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From Performance to Policy: A Cluster Analysis Using Logistics Performance Index Data

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ABSTRACT: Logistics performance plays a vital role in facilitating international trade and strengthening economic competitiveness by enabling efficient supply chain operations. The Logistics Performance Index (LPI), developed by the World Bank, evaluates countries based on six dimensions—customs, infrastructure, international shipments, logistics competence, tracking and tracing, and timeliness. Despite its extensive use, prior studies have focused primarily on ranking countries rather than identifying performance patterns and relationships within the dataset. With the increasing complexity of global trade, there is a need for advanced analytical approaches to explore insights beyond rankings. This study addresses this gap by applying clustering analysis techniques to the recent 2023 LPI dataset to classify countries based on logistics performance. The aim is to evaluate logistics performance clusters, highlight disparities, and provide policy recommendations. Three clustering algorithms (i.e., *k*-means, *k*-medoids, and CLARA) were applied to group countries based on LPI dimensions. Silhouette Index, Dunn Index, and Davies-Bouldin Index validated cluster quality. Countries were then classified into three clusters: high, moderate, and low performers. High performers exhibited advanced logistics systems, while low performers faced challenges in infrastructure and customs efficiency. The analysis effectively reveals logistics performance patterns, emphasizing the need for targeted policies to address inefficiencies in low-performing countries through investments in infrastructure, digitalization, and customs reforms.

KEYWORDS: Clustering; data mining; k-means; logistics performance index

1. INTRODUCTION

Logistics, as defined by the Council of Supply Chain Management Professionals (CSCMP), is "the process of planning, implementing, and controlling procedures for the efficient and effective transportation and storage of goods, including services and related information, from the point of origin to the point of consumption to meet customer requirements". This definition encompasses inbound, outbound, internal, and external movements, reflecting the multidimensional nature of logistics operations. Logistics has emerged as a key driver of trade competitiveness, not only for individual companies but also for entire economies (Martí et al., 2014). Efficient logistics systems facilitate bilateral trade growth, reduce costs, and support integration into global supply chains (Arvis et al., 2018). As such, countries are increasingly prioritizing logistics development to enhance their performance in world trade markets.

Given the critical role logistics plays in economic development, there is a pressing need to measure and evaluate logistics performance. One widely recognized metric is the Logistics Performance Index (LPI), introduced by the World Bank in 2007. The LPI serves as a benchmarking tool, enabling countries to assess their logistics performance, identify challenges, and develop strategies for improvement. With 160 countries participating in the 2018 LPI edition, it has become a global standard for evaluating supply chain efficiency and infrastructure quality (Arvis et al., 2018). Policymakers and international organizations have increasingly adopted the LPI framework for monitoring performance and implementing reforms. For example, the European Commission integrates LPI data into its Transport Evaluation Panel and Customs Union assessments. Similarly, organizations like APEC use LPI metrics to evaluate supply chain connectivity and trade efficiency initiatives.

The LPI evaluates logistics performance based on six key dimensions (i.e., customs, infrastructure, international shipments, logistics quality and competence, tracking and tracing, and timeliness) with scores ranging from 1 to 5, where higher values indicate better performance (Arvis et al., 2018). Countries with higher LPI scores demonstrate advanced customs clearance procedures, robust infrastructure, and efficient logistics services, while lower-ranked nations face bottlenecks such as inadequate transportation networks and delays in shipment tracking (Roy et al., 2018).

This research leverages clustering analysis, a widely used data mining technique, to classify countries based on their LPI 2023 dataset. Clustering involves grouping data points based on similar characteristics, enabling pattern recognition and segmentation across large datasets (Kaufman & Rousseeuw, 1990). Clustering techniques are highly versatile and have been applied across numerous disciplines, including banking (e.g., Bi et al., 2016; Kisore & Koteswaraiah, 2017), marketing (e.g., Minako et al., 2019; Utami et al., 2019), text mining (e.g., Thomas & Khan, 2016; Yang et al., 2014), education (e.g., Rana & Garg, 2016; Ovelade et al., 2010), medical sciences (e.g., Waheed et al., 2015; Akram et al., 2013), and even social indicators such as happiness index (e.g., Ulkhaq & Ayatama, 2021; Ulkhaq, 2020). Previous studies have utilized clustering techniques to analyze older LPI datasets (Ulkhaq, 2023) but lacked insights into more recent trends and dynamics in global logistics systems (Roy et al., 2018; Boujelben & Smet, 2016).

This research expands on prior work by applying three clustering algorithms—k-means, k-medoids, and CLARA—to the 2023 LPI dataset. Each algorithm is validated using internal validation indices, including the Silhouette Index, Dunn Index, and Davies-Bouldin Index, ensuring robust and reliable results (Arbelaitz et al., 2013). The research objective is then (i) to classify countries into distinct performance clusters based on their 2023 LPI scores; and (ii) to provide policy recommendations for improving logistics systems, particularly in emerging and low-performing clusters.

This study contributes to the growing body of literature on logistics performance by integrating clustering analysis with policy evaluations. It provides data-driven insights into global logistics capabilities, emphasizing the importance of infrastructure investments, digital tracking systems, and customs modernization for improving logistics efficiency. By offering recommendations tailored to specific clusters, the research supports targeted policy interventions to enhance global trade competitiveness and supply chain resilience.

The remainder of this paper is structured as follows. Section 2 reviews the existing literature on the application of clustering algorithms in the LPI context. Section 3 details the methodology, including clustering algorithms, clustering validation, and dataset used. Section 4 presents the results of the study. Section 5 offers insights into clustering outcomes and policy implications. Section 6 concludes the paper with key findings, recommendations, and directions for future research.

2. LITERATURE REVIEW

To ensure a comprehensive understanding of the application of clustering analysis in the context of the Logistics Performance Index (LPI), a structured literature search was conducted. The Scopus database was chosen as the primary search engine due to its extensive coverage of high-quality, peer-reviewed research articles across diverse disciplines. The search strategy employed the keywords "clustering" combined with "LPI" or "logistics performance index" to specifically focus on studies that intersect these areas. Filters were applied to refine the results to include only articles classified as "research articles," excluding reviews, conference papers, and other document types to maintain a clear focus on empirical studies.

The initial search yielded 25 articles that met the inclusion criteria. These articles were then subjected to a rigorous filtering and screening process. The abstracts and conclusions were read to determine relevance to the specific research objectives, focusing on studies that used clustering techniques to analyze logistics performance data. This step reduced the pool to a more manageable subset of articles. This scrutiny narrowed the selection to a more focused subset.

The next phase involved a detailed reading of the remaining articles to assess their methodological rigor, data sources, and overall relevance. After this comprehensive evaluation, it resulted only four articles that represent the most pertinent and methodologically sound contributions to the topic. These studies provide a solid foundation for the current research, offering insights into various clustering methodologies applied to LPI data and their implications for understanding global logistics performance. These four articles are discussed in the following.

Boujelben and De Smet (2016) introduced a multicriteria clustering algorithm that integrates k-means principles with the disjunctive sorting based on evidence theory (DISSET) method to create ordered clusters from best to worst. The method, applied to LPI-2014 data, uniquely allows for both precise and disjunctive partitions, enabling countries to belong to multiple clusters if their performance overlaps. Using a valued preference model, such as PROMETHEE, the algorithm incorporates multicriteria inputs for more nuanced analysis.

