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*Research Article*

# Integrating Clustering Models and RCA to Identify Emerging Textile Export Destinations for Indonesia

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**Abstract:**
This research investigates the strategic identification of new export destinations for Indonesian textile products by integrating international market segmentation and product competitiveness analysis. The study employs clustering techniques (K-Means, K-Medoids, and Hierarchical) validated through Silhouette and Davies-Bouldin indices to classify 149 countries based on trade indicators (import growth, trade balance, global market share), economic indicators (population, purchasing power parity, industrial proportion to GDP), and trade barrier indicators (logistics performance index, geographic distance, free trade agreements). Complementarily, the Revealed Comparative Advantage (RCA) framework is applied to evaluate Indonesia's product-level competitiveness in the global textile market. The results reveal that export opportunities are can be concentrated in 20 countries across Europe, Asia, Africa, the Caribbean, and Melanesia, characterized by positive import growth, significant trade deficits, large market capacities, and relatively low trade barriers. Moreover, Indonesia demonstrates high comparative advantages in artificial and synthetic fibbers, wigs, and leather footwear, while apparel products such as suits, shirts, knitwear, and brassieres represent moderately competitive but globally demanded items. The study concludes that Indonesia's export strategy should balance high purchasing power markets and emerging economies with high import dependency.

**Keywords:** Clustering, RCA, International Market Segmentation, Textile, Export.

**Dataset link:** https://www.kaggle.com/datasets/muhammadglennyunifer/textile-global-market

## 1. Introduction

The industrial sector plays a strategic role in the national economy as it accelerates economic growth, fosters innovation, mitigates the potential risks of poverty and hunger, and enhances income and societal welfare through the provision of adequate employment opportunities [1]. Over the past five years (2020–2024), the industrial sector (excluding oil and gas) has contributed an average of 18.64% to Indonesia's total gross domestic product (GDP) [2]. One of the strategic industries within Indonesia's economy is the textile sector. For developing countries, the textile industry represents a promising option to drive industrialization, increase national income through export performance, and absorb large-scale labour forces [1]. During the period 2020–2024, the textile industry accounted for 8.60% of total national exports [3], [4] making it one of the largest export contributors, supported by the availability of low-cost labour and abundant raw materials such as cotton and synthetic fibbers [5]. Nevertheless, this sector has faced serious challenges in the form of export growth deceleration in recent years.

The export value of textile products recorded a significant decline in 2023, falling by -21.19% compared to 2022, while in 2024 the growth rate was only 9.13%, considerably lower than the 19.7% growth achieved in 2022 [3], [4]. Furthermore, news reported that 939,038 workers were affected by layoffs between August 2024 and February 2025, with the majority occurring in the textile industry [6], [7]. One of the main factors was textile products from China have entered the domestic market with low or even zero tariffs, supported by low production costs and high manufacturing efficiency, enabling them to be sold at significantly lower prices have led to a domestic market inundated with inexpensive imported products, thereby undermining local textile producers, particularly small and medium-sized enterprises, which face difficulties in maintaining competitiveness [5]. In addition, demand for Indonesian textile products from major export destinations such as the United States, Europe (Germany, the Netherlands, the United Kingdom, Belgium), and Asia (Japan and South Korea) has also declined [3].

This can be observed in **Table 1**, which illustrates the decline in textile import values from these countries during 2022–2023, whereas 112 other countries—particularly in Africa and Asia—experienced an average growth of 2–5% during the same period. The imposition of a 19% import tariff by the United States on Indonesian textile products is also likely to hinder or even reduce U.S. imports from Indonesia, as importers may shift either toward domestic production or toward sourcing from countries unaffected by such tariff policies [8]. These conditions present both challenges and opportunities for Indonesia to expand its global export destinations, particularly in the textile sector, so that the ongoing export slowdown does not persist and the stability of this strategic industry can be restored.

**Table 1**. Comparative Growth of Textile Import Values Between Indonesian Major Export Destinations and Other Potential Countries, 2022–2023

| Top 10 Indonesian Textile Export Destination Countries | | 10 Other Potential Countries with Positive Textile Import Value Growth | |
|---|---|---|---|
| Country | Total Growth Import Value (Textile) 2022 - 2023 | Country | Total Growth Import Value (Textile) 2022 - 2023 |
| United States of America | -16.34% | Tajikistan | 61,3% |
| Japan | -9.00% | Kazakhstan | 56,9% |
| China | 7.78% | Algeria | 36,7% |
| South Korea | -5.73% | Libya | 32,5% |
| Germany | -6.64% | Ghana | 29,5% |
| Netherlands | -6.23% | Senegal | 22,6% |
| United Kingdom | -9.47% | Russia | 16,2% |
| Australia | -6.12% | Croatia | 10,0% |
| Canada | -12.72% | Serbia | 7,2% |
| Belgium | -7.93% | Saudi Arabia | 5,8% |

Source: [3] (processed data)

Government support and trade agreements can serve as highly valuable resources for firms seeking global expansion, as they provide access to market intelligence, financial incentives, and various forms of assistance that substantially strengthen internationalization strategies [9]. Free Trade Agreements (FTAs) are regarded as advantageous policies in enhancing competitive advantage and ensuring ease of market entry for Indonesian products in international markets [10]. Indonesia has implemented trade agreements with ASEAN (ATIGA), the Asia-Pacific region (RCEP), Pakistan (IPPTA), Chile (Indonesia–Chile EPA), India (AIFTA), Hong Kong (AHKFTA), Mozambique (IMPTA), EFTA–CEPA (Switzerland, Norway, Iceland, Liechtenstein), and the United Arab Emirates (IUAE CEPA), as well as agreements scheduled to take effect with the European Union (2027), the Eurasian Economic Union (2025), Peru (2025), and Canada (2026) [11]. Such agreements reduce trade barriers and facilitate the cross-border movement of goods and services, allowing firms to benefit from preferential tariffs, more efficient customs procedures, and harmonized regulations, thereby lowering costs and improving market access [9]. These opportunities should be optimized through comprehensive analyses of market characteristics, demand patterns, and cultural contexts across potential countries to identify the most promising export destinations and formulate strategies to enhance exports to these markets.

Market segmentation enables firms to gain a deeper understanding of target markets and to design more tailored marketing strategies, thereby facilitating effective resource allocation by focusing on the most profitable segments with the highest potential for success [9]. International Market Selection (IMS) constitutes a strategic decision of paramount importance for firms entering global markets, as it has long-term implications for overall international success and competitiveness which is closely related to the choice of entry mode and marketing strategy [12]. Consequently, market segmentation and international market selection, as integral components of comprehensive international market research, are essential for making informed decisions on product adaptation in accordance with market conditions, consumer preferences, and cultural contexts, thereby enabling firms to strengthen their competitive advantage [9].

