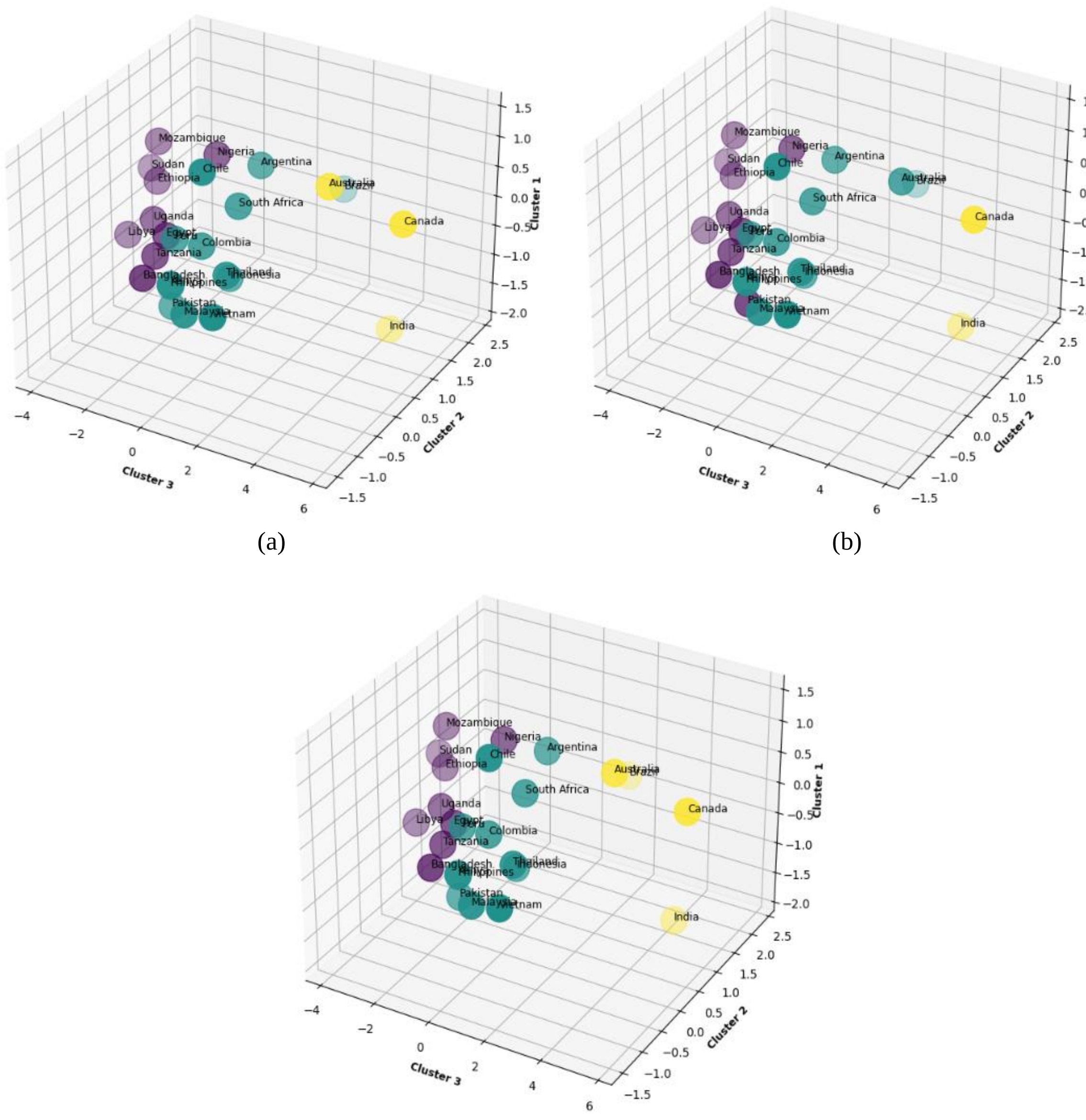
i) Cluster 1 (Global Trade Leaders): this cluster represents countries with strong, diversified, and influential global trade patterns, often driving global commerce. It comprises major economies, including Australia, Brazil, Canada, and India, all of which exhibit diverse trade structures and high overall trade volumes.
ii) Cluster 2 (Emerging Trade Powers): countries in this cluster may have growing trade influence, showing potential for expansion in international markets, but not yet at the scale of the global leaders. It encompasses Argentina, Chile, Colombia, Indonesia, Kenya, Nigeria, Peru, South Africa, and Thailand, which generally show mid-range trade intensity and greater reliance on primary goods or region-specific partners.
iii) Cluster 3 (Niche Exporters): this cluster comprises countries with more specialized trade patterns, focusing on specific industries or regional markets, with a smaller but significant presence in both exports and imports. It comprises lower-diversification, resource-dependent economies, including Bangladesh, Egypt, Ethiopia, Libya, Malaysia, Mozambique, Pakistan, Philippines, Sudan, Tanzania, Uganda, and Vietnam. These economies exhibit narrower export bases and often rely on a small number of commodities and partners.