Roy et al. (2018) proposed a two-stage methodological framework for extracting extended insights from the LPI dataset. The first stage applies k-means clustering to group countries based on their LPI dimensions, while the second stage employs Multivariate Adaptive Regression Spline (MARS) modeling to capture complex, non-linear relationships between LPI dimensions and macroeconomic variables of interest. This approach highlights the LPI dataset as a rich source for analyzing logistics performance at the national level and demonstrates how linking LPI dimensions with relevant variables can uncover deeper insights.

Granillo-Macías (2020) explores inventory management optimization using data mining techniques, focusing on how clustering can enhance logistics performance. The study applies the Partitioning Around Medoids (PAM) algorithm to classify inventory items based on qualitative and quantitative variables, such as picking frequency, consumption rates, and handling characteristics. For logistics performance analysis, this approach highlights the importance of clustering methods that account for both operational and qualitative variables, which could complement LPI-focused research by providing insights into specific logistics processes such as warehousing.

Saeed and Cullinane (2023) analyze China's maritime trading network by clustering 155 trading partners using five components of maritime connectivity and applying hierarchical clustering. The study identifies three distinct clusters for China and Singapore and two for Hong Kong, revealing that China leads in direct maritime connectivity with the highest number of trading partners requiring zero transshipment. The analysis also incorporates ordered logistic regression, demonstrating that the LPI and trade volume (exports/imports) significantly influence cluster membership.

Pehlivan et al. (2024) investigate the logistics performance of G20 countries using quantitative decision-making techniques to rank and cluster countries based on their logistics capabilities in 2023. The study aims to compare the results with the LPI published by the World Bank, assuming that their findings would align closely with the LPI rankings. The analysis confirms this assumption, revealing substantial similarity between the study's rankings and the World Bank's LPI.

The reviewed articles provide valuable insights and methodologies while highlighting gaps that this study aims to address. Boujelben and De Smet (2016) introduced a multicriteria clustering algorithm that allowed overlapping (disjunctive) clusters, demonstrating its application on earlier LPI datasets such as LPI-2014. However, their study does not explore the dynamics of all six LPI dimensions in detail or incorporate recent data. Similarly, Roy et al. (2018) developed a two-stage framework combining k-means clustering with MARS regression to analyze LPI data and link it with macroeconomic variables. While comprehensive, their focus on external variables limits detailed internal analysis of LPI dimensions, which this study addresses by focusing specifically on these criteria. Granillo-Macías (2020) utilized PAM clustering to optimize inventory management by integrating qualitative and quantitative factors, showcasing the versatility of clustering techniques. However, their research is operationally focused, targeting micro-level logistics challenges rather than macro-level performance indices like the LPI. Saeed and Cullinane (2023) applied hierarchical clustering to maritime connectivity, identifying clusters and linking them with trade performance. Their emphasis on East Asia and maritime metrics highlights the regional significance of logistics performance but lacks global applicability. Lastly, Pehlivan et al. (2024) validated G20 countries' LPI rankings using clustering techniques, demonstrating alignment with the World Bank's rankings. However, their study is limited to G20 countries and does not delve deeply into the interrelationships of the six LPI dimensions or include a broader, global dataset.

This research, thus, builds on these foundations while addressing the gaps in scope, recency, and focus. By using the latest LPI 2023 data, this study offers timely insights into global logistics performance. Unlike previous studies that in-

tegrate external variables or limit their analysis to subsets of countries, this research clusters countries based solely on the six LPI criteria, providing a detailed, dimension-specific understanding of logistics performance. Additionally, the global scope and focus on actionable clustering insights contribute to policy relevance, distinguishing this study as a comprehensive and impactful contribution to the field.

3. RESEARCH METHODS

Clustering is widely recognized as one of the most effective techniques in machine learning and data mining for identifying patterns and grouping similar data points, referred to as clusters. It involves dividing or partitioning datasets such that observations within the same cluster share greater similarity with each other than with those in different clusters (Tan et al., 2006). Clustering techniques are highly versatile and have been applied across numerous disciplines. In logistics and supply chain management, clustering has proven instrumental in analyzing performance metrics, optimizing inventory, and identifying trends in trade and transportation systems (Ulkhaq, 2023). Given its flexibility and broad applicability, clustering remains a fundamental approach for extracting insights, especially when analyzing complex datasets like the LPI, where relationships among dimensions are often non-linear and multidimensional.

3.1 Clustering Algorithm

Researchers have introduced a wide variety of clustering algorithms, each designed to address specific data structures and analytical objectives. Additionally, numerous taxonomies have been developed to categorize these algorithms based on their methodologies and applications. In this study, three clustering algorithms were carefully selected (i.e., k-means, k-medoid, and CLARA) to accommodate the characteristics of the dataset, align with the research objectives, and represent diverse categories of clustering techniques.

The k-means algorithm (McQueen, 1967) was selected due to its simplicity, scalability, and efficiency in partitioning data into clusters by minimizing intra-cluster variance. It is widely used in practice and is well-suited for large datasets with numerical attributes. However, as k-means relies on Euclidean distances, it is sensitive to outliers and requires careful pre-processing to standardize data.

To address the limitations of k-means, the k-medoids algorithm (Kaufman & Rousseeuw, 1990) was also included. Unlike k-means, k-medoids uses actual data points (medoids) as cluster centers, making it more robust to outliers and noise in the dataset. This characteristic is particularly useful when analyzing datasets that may contain anomalies or inconsistencies, such as LPI data from countries with varying levels of development.

Finally, CLARA (Clustering Large Applications) (Kaufman & Rousseeuw, 1986) was employed to handle scalability challenges associated with large datasets. CLARA is an extension of k-medoids designed for larger datasets by sampling subsets of data and applying the clustering algorithm iteratively, ensuring computational efficiency without compromising accuracy. This approach is ideal for large-scale clustering tasks, such as segmenting countries based on six LPI dimensions, where processing the entire dataset simultaneously may be computationally expensive.

The combination of these algorithms ensures robustness, accuracy, and scalability in the clustering process, enabling a more comprehensive analysis of logistics performance patterns across countries. The following section provides a concise explanation of each algorithm, highlighting its principles, implementation, and relevance to this research.

3.2 Clustering Validation

The process of evaluating the performance of clustering algorithms, known as cluster validation, is a fundamental aspect of clustering analysis (Kaufman & Rousseeuw, 1990). It ensures that the generated clusters are meaningful and effectively represent the structure of the data. Cluster validation primarily relies on two key criteria—compactness (or cohesion) and separation. Compactness refers to the closeness of data points within a cluster, ensuring high internal similarity, while separation emphasizes the distinctness between clusters, requiring them to be widely spaced apart (Ulkhaq & Adyatama, 2021).

To assess clustering performance based on these criteria, validation measures can be categorized into relative, internal, and external validation techniques (Kaufman & Rousseeuw, 1990). Relative validation evaluates clustering results by varying algorithm parameters, such as the number of clusters (k), to determine the optimal configuration. It is especially useful for selecting the most appropriate number of clusters. Internal validation focuses solely on the dataset's intrinsic properties, measuring clustering quality without relying on external references. On the other hand, external validation compares clustering results to a predefined "ground truth" or labeled data to assess similarity. However, in cases where labeled data is unavailable—such as studies using real-world datasets instead of artificial data—only relative and internal validation methods are applicable.

In this study, the elbow method was employed as a relative validation technique. This method involves running the clustering algorithm multiple times while incrementally increasing the number of clusters (k). The sum of squared errors (SSE) is computed for each iteration and plotted against the number of clusters. The resulting graph typically resembles an arm, where the "elbow" point—the point where adding more clusters results in diminishing improvement—represents the optimal number of clusters. This approach effectively balances compactness and separation, ensuring meaningful and well-defined clusters in the analysis.