Market segmentation constitutes a critical strategy in market development, involving the division of a broad market into distinct consumer groups based on similarities in needs, characteristics, and preferences [13], [14]. By identifying and targeting specific segments, firms can tailor their marketing efforts to effectively address the unique demands of each group [15]. Understanding the specific needs of individual segments enables companies to design more focused marketing strategies, allocate resources more efficiently, and identify new growth opportunities, ultimately enhancing business performance and profitability [9]. Firms generally seek to enter highly attractive markets with relatively low risk, where they can achieve competitive advantage by considering the target segment, product or service offerings and pricing, distribution channels, and potential customers of their campaigns [16]. Preferences for international markets are shaped by the interaction of multiple variables, including demographic, political, economic, socio-cultural, and trade barrier factors [17]. International segmentation is commonly conducted through macro-segmentation (country-based segmentation), which groups countries based on geographical, demographic, or socioeconomic similarities (e.g., GDP per capita, population size, and household size), followed by further subdivision according to consumer characteristics within each segment [18].

**Table 2**. Variables and Indicators

| Source | Variables/Indicators |
|---|---|
| [17] | Costs (cost to import border compliance, internal transport, international transportation cost, official exchange rate, target market price), cultural environment (corruption perceptions index, cultural distance, ease of doing business, and globalization index), Economic (cost of living index, GDP per capita, risk country time to resolve insolvency, unemployment rate), logistics (frequency, geographic location, geographical distance, logistics performance index, transit time), and trade barriers (index of economic freedom, international competitiveness, non-tariffs barriers, protectionism in general, and tariffs barriers). |
| [18] | Brand awareness, gross national income, and trade liberalization. |
| [19] | Society (advanced society, health infrastructure, education), cultural (cultural distance, religion, language, common language), transport and infrastructure (geographic distance, general infrastructure, transportation infrastructure), economic (economic development, economic growth, international trade engagement, market size, market prosperity, currency and monetary policy), and political (political stability, government effectiveness, rule of law, corruption control). |
| [12] | Market size/market potential, market receptivity, market attractiveness, market barrier, competitive intensity, market risk, commercial infrastructure, political stability, physical distance/ culture distance. |
| [20] | Economic (air transport, consumer price index, electric power consumption, electric production, energy use, export, GNI per capita, import, personal computers, phones, tv sets) and national culture. |
| [21] | Market size/potential (GDP, population, imports, energy consumption) and market development (GDP per capita, total employment rate, level of internet access, corruption perception index) |
| [22] | Geographic distance, market size, economic intensity, cultural distance, language difference, foreign direct investment, free trade agreement, physical infrastructure, market receptivity, and religious difference. |

The principal contribution of David Ricardo to international trade theory lies in the concept of comparative advantage, regarded as an analytical refinement of the absolute advantage theory, as it demonstrates that a nation's gains are determined by relative production costs rather than absolute efficiency [23]. In 1817, Ricardo advanced the classical theory of comparative advantage to explain that international trade occurs not merely due to absolute advantages, but because of differences in relative production costs, even when one country is more productive in all goods compared to another [24]. In 1965, Balassa developed the Revealed Comparative Advantage (RCA) index to operationalize and strengthen the concept of comparative advantage, which has since been widely applied by scholars to measure a nation's export competitiveness and analyse variations in trade patterns across time, sectors, and regions [25]. RCA retrospectively identifies comparative advantage through trade data by comparing the export share of commodity $j$ from country $i$ with the share of commodity $j$ in global exports, where RCA values < 1 indicate comparative disadvantage, = 1 neutrality, and > 1 comparative advantage [26]. Empirical applications of this approach include research to identify textile and apparel (TAP) products in the United States with export comparative advantage and their corresponding destination markets, with cotton fibbers emerging as the most significant source of the U.S. TAP advantage [26]. Similarly, the RCA index applied to assess Pakistan's export competitiveness vis-à-vis neighbouring countries (Afghanistan, China, India, and Iran), categorizing results into strong comparative advantage, marginal advantage, and comparative disadvantage according to relative rankings [25].

The phenomenon of Indonesia's textile export slowdown, marked by a significant decline in export values since 2023, intensifying domestic competition due to the influx of low-cost imports from China, and reduced demand from major markets such as the United States, Europe, and Asia, highlights serious challenges to the sector's sustainability, including declining production capacity and rising layoffs. On the other hand, opportunities for market expansion through government support and the utilization of Free Trade Agreements (FTAs) remain highly promising. However, these opportunities require research-driven strategies that can identify trade performance factors, economic potential, and trade barriers as critical considerations in international market selection for textile products. Moreover, it is necessary to develop appropriate models of market segmentation and international market selection while exploring potential products suitable for specific target markets. This study aims to address these needs, offering practical benefits for firms and exporters by providing a scientific foundation for identifying the most promising export destinations and determining potential products for international expansion.

## 2. Method

Clustering is a fundamental technique in unsupervised learning that groups data based on intrinsic similarities without prior labels, thereby uncovering hidden patterns that are critical across various disciplines, such as market segmentation with complex and multivariate datasets [27]. The market segmentation method in this study employs a clustering approach for 148 countries using three algorithms for each variable, namely k-means, k-medoids, and hierarchical clustering. Data were collected from COMTRADE, the World Bank, and CEPII, and subsequently processed using the Pandas library in Python via Kaggle Notebook. The research stages consisted of preprocessing (dataset inspection, ensuring that all variable values were numeric, handling missing values, and data standardization), application of clustering algorithms for each variable with different optimization methods (elbow method or dendrogram), and evaluation of model performance using the silhouette coefficient and Davies-Bouldin index. The model with the most optimal performance was then employed to analyse the characteristics of each cluster across the respective variables.