These groupings reflect variations in industrial capacity, regional integration, and trade dependency profiles across the global trade landscape. Based on trade theory and powerful computational techniques, the clustering results can provide a strategic roadmap for countries to improve their trade competitiveness and integrate into the global economy.

4.3. Comparison analysis

Clustering analysis is a fundamental technique in data mining that aims to group similar data points into clusters. Thereby uncovering the inherent structure of the data to understand its effectiveness and application across various datasets. The comparative visualization presented in Figure 3 demonstrates the differences in clustering outcomes using k-means (Figure 3(a)), hierarchical clustering (Figure 3(b)), and our proposed DBSCAN and SOM hybrid approach (Figure 3(c)).

Hybrid DBSCAN and SOM is a powerful and flexible clustering method that excels in handling complex, non-linear, and irregular data distributions. It is particularly useful in real-world scenarios where the data contains noise, outliers, and varying cluster densities. The ability to visualize clusters using SOM makes DBSCAN and SOM a superior choice compared to traditional methods, such as k-means and k-medoids, which may struggle with these challenges. In terms of clustering quality, adaptability to data structure, and visualization, the hybrid DBSCAN and SOM methods are the most effective, providing more accurate, meaningful, and interpretable results for complex datasets.



(a) (b) (c)

Figure 3. Visualization of clustering using (a) k-means, (b) hierarchical cluster, and (c) DBSCAN+SOM

4.4. Limitation

This study faces several limitations that need to be carefully considered when applying grouping techniques to analyze global export-import strategies. Firstly, the success of the grouping technique is highly dependent on the quality and completeness of the trade data. Therefore, the loss or incompleteness of data from several countries or regions can hinder accurate segmentation and potentially produce biased results. Secondly, global trade is influenced by various complex factors, including political relations, supply chain disruptions, and tariffs, which may not be fully captured by clustering methods that typically rely on quantitative trade data, resulting in a less comprehensive understanding of global export and import strategies.

5. CONCLUSION

This study employs a hybrid clustering methodology that integrates DBSCAN, elbow, and SOM methods to identify structural patterns in global trade data. The resulting clusters of Global Trade Leaders, Emerging Trade Powers, and Niche Exporters reveal significant differences in industrial capacity, trade diversification, and reliance on specific commodities or trading partners. These empirical classifications correspond to classical economic theories: the Heckscher-Ohlin model for diversified, resource-rich economies, the product life cycle theory for transitional economies with evolving trade structures, and the dependency theory for countries exhibiting limited export breadth and high external reliance. The proposed framework advances the analytical understanding of global trade typologies and offers a practical tool for informing targeted trade and economic policies. By capturing nuanced patterns in export-import behavior, the model supports evidence-based decision-making for improving competitiveness, regional integration, and trade sustainability. As global trade dynamics continue to shift in response to economic, technological, and geopolitical changes, future research could enhance this framework by incorporating longitudinal data, enabling the monitoring of inter-cluster transitions and policy impacts over time.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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