For the internal validation, this study, used three known indices: Silhouette Index, Dunn Index, and Davies-Bouldin Index (For a more comprehensive discussion of internal validation measures, readers may refer to Arbelaitz, 2013). The Silhouette Index (Rousseeuw, 1987) evaluates clustering quality by measuring both cohesion (how close an object is to other points within its own cluster) and separation (how far it is from points in the nearest neighboring cluster). It calculates the silhouette score for each data point, which ranges between -1 and 1. A higher score indicates that clusters are well-separated and internally compact. The Dunn Index (Dunn, 1974) focuses on compactness and separation by evaluating the ratio of the minimum inter-cluster distance to the maximum intra-cluster distance. A higher Dunn Index value suggests well-separated clusters with minimal internal spread, reflecting high-quality partitions. The Davies-Bouldin Index (Davies & Bouldin, 1979) evaluates clustering performance by measuring the average similarity ratio between each cluster and its most similar neighboring cluster. A lower value indicates better clustering results, as it reflects lower intra-cluster variation and higher inter-cluster separation.

These indices complement each other by assessing clustering performance from different perspectives—Silhouette focuses on both cohesion and separation, Dunn emphasizes cluster compactness and separation, and Davies-Bouldin evaluates inter-cluster similarity. Their combined application ensures a robust evaluation framework, particularly for analyzing multidimensional datasets such as the LPI-2023, where variations in logistics performance across countries demand precise validation of cluster quality.

3.3 Data

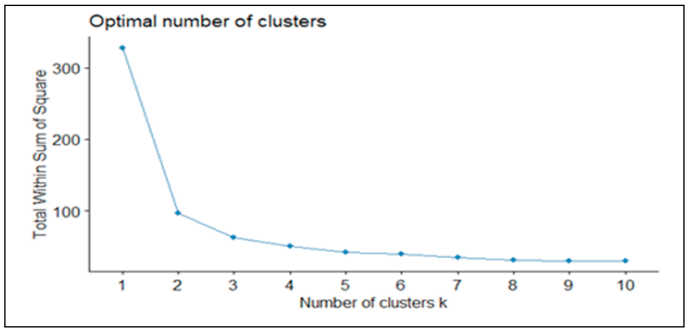
The data set used in this research is adopted from LPI of the World Bank. The LPI serves as a benchmark for assessing a country's logistics performance based on surveys conducted with logistics professionals. These surveys capture perceptions of logistics efficiency and effectiveness across six key indicators: customs, infrastructure, international shipments, logistics quality, tracking and tracing, and timeliness (Arvis et al., 2018). Score for each indicator ranges from 1 to 5, the highest score represents the best logistics performance.

The customs indicator evaluates the effectiveness and efficiency of customs clearance processes, encompassing border control, inspection procedures, and documentation requirements. It serves as a critical measure of a country's ability to facilitate smooth trade flows by minimizing delays and reducing costs. The infrastructure indicator assesses the quality and availability of physical facilities essential for logistics, including ports, airports, roads, railways, and warehouses. The international shipments indicator measures the ease and cost-effectiveness of arranging shipments across borders. It evaluates the reliability and flexibility of freight forwarders, logistics service providers, and shipping routes. The logistics quality and competence indicator focus on the professionalism and reliability of logistics service providers, including freight forwarders, transport operators, and customs brokers. It highlights the extent of expertise, training, and adoption of modern technologies within the logistics sector. The tracking and tracing indicator evaluates the ability to monitor shipments throughout the supply chain, ensuring transparency and accountability. Effective tracking systems allow businesses to predict arrival times, manage disruptions, and reduce losses due to theft or delays. The timeliness indicator assesses the reliability of on-time deliveries and the overall performance of the supply chain from production to distribution. It is particularly important for industries that rely on just-in-time (JIT) inventory systems, where delays can lead to significant disruptions.

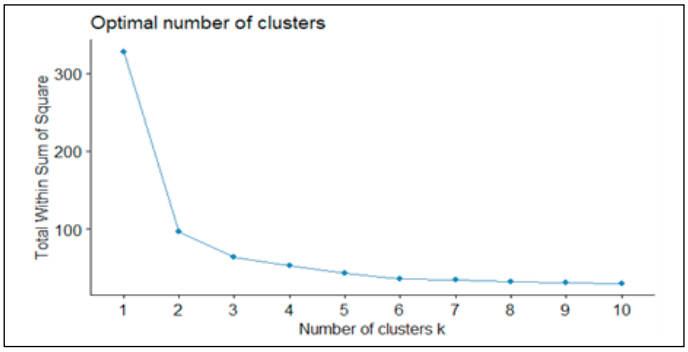
The LPI 2023 is the most recent edition of this global benchmarking tool that evaluates the logistics capabilities of 139 countries. It marks the continuation of a series of LPI surveys conducted periodically since 2007. This edition highlights the increasing importance of resilience, digitalization, and sustainability in global trade logistics, particularly in response to recent supply chain disruptions. Unlike previous editions, the 2023 LPI incorporates big data analytics from container shipping, aviation, and postal services to provide deeper insights into trade performance, including shipment tracking and port delays. The full report is accessible through the World Bank's official website for detailed country-specific data and rankings.

4. RESULTS

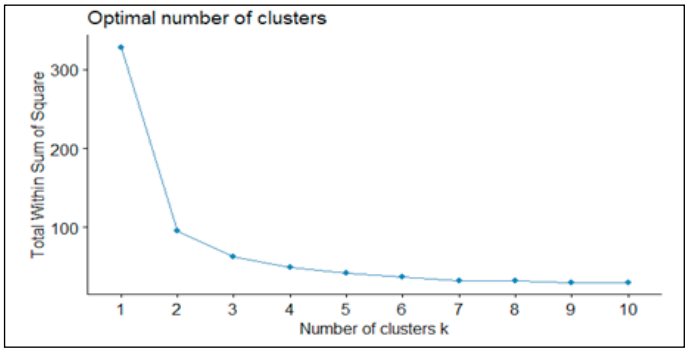
The first clustering algorithm employed in this study is *k*-means. To determine the optimal number of clusters, the elbow method was utilized (see Section 3.2). The elbow graph, depicted in Figure 1, displays a blue curve representing the within-cluster sum of squares (WSS). A blue line connects the start and end points of the curve, while an orange line, orthogonal to the blue line, intersects the blue curve, identifying the maximum distance between the two lines. Based



(a) *k*-means



(b) *k*-medoids



(c) CLARA

Figure 1. The elbow graphs

Algorithms and clusters	Customs	Infrastructure	Logistic quality	International shipments	Timeliness	Tracking and signals
k-means						
Cluster 1	3.6	3.9	3.9	3.5	3.9	3.9
Cluster 2	2.9	3.0	3.1	3.1	3.3	3.2
Cluster 3	2.3	2.3	2.4	2.5	2.8	2.4
k-medoids						
Cluster 1	3.4	3.8	3.8	3.4	3.9	3.9
Cluster 2	2.8	2.9	2.9	3.0	3.3	3.0
Cluster 3	2.3	2.3	2.4	2.5	2.8	2.5
CLARA						
Cluster 1	3.4	3.8	3.8	3.4	3.9	3.9
Cluster 2	3.1	3.0	3.2	2.8	3.5	3.2
Cluster 3	2.1	2.3	2.4	2.4	2.7	2.3