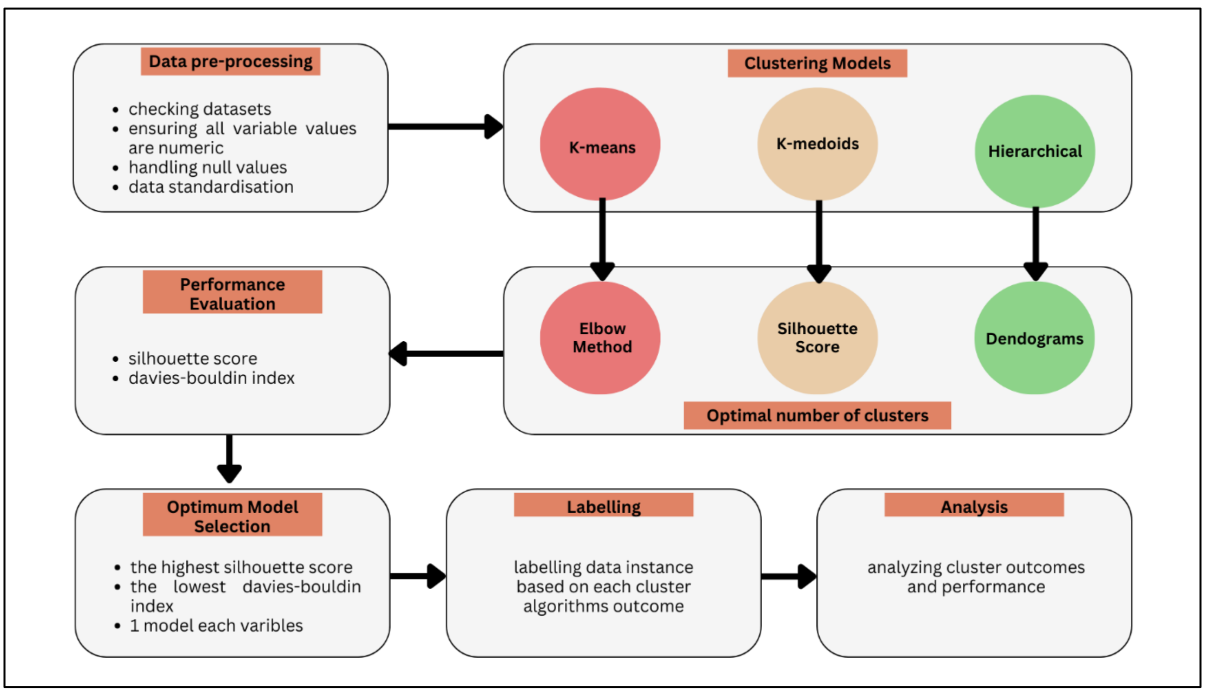


**Figure 1.** Workflow diagram of the proposed market segmentation method

### Dataset and Pre-processing:

International market segmentation in this study employs three dimensions, trade indicators (textile imports), economic potential, and trade barriers, across 148 countries. Since the primary objective of this research is to explore new export destinations for Indonesian textiles, the ten countries with the largest textile import values from Indonesia were excluded. These countries, United States, Japan, China, South Korea, Germany, Netherlands, United Kingdom, Australia, Canada, and Belgium, collectively accounted for 71.44% of Indonesia's total textile exports in 2023 [3]. In addition, countries with limited data availability were also excluded from the analysis. The trade indicators, economic potential, and trade barrier variables employed in this study are presented in **Table 3**.

**Table 3.** Data and Sources

| Variable | Indicator | Source |
|---|---|---|
| Trade | Average Growth of Textile Imports 2020–2023 | [3] |
| | Average Textile Trade Balance 2020–2023 | [3] |
| | Average Textile Import Market Share 2020–2023 | [3] |
| Economy | Population | [28] |
| | Purchasing Power Parity (PPP) | [29] |
| | Industry Share of GDP | [30] |
| Trade Barriers | Logistic Performance Index | [31] |
| | Distance from Indonesia | [32] |
| | Free Trade Agreement with Indonesia | [11] |

**Clustering Models:**

*K-Means clustering method*

K-Means is one of the most widely applied clustering algorithms in unsupervised learning. The algorithm partitions data into *k* clusters by minimizing the sum of squared distances between data points and the centroid of each cluster. K-Means operates iteratively by assigning data points to the nearest centroid, recalculating the centroids as the mean of the assigned points until convergence is achieved. It is advantageous due to its simplicity, computational efficiency, and scalability for large datasets. However, it has notable limitations, as it assumes clusters to be spherical and is highly sensitive to outliers as well as the initial placement of centroids [27]. The sensitivity of K-Means to centroid initialization may result in suboptimal clustering performance, thereby necessitating multiple trials or the adoption of more robust alternatives such as K-Medoids or hierarchical clustering.

*K-Medoids clustering method*

K-Medoids, also referred to as Partitioning Around Medoids (PAM), is a clustering algorithm similar to K-Means but exhibits greater robustness to outliers and noise. As explained by Sadeghi (2025), this algorithm does not compute centroids as the mean of data points; instead, it selects actual data points (medoids) as the center of clusters. The algorithm minimizes the total dissimilarity between data points and their respective medoids. This approach renders K-Medoids less sensitive to extreme values and more suitable for datasets with irregular structures or when employing non-Euclidean distance measures.

*Hierarchical clustering method*

Hierarchical clustering is a method that constructs a hierarchy of clusters through either a bottom-up (agglomerative) or top-down (divisive) approach. As described by Sadeghi (2025), in the agglomerative process each data point is initially treated as an individual cluster and then iteratively merged based on proximity until only a single cluster or the desired number of clusters remains. Conversely, the divisive approach begins with a single large cluster that is subsequently partitioned into smaller clusters. This process relies on distance or similarity measures, such as Euclidean distance, as well as linkage criteria that determine how clusters are merged or divided, including single linkage (minimum distance), complete linkage (maximum distance), and average linkage (mean distance). Such flexibility enables hierarchical clustering to adapt to diverse datasets and clustering objectives.

**Optimal number of clusters:**

*Elbow method*

Sadeghi (2025) explains that the Elbow Method is a widely used heuristic for determining the optimal number of clusters (k) in clustering algorithms such as K-Means and K-Medoids. This method involves plotting the within-cluster sum of squares (WCSS) against the number of clusters. The "elbow" point on the graph indicates the stage at which adding more clusters yields only marginal reductions in WCSS, thereby reflecting a balance between model complexity and performance (Ketchen & Shook, 1996). Its application requires running the clustering algorithm across multiple values of k, computing WCSS for each as a measure of cluster compactness, and identifying the elbow point where the rate of decline in WCSS levels off, representing the optimal number of clusters.

*Dendrograms*

According to Sadeghi (2025), hierarchical clustering produces a dendrogram, a tree-like diagram that visualizes the process of cluster formation and facilitates the identification of the optimal number of clusters by "cutting" the tree at a specific level. This method offers high interpretability and flexibility; however, it faces limitations when applied to large datasets due to high computational complexity and sensitivity to noise, which may affect clustering quality.

**Performance Evaluation:**

*Silhouette Score*

Sadeghi (2025) states that the Silhouette Score is a widely adopted metric for evaluating clustering quality by comparing cohesion (similarity of data points within the same cluster) and separation (difference from data points in the nearest cluster). The score ranges from $-1$ to $+1$, where values approaching $+1$ indicate well-defined clustering, values near 0 suggest overlapping clusters, and values close to $-1$ signify incorrect cluster assignments.

*Davies-Bouldin Index*

Sadeghi (2025) describes the Davies-Bouldin Index (DBI) as a clustering validation metric that assesses clustering quality based on the degree of cluster separation and compactness. It produces a single score, with lower values indicating better clustering performance. DBI is particularly useful for comparing the effectiveness of different clustering algorithms or for evaluating the performance of a single algorithm under varying parameter settings.

**Product Selection:**

*Revealed Comparative Advantage*

Balassa developed the Revealed Comparative Advantage (RCA) index to simplify and reinforce the concept of comparative advantage, which has since been widely employed to measure a country's export competitiveness and to analyse variations in trade patterns across time, sectors, and regions [25]. RCA reveals comparative advantage retrospectively through trade data analysis by comparing the export share of a commodity (j) from a country (i) with the share of the same commodity (j) in world exports. An RCA value $< 1$ indicates comparative disadvantage, $= 1$ neutrality, and $> 1$ comparative advantage [26].