Table 1. The cluster centers(medoids)

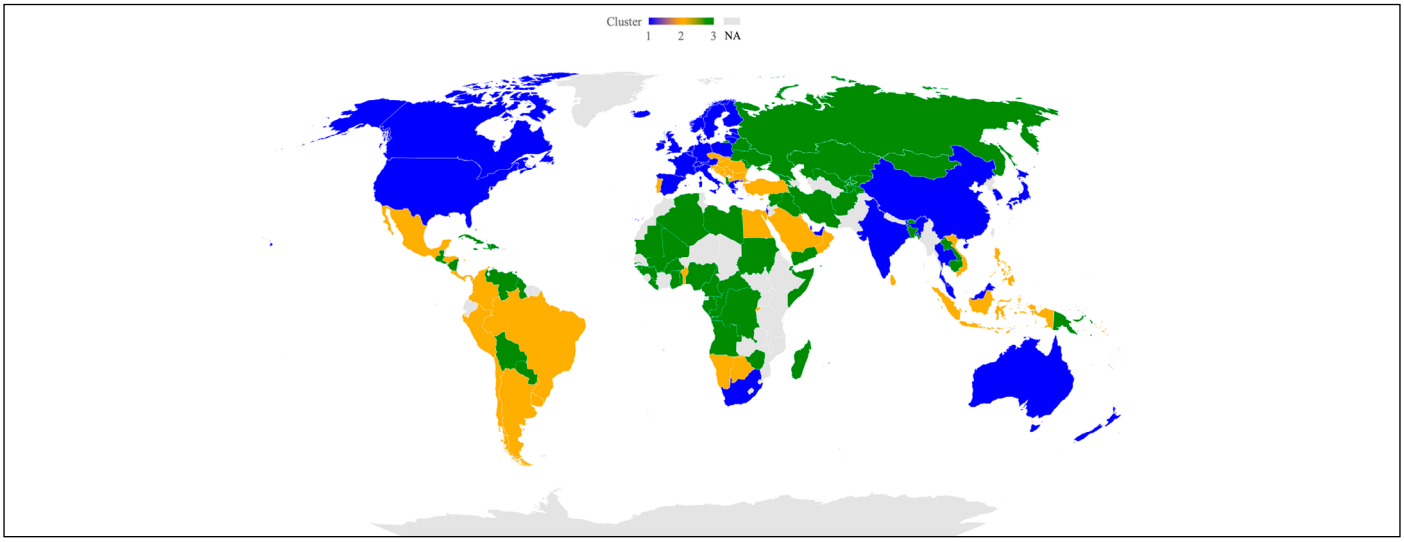


Figure 2. Map of cluster membership according to the *k*-means algorithm

on this method, the optimal number of clusters was found to be 3. Following this, the *k*-medoids algorithm was applied. The elbow method was again used to determine the optimal number of clusters, which was 3 (see again Figure 1). Finally, the CLARA algorithm was implemented. Using the elbow method, the optimal number of clusters was confirmed as 3 (see Figure 1). The results of these three algorithms—*k*-means, *k*-medoids, and CLARA—demonstrate stability in cluster memberships, confirming the robustness of the clustering process. The use of multiple algorithms provides validation and confidence in the findings, ensuring that the clusters effectively represent underlying patterns in the LPI 2023 dataset. The centroids (or medoids) of each cluster for each algorithm are presented in Table 1.

The performance of three clustering algorithms—*k*-means, *k*-medoids, and CLARA—was evaluated using average within-cluster SSE, average between-cluster SSE, and three internal validation indices: Silhouette Index, Dunn Index, and Davies-Bouldin Index (see Table 2). The results indicate that k-means achieved the lowest average within-cluster SSE (0.8873), suggesting it forms more compact clusters compared to k-medoids (0.8972) and CLARA (0.8938). In terms of average between-cluster SSE, k-means also performed slightly better (2.3959) than k-medoids (2.3754) and CLARA (2.3884), indicating superior cluster separation. For internal validation, the Silhouette Index showed that k-means (0.44) slightly outperformed CLARA (0.43) and k-medoids (0.42), reflecting better-defined clusters. However, based on the Dunn Index, k-Medoids (0.1004) exhibited slightly better compactness and separation compared to k-means (0.0990) and CLARA (0.0959). When considering the Davies-Bouldin Index, lower values indicate better clustering quality, and k-means (0.8053) outperformed both k-medoids (0.9751) and CLARA (1.0081).

Algorithms	Average within SSE	Average between SSE	Silhouette index	Dunn index
k-means	0.8873	2.3959	0.44	0.0990
k-medoids	0.8972	2.3754	0.42	0.1004
CLARA	0.8938	2.3884	0.43	0.0959

Table 2. Cluster validation

Overall, *k*-means emerged as the most suitable algorithm for this dataset, balancing compactness, separation, and cluster quality. Its performance is particularly notable in terms of within-cluster SSE and Davies-Bouldin Index, making it ideal for compact and well-separated clusters. On the other hand, *k*-medoids demonstrated robustness based on the Dunn Index, making it a preferable choice when data contains noise or outliers. CLARA performed similarly to k-medoids but was slightly less effective based on the Davies-Bouldin Index, likely due to its design for larger datasets.[1] In conclusion, *k*-means is recommended for this study due to its overall superior performance, while *k*-medoids can serve as an alternative where robustness is a priority.

These clustering outcomes provide a clear segmentation of global logistics performance based on the six LPI dimensions. The consistent identification of three clusters across all algorithms indicates that countries naturally group into high-, moderate-, and low-performing categories. This pattern directly supports the objective of this study, which is to classify countries according to their logistics capabilities using data-driven techniques rather than simple ranking comparisons. The complete list is available in the Appendix, while the map of cluster membership is shown in Figure 2 (Note that several data/countries are not available in the LPI 2023 dataset).

Cluster 1 (High Performers: Advanced and Integrated Policies) represents countries with uniformly high LPI scores, reflecting strong customs systems, advanced infrastructure, and highly developed logistics services. Cluster 1 comprises 39 countries, including highly developed economies such as Singapore, Germany, the United States, and Japan. Their presence in the same group indicates that their logistics systems share similar structural strengths. The customs dimension achieves an average score of 3.94 with minimal variability (std = 0.16), indicating that countries in this cluster maintain consistent efficiency in border clearance and regulatory processes. Similarly, the infrastructure dimension exhibits strong performance, with a mean score of 4.20 and moderate variability (std = 0.19), reflecting well-developed transportation networks, ports, and logistics hubs. The international shipments dimension shows slightly lower scores, averaging 3.76 with a higher variability (std = 0.20), suggesting that while these countries provide competitive shipping options, some variability exists in the ease of arranging international shipments. The logistics quality dimension highlights the high competence and professionalism of logistics service

1 The discrepancies across validation indices are not unexpected, as previous research has shown that no single validation index consistently outperforms others in all scenarios (Arbelaitz et al., 2013; Milligan & Cooper, 1985).

providers, with an average score of 4.17 and low variability (std = 0.12), pointing to consistently reliable services. In terms of timeliness, Cluster 1 performs exceptionally well, with a mean score of 4.18 and very low variability (std = 0.10), reflecting the ability to deliver shipments within the expected timeframe with minimal delays. The tracking and tracing dimension also demonstrates strong capabilities, averaging 4.18 with consistent scores (std = 0.10), indicating the widespread adoption of advanced tracking technologies that ensure shipment visibility and reliability. Overall, Cluster 1 represents countries with highly developed logistics systems, supported by efficient processes, modern infrastructure, and technological advancements. These countries set benchmarks in logistics performance and serve as models for global best practices. Their strengths in customs, infrastructure, and service quality highlight their readiness to support complex supply chains and international trade effectively.

Cluster 2 (Moderate Performers: Transitional and Growth-Oriented Policies) forms a transitional group of economies with moderate performance. Cluster 2 includes 37 countries, such as Portugal, Saudi Arabia, Indonesia, and Brazil. These countries exhibit moderate logistics performance, with some strengths in specific areas like infrastructure or customs but face challenges in achieving the consistency and efficiency observed in Cluster 1. Their mixed scores across indicators suggest partial progress but remaining inefficiencies. The customs score (mean = 3.10) suggests that these countries have functional customs processes but face occasional inefficiencies and variability in clearance times. Infrastructure (mean = 3.57) is generally adequate but often requires further investment to meet international standards, particularly in multimodal transportation systems. International shipments (mean = 3.30) are relatively competitive, although higher costs or processing delays may impact reliability. The logistics quality score (mean = 3.50) indicates moderate competence among service providers, but gaps in technology adoption and training may limit efficiency. Timeliness (mean = 3.60) is fairly dependable, although some countries may experience sporadic delays due to infrastructure constraints or regulatory bottlenecks. Tracking and tracing (mean = 3.60) capabilities are functional but less sophisticated, lacking real-time updates and predictive analytics. Cluster 2 countries demonstrate significant potential for improvement through targeted infrastructure upgrades, regulatory reforms, and adoption of advanced technologies to enhance overall logistics performance.

Cluster 3 (Low Performers: Fragmented and Reactive Policies) consists of 61 countries, including Afghanistan, Nigeria, Haiti, and Libya. Cluster 3 comprises countries facing systemic challenges across all logistics dimensions, highlighting the presence of bottlenecks in customs, infrastructure, and tracking capabilities. Their customs score (mean = 2.13) highlights inefficiencies in clearance processes, compounded by outdated systems and lack of automation. Infrastructure (mean = 2.13) is a major constraint, characterized by poor road networks, limited port capacity, and inadequate storage facilities. International shipments (mean = 2.23) are unreliable and costly, reflecting difficulties in accessing global trade routes and negotiating favorable terms with carriers. Logistics quality (mean = 2.40) suffers from a lack of skilled service providers, outdated practices, and limited capacity to handle complex logistics operations. Timeliness (mean = 2.27) is highly variable, with frequent delays and inconsistent delivery schedules undermining supply chain reliability. Similarly, tracking and tracing (mean = 2.13) capabilities are weak, offering minimal visibility into shipment status and posing risks to cargo security. Cluster 3 countries require substantial investments in infrastructure, customs modernization, and workforce development, along with policy reforms to establish reliable logistics networks and support economic growth.

These results allow policymakers and analysts to identify performance patterns beyond individual rankings. By observing how countries group together based on overall logistics profiles, stakeholders can better understand whether improvements should focus on customs reform, infrastructure investment, or capacity building. Thus, the cluster structures serve as a foundation for developing targeted recommendations, which are further elaborated in the Discussion section.

5. DISCUSSION

The primary objective of clustering analysis is to provide users with meaningful insights derived from the original data, enabling them to effectively address specific problems and make informed decisions. By grouping similar data points, clustering reveals underlying patterns and relationships that may not be immediately apparent, offering a deeper understanding of the dataset. This section focuses on interpreting the results obtained from the *k*-means algorithm, which was previously identified as the most suitable clustering method for further analysis based on its overall performance across internal validation indices.

The *k*-means results reveal three distinct clusters of countries with similar logistics performance profiles. Each cluster's centroid reflects the average performance across all six LPI dimensions—customs, infrastructure, international shipments, logistics quality, tracking and tracing, and timeliness—providing a meaningful basis for comparison. Countries grouped within the same cluster therefore share comparable logistics strengths and weaknesses, indicating similar levels of logistics system maturity and institutional capability. These empirical patterns align closely with prior research demonstrating that logistics performance is a core determinant of national competitiveness, trade facilitation, and economic development (Martí et al., 2014; Arvis et al., 2018).

The importance of logistics for competitiveness is well-established. Scriosteanu and Popescu (2010, 2014) show that logistics creates competitive advantage through cost reduction, service diversification, and improved fulfillment of customer requirements. Because the same logistics activity may be executed with vastly different efficiencies, evaluating logistics processes and understanding their value-chain linkages are essential for identifying opportunities to enhance performance. These linkages determine how effectively logistics activities synchronize to create value. Christopher (1993) similarly emphasizes that logistics contributes to sustainable competitive advantage by simultaneously elevating customer service and reducing the cost-to-serve, strengthening customer relationships and supporting long-term market differentiation. Recent work further reinforces that logistics has become a cornerstone of trade competitiveness—facilitating global market integration, supporting international trade, and enabling economies to respond to increasing supply chain complexity (Gani, 2017; Song & Lee, 2022). Modern logistics encompasses infrastructure quality, customs efficiency, technological adoption, and delivery reliability (Pindi, 2025), dimensions that correspond directly to the LPI indicators analyzed in this study.

Firm-level evidence complements these macroeconomic dynamics. Chang et al. (2021) highlight that infrastructure, technology, integration, and regulation are key drivers of competitive advantage in the logistics industry, with integration mediating the relationship between technology and performance. This pattern mirrors the characteristics of high-performing countries in Cluster 1, where advanced digitalization, cohesive regulation, and strong infrastructure

work in tandem to reinforce logistics capability. Sandberg and Abrahamsson (2011) further show that sustainable logistics-based competitive advantage stems not only from operational efficiency but also from dynamic capabilities such as learning, managerial expertise, cross-functional teamwork, and strong supply chain relationships—capabilities that similarly resonate with Cluster 1 economies.

The cluster results also align with broader empirical findings on global logistics patterns. Further insights can be drawn by analyzing the distribution of countries within each cluster. The comparison of all clusters according to the six LPI dimensions is provided in Figure 3. Analysis for each cluster will be provided as the following.

Countries in Cluster 1 (High Performers) exhibit consistently high performance across all logistics dimensions, confirming earlier findings that advanced economies benefit from efficient customs systems, sophisticated multimodal infrastructure, and strong governance structures that facilitate trade (Sheffi, 2017). Countries in Cluster 1 are characterized by advanced infrastructure, efficient customs processes, reliable logistics services, and strong performance in tracking and tracing capabilities. They represent global leaders in logistics performance, benefiting from modern technologies, streamlined processes, and robust supply chain networks. These nations prioritize trade facilitation reforms, including streamlined customs procedures, Single Window Systems, and automated clearance processes, which reduce delays and enhance border efficiency. Investments in multimodal transportation networks and smart infrastructure ensure seamless connectivity between ports, roads, railways, and airports (Arvis et al., 2018). Additionally, policies emphasize public-private partnerships (PPPs) to fund infrastructure projects and drive innovation. Advanced digitalization policies, such as the adoption of blockchain technologies, RFID tracking, and Artificial Intelligence (AI) in supply chain monitoring, further strengthen their logistics capabilities (Sheffi, 2017). Environmental policies also play a key role, with incentives for green logistics—reducing emissions through energy-efficient transportation modes and electrification of fleets. Regulatory frameworks in these countries promote logistics competitiveness, enabling fast-tracked customs clearances and harmonized standards aligned with international trade agreements. For these countries, policy directions should focus on sustaining their competitive edge through further digitalization, investment in smart and green logistics infrastructure, and the strengthening of resilience-oriented supply chain policies. Enhancing interoperability of digital platforms, supporting low-carbon freight initiatives, and deepening cross-border regulatory harmonization will allow them to preserve and extend their leadership.