## 3. Result and Discussion

### Results

Cluster analysis was conducted for each variable (each comprising three indicators) using three different clustering models, namely K-means, K-medoids, and Hierarchical Clustering. The analytical procedure for each model involved determining the optimal number of clusters, applying machine learning modeling, and evaluating model performance. The clustering model selected for further analysis was the one demonstrating the most optimal performance evaluation, with one model chosen for each variable.

*Results of K-means Clustering*

The determination of the optimal number of clusters employed the elbow method. The results of the elbow analysis on **Figure 2** indicated that the optimal number of clusters for the trade and economic variables was four clusters, while the trade barriers variable exhibited three clusters. Model performance evaluation was assessed using the silhouette score and Davies–Bouldin Index, as presented in **Table 4**.

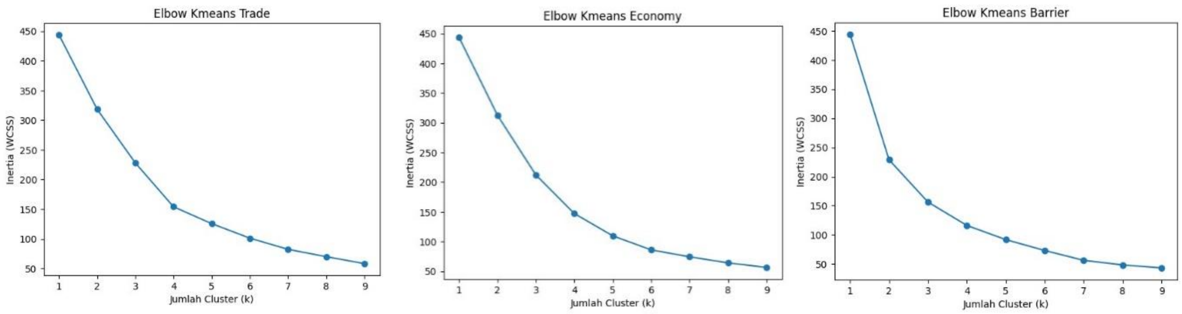


**Figure 2.** Elbow Analysis (K-means)

**Table 4.** Model Evaluation (K-means)

| Evaluation | Trade | Economy | Barrier |
|---|---|---|---|
| Silhouette score | 0.444 | 0.395 | 0.446 |
| Davies-Bouldin Index | 0.750 | 0.698 | 0.797 |

*Results of K-medoids Clustering*

The determination of the optimal number of clusters was initially conducted using the elbow method and subsequently validated through the silhouette score. The silhouette analysis presented in **Figure 3** and the silhouette scores in **Table 5** indicated that the optimal number of clusters was five for the trade variable, three for the economic variable, and two for the trade barriers variable. Model performance evaluation was carried out using both the silhouette score and the Davies–Bouldin Index, as summarized in **Table 6**.

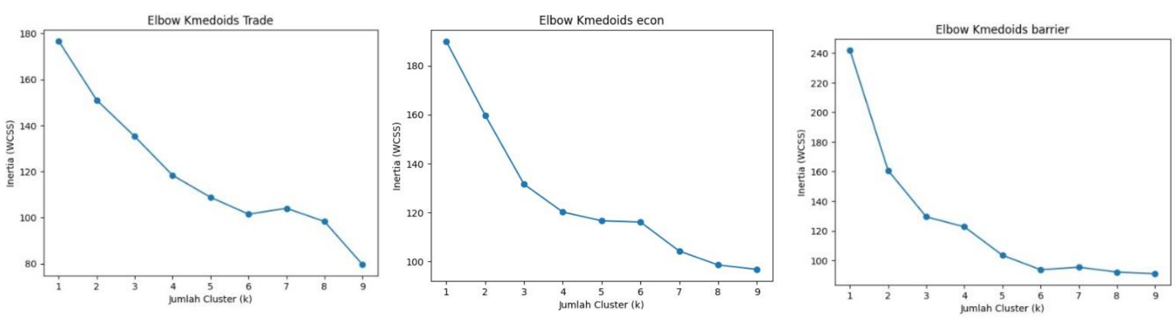


**Figure 3.** Elbow Analysis (K-medoids)

**Table 5.** Silhouette Scores (K-medoids)

| Number of Clusters | Trade | Economy | Barrier |
|---|---|---|---|
| 2 | 0.236 | 0.254 | **0.492** |
| 3 | 0.214 | **0.311** | 0.432 |
| 4 | 0.217 | 0.214 | 0.367 |
| 5 | **0.271** | 0.221 | 0.385 |
| 6 | 0.228 | 0.128 | 0.386 |

**Table 6.** Model Evaluation (K-medoids)

| Evaluation | Trade | Economy | Barrier |
|---|---|---|---|
| Silhouette score | 0.271 | 0.311 | 0.492 |
| Davies-Bouldin Index | 1.046 | 1.137 | 0.874 |

*Results of Hierarchical Clustering*

The determination of the optimal number of clusters was conducted using a dendrogram. The dendrogram analysis presented in **Figure 4** indicated that the optimal number of clusters was four for the trade variable, three for the economic variable, and two for the trade barriers variable. Model performance was evaluated using the silhouette score and the Davies–Bouldin Index, as reported in **Table 7**.

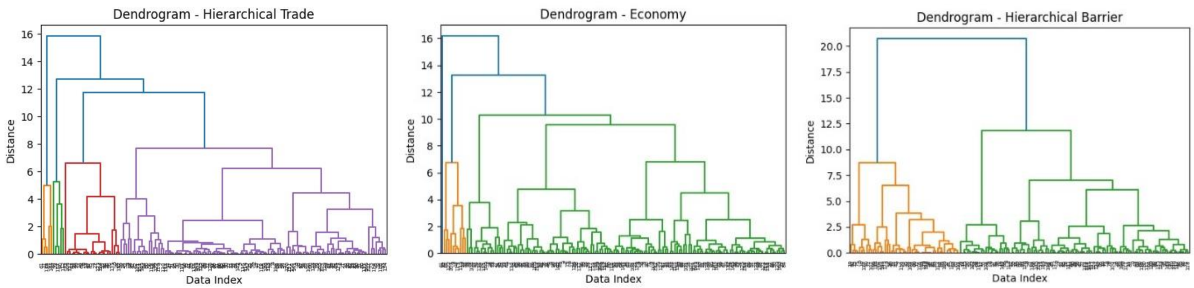


**Figure 4.** Dendrogram Analysis (Hierarchical)

**Table 7**. Silhouette Scores (Hierarchical)

| Evaluation | Trade | Economy | Barrier |
|---|---|---|---|
| Silhouette score | 0.424 | 0.557 | 0.492 |
| Davies-Bouldin Index | 0.731 | 0.635 | 0.874 |

**Selection of the Optimal Model**

Based on the evaluation results, the optimal model was determined by comparing the highest silhouette score and the lowest Davies–Bouldin Index across each variable. For the trade variable, the K-Means algorithm demonstrated the best performance with the highest silhouette score (0.444), although its Davies–Bouldin Index was slightly higher than that of the Hierarchical model, indicating stronger clustering consistency in K-Means. For the economy variable, the Hierarchical model emerged as the most optimal, achieving both the highest silhouette score (0.557) and the lowest Davies–Bouldin Index (0.635), thereby reflecting clearer and more distinct cluster structures. In the case of the barrier variable, both K-Medoids and Hierarchical exhibited the highest silhouette score (0.492) and identical Davies–Bouldin Index values (0.874). Under such circumstances, the Hierarchical model was considered more appropriate due to its consistent stability across other variables. Accordingly, the best-performing models selected were K-Means for the trade variable, and Hierarchical for both the economy and barrier variables.