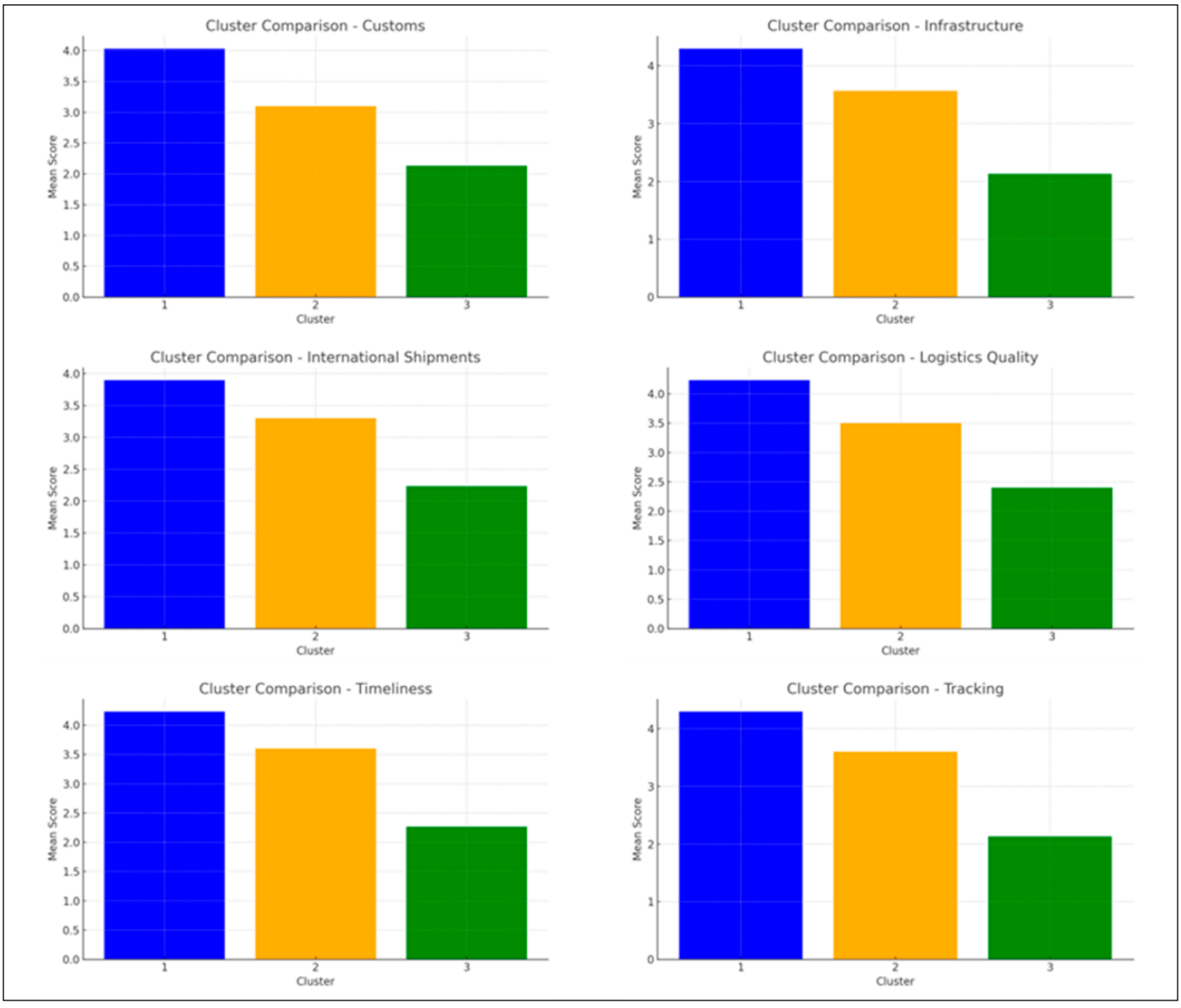


Figure 3. Cluster comparison for each LPI dimension

Countries in Cluster 2 (Moderate Performers) display transitional or moderately developed logistics systems: they show promise in some areas—typically infrastructure or timeliness—but remain limited by uneven progress in customs performance, international shipments, or tracking and tracing. These patterns are consistent with Roy et al. (2018), who noted that emerging economies often experience fragmented progress due to inconsistent investment strategies and regulatory gaps. Countries in Cluster 2 likely have emerging logistics systems that are improving but still require targeted investments and reforms to close the gap with higher-performing nations. Policies in this cluster often focus on infrastructure expansion through large-scale development projects, such as new ports, highways, and logistics hubs, supported by foreign investments and public-private collaborations. However, customs modernization efforts may still be incomplete, leading to inconsistencies in border management practices and longer clearance times compared to Cluster 1 (World Bank, 2016). Digitalization policies are emerging, with a focus on electronic data interchange (EDI) systems and basic tracking technologies to enhance logistics transparency. Efforts to implement regional trade agreements and harmonize customs procedures are ongoing, but regulatory gaps and bureaucratic inefficiencies continue to hinder progress. Sustainability policies in Cluster 2 countries are generally in their early stages, with some emphasis on reducing emissions and adopting fuel-efficient technologies, though implementation often lags due to funding constraints. While countries in this cluster are making strides toward integrating logistics frameworks, they still require capacity building, improved policy enforcement, and greater adoption of smart technologies to compete with Cluster 1 nations. Policy efforts in these countries should therefore prioritize the completion of customs modernization initiatives, expansion of multimodal infrastructure, and accelerated adoption of digital logistics technologies. Strengthening institutional coordination, developing human capital in logistics professions, and leveraging public–private partnerships can help these economies transition more consistently toward higher logistics performance.

Cluster 3 (Low Performers) countries face systemic constraints that significantly hinder their ability to participate effectively in global supply chains. This pattern aligns with the World Bank (2016), which documented that countries with inadequate infrastructure and outdated customs procedures face persistent delays, high trade costs, and low reliability. Weak tracking capabilities further limit supply chain visibility. Countries in this cluster require foundational reforms, including large-scale investment in transport and port infrastructure, simplification and digitalization of customs procedures, anti-corruption measures at border agencies, and targeted capacity-building initiatives. International development assistance and regional cooperation frameworks can play a critical role in helping them overcome structural limitations and gradually build logistics capability. Policies in this cluster primarily address basic infrastructure development, including road construction, port upgrades, and warehouse improvements to tackle physical bottlenecks. However, weak governance, political instability, and lack of funding often slow progress, leading to poor infrastructure quality and unreliable transportation networks (Arvis et al., 2018). Customs policies in these countries are generally outdated, heavily reliant on manual procedures with limited use of electronic systems, contributing to delays, corruption, and inefficiency. Efforts to implement trade facilitation agreements often stall due to limited technical expertise and resistance to reforms. Digitalization remains underdeveloped, with minimal adoption of tracking systems and electronic documentation, making shipment monitoring and risk management challenging. Environmental sustainability policies are largely absent, with most efforts focused on addressing immediate logistical barriers rather than long-term sustainability goals. These countries require donor-funded programs, capacity-building initiatives, and regional cooperation agreements to create a more integrated and efficient logistics ecosystem. Policies must prioritize anti-corruption reforms, digital adoption, and training programs for logistics professionals to improve operational efficiency (World Bank, 2016).