**Table 8.** Evaluation results of three clustering models for the trade, economy, and barrier variables

| **Model** | **Trade** | | **Economy** | | **Barrier** | |
|---|---|---|---|---|---|---|
| | ***Silhouette*** | ***Davies-Bouldin*** | ***Silhouette*** | ***Davies-Bouldin*** | ***Silhouette*** | ***Davies-Bouldin*** |
| K-Means | 0.444 | 0.750 | 0.395 | 0.698 | 0.446 | 0.797 |
| K-Medoids | 0.271 | 1.046 | 0.311 | 1.137 | 0.492 | 0.874 |
| Hierarchical | 0.424 | 0.731 | 0.557 | 0.635 | 0.492 | 0.874 |

*Relative Comparative Analysis*

The analysis of Indonesia's textile products based on the Revealed Comparative Advantage (RCA) index demonstrates varying levels of comparative advantage across different commodities. Products with exceptionally high RCA values, such as artificial staple fibers (HS 5504; RCA 14.42) and yarn of artificial staple fibers (HS 5510; RCA 12.89), reveal Indonesia's global export dominance, contributing significantly to total world exports (23.37% and 20.90%, respectively), thereby reflecting production specialization and strong international competitiveness. Other products, including yarn of synthetic staple fibers (HS 5509; RCA 6.42), cotton yarn containing less than 85% cotton (HS 5206; RCA 4.31), and wigs (HS 6704; RCA 4.01), also indicate relatively high competitiveness with global export shares ranging between 6–10%, forming the basis of a moderately competitive industry. Meanwhile, product categories such as leather footwear (HS 6403; RCA 3.26), gloves (HS 6216; RCA 3.20), and various apparel items (e.g., women's shirts HS 6206; RCA 2.69 and brassieres HS 6212; RCA 2.34) still demonstrate positive competitiveness, albeit with relatively smaller global contributions. Conversely, several commodities such as sweaters and pullovers (HS 6110; RCA 1.16), mattresses (HS 9404; RCA 1.12), and other footwear of rubber or plastics (HS 6402; RCA 1.09) exhibit low comparative advantage, yet remain competitive despite their less dominant position in the international market. Overall, the structure of Indonesia's textile exports highlights major strengths in artificial and synthetic fiber-based products as well as certain labor-intensive segments such as wigs and footwear, while most apparel products fall within moderate to low RCA levels, underscoring the necessity for strategies aimed at enhancing value-added production and market differentiation to reinforce global competitiveness.

**Table 9.** Relative Comparative Analysis for Indonesian Textile Products

| **Name** | **Code** | **Total Indonesian Export** | **Total World Export** | **Indonesian Share (%)** | **RCA** |
|---|---|---|---|---|---|
| Artificial staple fibers, not processed for spinning | 5504 | 2,759,500,405 | 11,807,609,873 | 23.37% | 14.42 |
| Yarn of artificial staple fibers, not for retail sale | 5510 | 1,077,157,049 | 5,154,363,313 | 20.90% | 12.89 |
| Yarn of synthetic staple fibers, not for retail sale | 5509 | 2,123,681,300 | 20,416,269,368 | 10.40% | 6.42 |
| Cotton yarn of < 85% | 5206 | 437,012,848 | 6,261,817,655 | 6.98% | 4.31 |
| Cotton, carded or combed | 5203 | 72,003,102 | 1,046,206,463 | 6.88% | 4.25 |
| Wigs | 6704 | 1,539,649,259 | 23,685,645,657 | 6.50% | 4.01 |
| Textile footwear | 6404 | 9,592,473,962 | 158,767,623,346 | 6.04% | 3.73 |
| Leather footwear | 6403 | 10,282,729,315 | 194,626,689,929 | 5.28% | 3.26 |
| Gloves | 6216 | 227,729,086 | 4,385,359,127 | 5.19% | 3.20 |
| Women's shirts | 6206 | 1,783,805,671 | 40,951,400,342 | 4.36% | 2.69 |
| Brassieres | 6212 | 1,682,844,836 | 44,322,903,295 | 3.80% | 2.34 |
| Women's undergarments | 6208 | 379,494,829 | 10,406,113,971 | 3.65% | 2.25 |
| Synthetic staple fibers | 5503 | 951,515,905 | 26,857,720,385 | 3.54% | 2.19 |
| Women's shirts, knit | 6106 | 496,371,012 | 14,802,494,196 | 3.35% | 2.07 |
| Artificial filament yarn | 5403 | 153,717,388 | 4,760,953,000 | 3.23% | 1.99 |
| Cotton yarn of > 85% | 5205 | 1,561,096,816 | 49,482,605,315 | 3.15% | 1.95 |
| Men's overcoats, knit | 6101 | 324,539,826 | 10,588,876,880 | 3.06% | 1.89 |
| Men's shirts | 6205 | 1,330,071,589 | 43,539,281,080 | 3.05% | 1.88 |
| Woven fabrics of < 85% synthetic staple fibers weighing < 170 g/m2 | 5513 | 260,298,308 | 8,634,062,896 | 3.01% | 1.86 |
| Women's overcoats, knit | 6102 | 421,750,166 | 14,437,312,937 | 2.92% | 1.80 |
| Babies' garments | 6209 | 217,243,807 | 7,904,152,178 | 2.75% | 1.70 |
| Name | Code | Total Indonesian Export | Total World Export | Indonesian Share (%) | RCA |
| Tire cord fabric | 5902 | 310,541,917 | 11,410,009,287 | 2.72% | 1.68 |
| Woven fabrics of coarse animal hair | 5113 | 1,042,663 | 38,766,352 | 2.69% | 1.66 |
| Men's overcoats, not knit | 6201 | 1,643,908,394 | 62,088,977,243 | 2.65% | 1.63 |
| Activewear, knit | 6112 | 547,549,113 | 20,898,935,171 | 2.62% | 1.62 |
| Men's suits, knit | 6103 | 1,324,447,815 | 56,840,186,476 | 2.33% | 1.44 |
| Women's suits, knit | 6104 | 3,315,828,818 | 147,733,760,508 | 2.24% | 1.38 |
| Cotton waste | 5202 | 38,964,625 | 1,751,934,999 | 2.22% | 1.37 |
| Other woven fabrics of synthetic staple fibers | 5515 | 310,013,081 | 14,248,123,085 | 2.18% | 1.34 |

| Name | Code | Total Indonesian Export | Total World Export | Indonesian Share (%) | RCA |
|---|---|---|---|---|---|
| Men's undergarments | 6207 | 112,781,541 | 5,270,172,986 | 2.14% | 1.32 |
| Babies' garments, knit | 6111 | 619,807,466 | 29,704,927,401 | 2.09% | 1.29 |
| Sweaters, pullovers, sweatshirts etc., knit | 6110 | 4,239,413,799 | 225,132,083,354 | 1.88% | 1.16 |
| Woven fabrics of cotton of < 85% weighing < 200 g/m2 | 5210 | 129,807,100 | 6,981,446,998 | 1.86% | 1.15 |
| Mattresses and bedding | 9404 | 1,448,765,612 | 79,877,839,520 | 1.81% | 1.12 |
| Men's suits and pants | 6203 | 3,140,394,488 | 173,732,561,291 | 1.81% | 1.12 |
| Gloves, knit | 6116 | 369,366,117 | 20,825,359,265 | 1.77% | 1.09 |
| Other footwear of rubber or plastics | 6402 | 2,671,247,221 | 151,637,286,436 | 1.76% | 1.09 |
| Synthetic filament yarn | 5402 | 1,196,972,750 | 69,043,875,899 | 1.73% | 1.07 |
| Men's shirts, knit | 6105 | 512,486,061 | 30,825,606,986 | 1.66% | 14.42 |

## Discussion

Based on the three primary indicators, average growth of textile imports, textile trade balance, and global market share of textile imports, substantial differences are observed across clusters. Cluster 3 records the highest import growth rate (25.22%), coupled with a significant trade deficit (–USD 1.11 billion) but a relatively small market share (0.10%), suggesting high growth potential despite limited market scale. Cluster 1 demonstrates a more balanced combination, with an import growth rate of 7.75%, a substantial trade deficit (–USD 10.08 billion), and a relatively high global market share (1.76%), indicating strong import demand and significant market capacity. Conversely, Cluster 2 reflects moderate import growth (6.55%), a relatively small trade deficit (–USD 768.59 million), and a low market share (0.20%), suggesting limited attractiveness as an export destination. Cluster 4 presents relatively high import growth (13.38%) and a market share nearly equivalent to Cluster 1 (1.75%), but its large trade surplus (USD 27.79 billion) indicates export dominance and strong domestic supply capacity. Considering these indicators, Clusters 1 and 3 can be categorized as the most promising emerging export destinations for Indonesian textiles, given the combination of positive import growth, substantial trade deficits, and considerable global market shares. Potential priority countries include Austria, France, Hong Kong, the Philippines, Poland, Russia, Spain, and Switzerland.

**Table 10.** Trade Indicator Clusters

| Cluster | Average Growth of Textile Imports 2020–2023 | Average Textile Trade Balance 2020–2023 (USD) | Average Global Textile Import Market Share 2020–2023 | Rank |
|---|---|---|---|---|
| 1 | 7.75% | –10,088,242,367 | 1.76% | 1 |
| 2 | 6.55% | –768,595,380 | 0.20% | 4 |
| 3 | 25.22% | –1,114,044,253 | 0.10% | 2 |
| 4 | 13.38% | 27,790,017,872 | 1.75% | 3 |

The economic potential analysis, based on population size, purchasing power parity (PPP), and the industrial sector's proportion of GDP, highlights distinct characteristics across clusters. Cluster 1 is characterized by very high purchasing power (PPP USD 104,610), but also a large industrial proportion (42.88%) and a relatively small population (6.96 million), resulting in limited market absorption despite strong per-capita purchasing capacity. Cluster 2 exhibits a medium-sized population (27.25 million), moderate PPP (USD 23,957), and a lower industry proportion (25.46%), suggesting a market with considerable demand capacity and greater dependence on imports of finished products compared to domestic production. Meanwhile, Cluster 3 comprises the largest population (1.45 billion) with relatively low PPP (USD 11,159) and a modest industrial proportion (24.46%), indicating vast market scale despite limited per-capita purchasing power. Considering the combination of large populations, relatively high PPP, and lower industrial shares, Clusters 2 and 3 can be identified as the most promising new destinations for Indonesian textile exports, offering an equilibrium between market size, consumer purchasing capacity, and import dependence. Key prospective countries include Austria, France, Hong Kong, the Philippines, Poland, Russia, Spain, Switzerland, Armenia, Greece, India, Kazakhstan, and Kyrgyzstan.

**Table 11.** Economy Indicator Clusters

| **Cluster** | **Average Population** | **Average Purchasing Power Parity (USD)** | **Average Industry Proportion of GDP (%)** | **Rank** |
|---|---|---|---|---|
| 1 | 6,958,467 | 104,610 | 42.88 | 3 |
| 2 | 27,251,966 | 23,957 | 25.46 | 2 |
| 3 | 1,450,935,791 | 11,159 | 24.46 | 1 |

Analysis of trade barrier indicators reveals clear differences between clusters. Cluster 1 is characterized by a relatively low Logistics Performance Index (LPI 2.64), a greater geographical distance from Indonesia (11,068 km), and the absence of a Free Trade Agreement (FTA) with Indonesia, indicating higher trade barriers in terms of logistical efficiency, transportation costs, and tariff restrictions. Conversely, Cluster 2 demonstrates stronger logistical performance (LPI 3.35), closer average geographical proximity (8,565 km), and the presence of FTAs with Indonesia, providing tariff preferences and enhanced market accessibility. Taken together, these indicators suggest that Cluster 2 offers greater potential as a destination for Indonesian textile exports, as its trade barriers are relatively lower compared to Cluster 1. Prominent countries in this group include Austria, France, Hong Kong, the Philippines, Poland, Russia, Spain, and Switzerland.

**Table 12.** Trade Barrier Indicator Clusters

| **Cluster** | **Average Logistics Performance Index** | **Average Distance from Indonesia (KM)** | **Average FTA with Indonesia (1 = FTA, 0 = no FTA)** | **Rank** |
|---|---|---|---|---|
| 1 | 2.64 | 11,068 | 0 | 2 |
| 2 | 3.35 | 8,565 | 1 | 1 |

Based on the results of the analysis of textile import performance, economic potential, and trade barriers across clusters, an evaluation was conducted on 149 countries according to the ranking of each cluster indicator. Countries that exhibit the most favourable average cluster ranks are identified as the primary prospective destinations for Indonesia's textile export market expansion. The classification of destination countries was also conducted by sub-regional grouping, based on the highest cluster ranks. Subsequently, several countries with the greatest potential were selected from each sub-region, resulting in the identification of 20 key countries that constitute the most promising new destinations for Indonesia's textile exports.