The analysis underscores the disparities between clusters, with Cluster 1 showcasing world-leading logistics capabilities, Cluster 2 representing emerging economies with moderate performance, and Cluster 3 highlighting significant challenges in logistics infrastructure and processes. These differences emphasize the need for tailored policy interventions, infrastructure investments, and technology adoption strategies to bridge the performance gap, particularly for countries in Clusters 2 and 3.

6. CONCLUSION

This study utilized clustering analysis to examine global logistics performance using the latest LPI 2023 dataset. By employing k-means, k-medoids, and CLARA algorithms, the research effectively grouped countries into three distinct clusters based on six LPI dimensions—customs, infrastructure, international shipments, logistics quality, tracking and tracing, and timeliness. Each algorithm's performance was validated using internal evaluation indices, including the Silhouette Index, Dunn Index, and Davies-Bouldin Index, ensuring robust and reliable results.

Cluster 1 represents high-performing countries with advanced logistics capabilities, streamlined customs procedures, and modern infrastructure. These nations benefit from integrated policies emphasizing digitalization, PPPs, and sustainability practices. In contrast, Cluster 2 consists of moderate performers demonstrating transitional growth, driven by infrastructure expansions and technology adoption, yet constrained by regulatory inefficiencies and slower implementation of reforms. Finally, Cluster 3 highlights low-performing nations facing fragmented logistics systems, poor infrastructure, and outdated customs processes. These countries require international support, policy reforms, and capacity-building programs to enhance logistics efficiency and competitiveness.

The results underscore the persistent disparities in logistics performance across countries, emphasizing the need for targeted interventions to bridge gaps, particularly in Clusters 2 and 3. Policies promoting customs modernization, multimodal transportation networks, and advanced digital tracking technologies could significantly improve logistics performance. Moreover, Cluster 3 countries must prioritize basic infrastructure development and governance reforms to achieve sustainable growth.

By leveraging recent data and evaluating all six LPI dimensions, this study contributes to the literature by providing timely, data-driven insights into global logistics performance. The findings highlight the importance of customized strategies and policy frameworks to improve logistics efficiency and support global trade competitiveness. Future research could expand the analysis by incorporating additional economic and trade variables, enabling a deeper understanding of the factors influencing logistics performance worldwide.

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CONFLICT OF INTEREST

The authors report there are no competing interests to declare.

REFERENCES

Akram, M. U., Khalid, S., Tariq, A., & Javed, M. Y. (2013). Detection of neovascularization in retinal images using multivariate m-medoids based classifier. *Computerized Medical Imaging and Graphics, 37*(5–6), 346–357. https://doi.org/10.1016/j.compmedimag.2013.06.008

Arbelaitz, O., Gurrutxaga, I., Muguerza, J., Pérez, J. M., & Perona, I. (2013). An extensive comparative study of cluster validity indices. *Pattern Recognition, 46*(1), 243–256. https://doi.org/10.1016/j.patcog.2012.07.021

Arvis, J. F., Saslavsky, D., Ojala, L., Shepherd, B., Busch, C., & Raj, A. (2018). *Connecting to Compete 2018: Trade logistics in the global economy*. The World Bank.

Bi, W., Cai, M., Liu, M., & Li, G. (2016). A big data clustering algorithm for mitigating the risk of customer churn. *IEEE Transactions on Industrial Informatics, 12*(3), 1270–1281. https://doi.org/10.1109/TII.2016.2547584

Boujelben, M. A., & Smet, Y. D. (2016). A multicriteria ordered clustering algorithm to determine precise or disjunctive partitions. *International Journal of Multicriteria Decision Making*, *6*(2), 157-187. https://doi.org/10.1504/IJMCDM.2016.077886

Chang, C. H., Lu, C. S., & Lai, P. L. (2022). Examining the drivers of competitive advantage of the international logistics industry. *International Journal of Logistics Research and Applications*, *25*(12), 1523-1541. https://doi.org/10.1080/13675567.2021.1915263

Christopher, M. (1993). Logistics and competitive strategy. *European Management Journal*, *11*(2), 258-261. https://doi.org/10.1016/0263-2373(93)90049-N

Davies, D. L., & Bouldin, D. W. (1979). A cluster separation measure. *IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-1*(2), 224–227. https://doi.org/10.1109/TPAMI.1979.4766909

Dunn, J. C. (1974). Well-separated clusters and optimal fuzzy partitions. *Journal of Cybernetics, 4*(1), 95–104. https://doi.org/10.1080/01969727408546059

Gani, A. (2017). The logistics performance effect in international trade. *The Asian Journal of Shipping and Logistics*, *33*(4), 279-288. https://doi.org/10.1016/j.ajsl.2017.12.012

Granillo-Macías, R. (2020). Inventory management and logistics optimization: A data mining practical approach. *LogForum, 16* (4), 535–547. https://doi.org/10.17270/J.LOG.2020.512

Kaufman, L., & Rousseeuw, P. J. (1986). Clustering large data sets (with discussion). In E. S. Gelsema & L. N. Kanal (Eds.), *Pattern recognition in practice II* (pp. 425–437). Amsterdam, Netherlands: Elsevier. https://doi.org/10.1016/B978-0-444-87877-9.50039-X

Kaufman, L., & Rousseeuw, P. J. (1990). *Finding groups in data: An introduction to cluster analysis*. Hoboken, NJ: John Wiley & Sons. https://doi.org/10.1002/9780470316801

Kisore, N. R., & Koteswaraiah, C. B. (2017). Improving ATM coverage area using density-based clustering algorithm and Voronoi diagrams. *Information Sciences, 376*, 1–20. https://doi.org/10.1016/j.ins.2016.09.058

Martí, L., Puertas, R., & García, L. (2014). The importance of the Logistics Performance Index in international trade. *Applied Economics, 46*(24), 2982–2992. https://doi.org/10.1080/00036846.2014.916394

McQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In L. M. Le Cam & J. Neyman (Eds.), *Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability* (Vol. 1, pp. 281–297). The Regents of the University of California.

Minako, F. S., Ulkhaq, M. M., Pratiwi, A. R. A., Sa Nu, D., & Akshinta, P. Y. (2019). Clustering internet shoppers: An empirical finding from Indonesia. In *Proceedings of the 5th International Conference on E-business and Mobile Commerce* (pp. 21–24). Taichung, Taiwan. https://doi.org/10.1145/3332324.333232

Pehlivan, P., Aslan, A. I., David, S., & Bacalum, S. (2024). Determination of Logistics Performance of G20 Countries Using Quantitative Decision-Making Techniques. *Sustainability*, *16*(5), 1852. https://doi.org/10.3390/su16051852

Pindi, M. (2025). Integrating green logistics solutions into transportation management systems for sustainable freight operations. *World Journal of Advanced Engineering Technology and Sciences*, *15*(2), 1150–1158. https://doi.org/10.30574/wjaets.2025.15.2.0574

Rana, S., & Garg, R. (2016). Application of hierarchical clustering algorithm to evaluate students' performance of an institute. In *2016 Second International Conference on Computational Intelligence & Communication Technology (CICT)* (pp. 498–502). IEEE. https://doi.org/10.1109/CICT.2016.143

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics, 20*(1), 53–65. https://doi.org/10.1016/0377-0427(87)90125-7

Roy, V., Mitra, S. K., Chattopadhyay, M., & Sahay, B. S. (2018). Facilitating the extraction of extended insights on logistics performance from the logistics performance index dataset: A two-stage methodological framework and its application. *Research in Transportation Business & Management*, *28*, 23-32. https://doi.org/10.1016/j.rtbm.2017.10.001

Saeed, N., & Cullinane, K. (2023). Identifying the characteristics of China's maritime trading partners on the basis of bilateral shipping connectivity: A cluster analysis. *Maritime Policy & Management*, *50*(1), 42-57. https://doi.org/10.1080/03088839.2021.1954256

Sandberg, E., & Abrahamsson, M. (2011). Logistics capabilities for sustainable competitive advantage. *International Journal of Logistics Research and Applications*, *14*(1), 61-75. https://doi.org/10.1080/13675567.2010.551110

Scriosteanu, A., & Popescu, D. (2010). Logistics and competitive advantage. *Metalurgia International*, *15*, 85-88.