**Table 13.** 20 Selected Countries Over Top Sub-Regions

| Sub Region | Rank Sub-Region | Country | Sub Region | Rank Sub-Region | Country |
|---|---|---|---|---|---|
| Eastern Asia | 1 | Hongkong | Central Asia | 1 | Kazakhstan |
| | 2 | Mongolia | | 2 | Kyrgyzstan |
| Western Europe | 1 | Austria | | 3 | Tajikistan |
| | 2 | France | Caribbean | 1 | Jamaica |
| | 3 | Switzerland | | 2 | Bahamas |
| Middle Africa | 1 | Angola | Eastern Europe | 1 | Poland |
| | 2 | Cameroon | | 2 | Russia |
| | 3 | Rep. Congo | South-eastern Asia | 1 | Philippines |
| Sub Region | Rank Sub-Region | Country | Sub Region | Rank Sub-Region | Country |
| Melanesia | 1 | Fiji | Sothern Europe | 1 | Spain |
| | 2 | Solomon | | 2 | Greece |

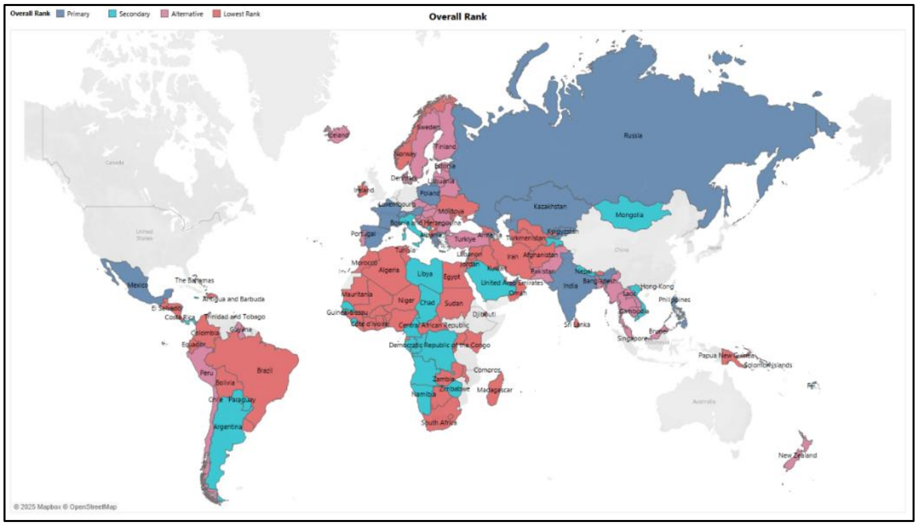


**Figure 5.** Overall Rank of 149 Potential Market for Indonesian Textile Export

Based on the results of the international market selection analysis and the relative comparative advantage of Indonesia's textile products, several countries can be identified as priority destinations for new textile exports, along with the potential products to be offered. **Table 15** presents the selected key export products for each target market, considering those with import values exceeding USD 100 million or accounting for more than 1% of the destination country's total textile imports, as well as products in which Indonesia demonstrates a comparative advantage relative to other countries globally.

**Table 14.** Selected Products for Certain Selected Markets

| Market | Products |
|---|---|
| Hongkong | Men's shirts (6205), Men's suits, knit (6103), Wigs (6704), Women's shirts (6206), Textile footwear (6404), Men's overcoats, not knit (6201), Women's suits, knit (6104), Brassieres (6212), Other footwear of rubber or plastics (6402), Leather footwear (6403), Men's suits and pants (6203), Sweaters, pullovers, sweatshirts etc., knit (6110), Mattresses and bedding (9404) |
| Mongolia | Sweaters, pullovers, sweatshirts etc., knit (6110), Leather footwear (6403), Gloves, knit (6116), Men's suits and pants (6203), Men's overcoats, not knit (6201), Mattresses and bedding (9404), Men's suits, knit (6103), Textile footwear (6404) |
| Austria | Leather footwear (6403), Women's suits, knit (6104), Women's shirts (6206), Men's suits and pants (6203), Men's shirts, knit (6105), Men's overcoats, not knit (6201), Brassieres (6212), Women's overcoats, knit (6102), Other footwear of rubber or plastics (6402), Textile footwear (6404), Mattresses and bedding (9404), Men's shirts (6205), Sweaters, pullovers, sweatshirts etc., knit (6110) |
| France | Men's overcoats, knit (6101), Women's shirts, knit (6106), Other footwear of rubber or plastics (6402), Mattresses and bedding (9404), Men's shirts (6205), Babies' garments (6209), Gloves, knit (6116), Babies' garments, knit (6111), Men's overcoats, not knit (6201), Activewear, knit (6112), Men's suits and pants (6203), Women's suits, knit (6104), Sweaters, pullovers, sweatshirts etc., knit (6110), Men's suits, knit (6103), Women's overcoats, knit (6102), Synthetic filament yarn (5402), Synthetic staple fibers (5503), Women's undergarments (6208), Women's shirts (6206), Textile footwear (6404), Leather footwear (6403), Brassieres (6212), Men's shirts, knit (6105) |
| Swiss | Women's shirts (6206), Textile footwear (6404), Activewear, knit (6112), Men's shirts (6205), Brassieres (6212), Women's overcoats, knit (6102) |
| Angola | Leather footwear (6403), Mattresses and bedding (9404), Other footwear of rubber or plastics (6402), Women's suits, knit (6104), Men's suits and pants (6203), Men's suits, knit (6103) |
| Cameroon | Leather footwear (6403), Men's suits, knit (6103), Other footwear of rubber or plastics (6402), Other woven fabrics of synthetic staple fibers (5515), Textile footwear (6404), Women's suits, knit (6104), Wigs (6704), Men's suits and pants (6203) |
| Congo | Textile footwear (6404), Men's suits, knit (6103), Leather footwear (6403), Men's suits and pants (6203), Other footwear of rubber or plastics (6402), Women's suits, knit (6104) |

| Market | Products |
|---|---|
| Fiji | Men's suits, knit (6103), Synthetic filament yarn (5402), Men's shirts (6205), Other woven fabrics of synthetic staple fibers (5515), Other footwear of rubber or plastics (6402), Leather footwear (6403), Men's suits and pants (6203), Woven fabrics of < 85% synthetic staple fibers weighing < 170 g/m2 (5513), Textile footwear (6404), Mattresses and bedding (9404) |
| Solomon | Men's suits and pants (6203), Other footwear of rubber or plastics (6402), Women's suits, knit (6104) |
| Kazakhstan | Gloves, knit (6116), Women's suits, knit (6104), Men's suits and pants (6203), Men's shirts (6205), Men's suits, knit (6103), Brassieres (6212), Men's overcoats, not knit (6201), Leather footwear (6403), Textile footwear (6404), Other footwear of rubber or plastics (6402), Activewear, knit (6112), Sweaters, pullovers, sweatshirts etc., knit (6110) |
| Kyrgyzstan | Sweaters, pullovers, sweatshirts etc., knit (6110), Brassieres (6212), Leather footwear (6403), Men's overcoats, not knit (6201), Men's suits, knit (6103), Men's suits and pants (6203), Other footwear of rubber or plastics (6402), Women's suits, knit (6104), Textile footwear (6404) |
| Tajikistan | Textile footwear (6404), Sweaters, pullovers, sweatshirts etc., knit (6110), Men's shirts, knit (6105), Men's suits, knit (6103), Brassieres (6212), Other footwear of rubber or plastics (6402), Men's suits and pants (6203), Men's overcoats, not knit (6201), Women's suits, knit (6104), Men's shirts (6205) |
| Jamaica | Men's suits, knit (6103), Women's suits, knit (6104), Men's suits and pants (6203), Textile footwear (6404), Mattresses and bedding (9404), Other footwear of rubber or plastics (6402), Men's shirts (6205) |
| Bahamas | Men's suits and pants (6203), Men's shirts (6205), Mattresses and bedding (9404), Leather footwear (6403) |
| Poland | Mattresses and bedding (9404), Brassieres (6212), Men's shirts (6205), Sweaters, pullovers, sweatshirts etc., knit (6110), Men's suits and pants (6203), Other footwear of rubber or plastics (6402), Babies' garments (6209), Activewear, knit (6112), Men's overcoats, not knit (6201), Men's shirts, knit (6105), Synthetic staple fibers (5503), Men's suits, knit (6103), Babies' garments, knit (6111), Leather footwear (6403), Women's shirts, knit (6106), Women's shirts (6206), Women's suits, knit (6104), Synthetic filament yarn (5402), Gloves, knit (6116), Textile footwear (6404), Women's overcoats, knit (6102) |
| Russia | Other footwear of rubber or plastics (6402), Synthetic filament yarn (5402), Men's suits and pants (6203), Gloves, knit (6116), Yarn of synthetic staple fibers, not for retail sale (5509), Sweaters, pullovers, sweatshirts etc., knit (6110), Cotton yarn of > 85% (5205), Synthetic staple fibers (5503), Men's overcoats, not knit (6201), Activewear, knit (6112), Brassieres (6212), Men's suits, knit (6103), Women's shirts (6206), Men's shirts (6205), Women's suits, knit (6104), Leather footwear (6403), Textile footwear (6404) |
| Philippines | Sweaters, pullovers, sweatshirts etc., knit (6110), Leather footwear (6403), Men's suits, knit (6103), Other footwear of rubber or plastics (6402), Women's suits, knit (6104), Textile footwear (6404), Men's suits and pants (6203) |
| Spain | Other footwear of rubber or plastics (6402), Sweaters, pullovers, sweatshirts etc., knit (6110), Leather footwear (6403), Brassieres (6212), Women's undergarments (6208), Textile footwear (6404), Synthetic staple fibers (5503), Women's shirts, knit (6106), Synthetic filament yarn (5402), Women's shirts (6206), Men's shirts, knit (6105), Babies' garments, knit (6111), Women's suits, knit (6104), Women's overcoats, knit (6102), Babies' garments (6209), Men's suits and pants (6203), Men's overcoats, not knit (6201), Men's suits, knit (6103), Activewear, knit (6112), Other woven fabrics of synthetic staple fibers (5515), Men's shirts (6205), Mattresses and bedding (9404) |
| Greece | Activewear, knit (6112), Men's suits and pants (6203), Leather footwear (6403), Men's suits, knit (6103), Women's shirts (6206), Other footwear of rubber or plastics (6402), Men's shirts (6205), Textile footwear (6404), Men's overcoats, not knit (6201), Brassieres (6212), Sweaters, pullovers, sweatshirts etc., knit (6110), Women's suits, knit (6104) |

**Table 14** indicates a diverse range of textile and footwear products with high Revealed Comparative Advantage (RCA) values for Indonesia, highlighting their potential for export to various emerging destination markets. Products consistently appearing across multiple countries include men’s suits (both knit and non-knit), men’s shirts, women’s knit suits, sweaters/pullovers/sweatshirts (knit), leather footwear, textile footwear, and brassieres, reflecting a stable pattern of global demand. European countries such as Austria, France, Poland, Spain, and Greece exhibit substantial market potential with diversified demand for textiles and synthetic fibers, while Central Asian countries such as Kazakhstan, Kyrgyzstan, and Tajikistan demonstrate significant demand for knitwear and footwear. Moreover, markets in Africa (e.g., Angola, Cameroon, and the Republic of Congo) and the Caribbean (e.g., Jamaica and the Bahamas) represent promising new opportunities for Indonesia’s export expansion. The alignment between Indonesia’s high RCA values and the substantial textile import levels in these destination countries underscores a strategic synergy that can be leveraged to enhance export penetration while simultaneously strengthening Indonesia’s position within the global textile value chain.

## 4. Conclusion

The clustering analysis integrating trade indicators (textile import growth, trade balance, and global market share), economic indicators (population, purchasing power parity, and industrial sector contribution to GDP), and trade barrier indicators (logistics performance index, geographic distance, and free trade agreement status) reveals that Indonesia's textile export potential is concentrated in countries with positive import growth, significant trade deficits, large market capacity, sufficient purchasing power, and relatively low trade barriers. Regional grouping identified 20 priority destinations spanning Western Europe (Austria, France, Switzerland), Eastern Europe (Poland, Russia), Southern Europe (Spain, Greece), East Asia (Hong Kong, Mongolia), Central Asia (Kazakhstan, Kyrgyzstan, Tajikistan), Southeast Asia (Philippines), Central Africa (Angola, Cameroon, Republic of Congo), the Caribbean (Jamaica, Bahamas), and Melanesia (Fiji, Solomon Islands). Complementary Revealed Comparative Advantage (RCA) analysis highlights Indonesia's strengths in artificial and synthetic staple fibers, as well as labor-intensive products such as wigs and leather footwear, while apparel products (men's suits, men's shirts, women's knit suits, sweaters/pullovers, and brassieres) demonstrate moderate competitiveness but stable global demand, supporting export diversification. Key markets include Europe, with high demand for synthetic fiber-based textiles and apparel, and Central Asia, with significant demand for knitwear and footwear, alongside emerging frontier markets in Africa and the Caribbean. Collectively, these findings underscore strategic opportunities for Indonesia to expand exports, enhance market penetration, and strengthen its position in the global textile value chain through product differentiation and diversified market development.

This research contributes to the academic discourse by integrating trade, economic, and trade barrier indicators with Revealed Comparative Advantage (RCA) analysis to provide a comprehensive framework for international market selection in the Indonesian textile industry, thereby offering both methodological advancement and empirical evidence on strategic export diversification. The study not only identifies priority destinations and product groups with strong competitiveness but also demonstrates how clustering techniques can enhance decision-making in global market targeting. For future research, micro-segmentation at the firm or product-category level, longitudinal analyses of shifting trade dynamics, and the incorporation of non-tariff barriers, sustainability standards, and digital trade infrastructures could provide deeper insights. From a practical perspective, policymakers and industry stakeholders are encouraged to adopt differentiated market penetration strategies, balancing advanced economies with high purchasing power and emerging markets with large populations and high import dependency, to strengthen Indonesia's role in the global textile value chain.

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