Scriosteanu, A., & Popescu, D. (2014). Logistics-source of competitive advantage. *Annals of the University of Craiova, Economic Sciences Series*, *1*(42), 53-60.

Sheffi, Y. (2017). *Balancing Green and Growth in Logistics*. MIT Press.

Song, M. J., & Lee, H. Y. (2022). The relationship between international trade and logistics performance: A focus on the South Korean industrial sector. *Research in Transportation Business & Management*, *44*, 100786. https://doi.org/10.1016/j.rtbm.2022.100786

Tan, P. N., Steinbach, M., & Kumar, V. (2006). *Introduction to Data Mining*. Pearson.

Thomas, R. E., & Khan, S. S. (2016). Improved clustering technique using metadata for text mining. In *2016 International Conference on Communication and Electronics Systems (ICCES)* (pp. 1–5). IEEE. https://doi.org/10.1109/CESYS.2016.7889835

Ulkhaq, M. M. (2023). Clustering countries according to the logistics performance index. *Jurnal Teknik Informatika dan Sistem Informasi*, 10(1), 1010-1018. https://doi.org/10.35957/jatisi.v10i1.4755

Ulkhaq, M. M., & Adyatama, A. (2021). Clustering countries according to the world happiness report 2019. *Engineering & Applied Science Research*, *48*(2), 137-150. https://doi.org/10.14456/easr.2021.16

Ulkhaq, M.M. (2020). Clustering countries according to the World Happiness Report, *Statistica & Applicazioni*, XVIII(2), 197-220. https://doi.org/10.26350/999999_000036

Utami, A. A., Ginanjar, A. G., Fadlia, N., Lubis, I. A., & Ulkhaq, M. M. (2019). Using shopping and time attitudes to cluster food shoppers: An empirical finding from Indonesia. In *Proceedings of the 3rd International Conference on Data Mining, Communications and Information Technology* (pp. 24–26). Beijing, China. https://doi.org/10.1088/1742-6596/1284/1/012005

Waheed, A., Akram, M. U., Khalid, S., Waheed, Z., Khan, M. A., & Shaukat, A. (2015). Hybrid features and medoids classification-based robust segmentation of blood vessels. *Journal of Medical Systems, 39*(11), 1–14. https://doi.org/10.1007/s10916-015-0316-1

World Bank (2016). Connecting to Compete 2016: Trade Logistics in the Global Economy. World Bank. Retrieved from: https://www.worldbank.org/en/news/feature/2016/06/28/connecting-to-compete-2016-trade-logistics-in-the-global-economy

Yang, C., Benjamasutin, N., & Chen-Burger, Y. (2014). Mining hidden concepts: Using short text clustering and Wikipedia knowledge. In *2014 28th International Conference on Advanced Information Networking and Applications Workshops* (pp. 675–680). IEEE. https://doi.org/10.1109/WAINA.2014.109

APPENDIX: CLUSTER MEMBERSHIP ACCORDING TO THE *K*-MEANS ALGORITHM

Note: Cluster 1: High Performers: Advanced and Integrated Policies; Cluster 2: Moderate Performers: Transitional and Growth-Oriented Policies; Cluster 3: Low Performers: Fragmented and Reactive Policies

No	Countries	Cluster
1	Singapore	1
2	Finland	1
3	Denmark	1
4	Germany	1
5	Netherlands	1
6	Switzerland	1
7	Austria	1
8	Belgium	1
9	Canada	1
10	Hong Kong SAR, China	1
11	Sweden	1
12	United Arab Emirates	1
13	France	1
14	Japan	1
15	Spain	1
16	Taiwan, China	1
17	Korea, Rep.	1
18	United States	1
19	Australia	1
20	China	1
21	Greece	1
22	Italy	1
23	Norway	1
24	South Africa	1
25	United Kingdom	1
26	Estonia	1
27	Iceland	1
28	Ireland	1
29	Israel	1
30	Luxembourg	1
31	Malaysia	1
32	New Zealand	1
33	Poland	1
34	Bahrain	1
35	Latvia	1
36	Qatar	1
37	Thailand	1
38	India	1
39	Lithuania	1
40	Portugal	2
41	Saudi Arabia	2
42	Turkiye	2
43	Croatia	2
44	Czech Republic	2
45	Malta	2
46	Oman	2
47	Philippines	2
48	Slovak Republic	2
49	Slovenia	2

No	Countries	Cluster
50	Vietnam	2
51	Brazil	2
52	Bulgaria	2
53	Cyprus	2
54	Hungary	2
55	Kuwait	2
56	Romania	2
57	Botswana	2
58	Arab Rep. of Egypt	2
59	North Macedonia	2
60	Panama	2
61	Bosnia and Herzegovina	2
62	Chile	2
63	Indonesia	2
64	Peru	2
65	Uruguay	2
66	Antigua and Barbuda	2
67	Benin	2
68	Colombia	2
69	Costa Rica	2
70	Honduras	2
71	Mexico	2
72	Namibia	2
73	Argentina	2
74	Montenegro	2
75	Rwanda	2
76	Serbia	2
77	Solomon Islands	2
78	Sri Lanka	2
79	The Bahamas	3
80	Belarus	3
81	Djibouti	3
82	El Salvador	3
83	Georgia	3
84	Kazakhstan	3
85	Papua New Guinea	3
86	Paraguay	3
87	Ukraine	3
88	Bangladesh	3
89	Rep. Congo.	3
90	Dominican Republic	3
91	Guatemala	3
92	Guinea-Bissau	3
93	Mali	3
94	Nigeria	3
95	Russian Federation	3
96	Uzbekistan	3
97	Albania	3
98	Algeria	3

No	Countries	Cluster
99	Armenia	3
100	Bhutan	3
101	Central African Republic	3
102	Rep. Dem. Congo	3
103	Ghana	3
104	Grenada	3
105	Guinea	3
106	Jamaica	3
107	Mauritius	3
108	Moldova	3
109	Mongolia	3
110	Nicaragua	3
111	Tajikistan	3
112	Togo	3
113	Trinidad and Tobago	3
114	Zimbabwe	3
115	Bolivia	3
116	Cambodia	3
117	Gabon	3
118	Guyana	3
119	Iraq	3
120	Lao PDR	3
121	Liberia	3
122	Sudan	3
123	Burkina Faso	3
124	Fiji	3
125	The Gambia	3
126	Iran, Islamic Rep.	3
127	Kyrgyz Republic	3
128	Madagascar	3
129	Mauritania	3
130	Syrian Arab Republic	3
131	Venezuela	3
132	Cuba	3
133	Yemen, Rep.	3
134	Angola	3
135	Cameroon	3
136	Haiti	3
137	Somalia	3
138	Afghanistan	3
139	Libya	3