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Cluster Analysis on Supply Chain Management-Related Indicators

Metin YILDIRIM [1]

Abstract

The supply chain performance of countries has a significant impact on the overall performance of countries. These indices primarily emphasized countries' standings, rankings, and improvement areas. Clustering countries based on a single index does not always yield the desired results. Using cluster analysis may help get critical information when many indicators are evaluated. The supply chain-connected indicators were chosen to be included in the research initially. In this study, three global indices were selected. We chose the Logistics Performance Index(LPI) to evaluate the logistics industry, which is essential in supply chain management. Logistics is one of the critical areas that affect and have also been affected by many fundamental indicators used to evaluate a country's performance. One critical indicator that globally measures the processes is the Logistics Performance Index. We included Environmental Performance Index(EPI) in the study to evaluate environmental policies that impact supply chain operations. The final index used in the study is the Global Competitiveness Index(GCI), which examines the competitiveness of countries with a heavy dependence on supply chain management performance. It is one of the crucial indications in evaluating a country's productivity. We used clustering analysis based on supply chain management-related indicators in the following phase. K-Means clustering algorithm was applied to the extracted data set. Python code is written to implement the K-Means clustering algorithm. In the final part of the study, differences between clusters and submitted research proposals ideas were discussed. This research proposes a three-step methodological framework for mining supply chain indicators derived from the LPI, GCI, and EPI indicators. The research aims to conclude from the analyses of the change in centers based on indicators, the variation based on datasets between clusters, and the grouping of countries based on any combination of the LPI, GCI, and EPI indicators .

Keywords: Cluster Analysis, K-Means, Logistics Performance Index, Environmental Performance Index, Global Competitiveness Index

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[1] Asst. Prof., İstanbul Gelişim University, Faculty of Economics, Administrative and Social Sciences, Department of Logistics Management, İstanbul, Türkiye, meyildirim@gelisim.edu.tr, ORCID: 0000-0003-0424-9834.

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Tedarik Zinciri Yönetimine İlişkin Göstergeler ile Kümeleme Analizi

Metin YILDIRIM[1]

Öz

Ülkelerin tedarik zinciri performansı, ülkelerin genel performansı üzerinde önemli bir etkiye sahiptir. Çevresel performans ve rekabet gücü, tedarik zinciri performansıyla doğrudan ilişkili olmakla kalmayıp ülkelerin performansını da önemli ölçüde etkileyen önemli özellikler arasında yer almaktadır. Akademik kurumlar ve uluslararası kuruluşlar bu alanlarda çok sayıda tanınmış endeks oluşturtmuşlardır. Bu endeksler öncelikli olarak ülkelerin mevcut sıralamalarını ve geliştirilmesi gereken alanları ortaya koymaktadır. Ülkeleri tek bir göstergeye göre kümelemek her zaman istenen sonuçları vermemektedir. Birçok gösterge değerlendirildiğinde, kritik bilgilere ulaşılmasında küme analizi kullanılabilmektedir. Araştırmanın başlangıç aşamasında, tedarik zinciri ile bağlantılı üç küresel temel endeksler seçilmiştir. Tedarik zinciri yönetiminde önemli bir rol oynayan lojistik sektörünü değerlendirmesinde Lojistik Performans Endeksini kullanılmıştır. Lojistik, bir ülkenin performansını değerlendirmek için kullanılan birçok temel göstergeyi etkileyen ve aynı zamanda bu göstergelerden etkilenen kritik alanlardan biridir. Süreçleri küresel olarak ölçen temel göstergelerin başında, Lojistik Performans Endeksi gelmektedir. Tedarik zinciri operasyonları üzerinde etkisini her geçen gün artıran çevre politikalarını değerlendirilmesi amacıyla, Çevresel Performans Endeksi çalışmaya dâhil edilmiştir. Çalışmada kullanılan son endeks, tedarik zinciri yönetimi performansına büyük ölçüde bağımlı olan ülkelerin rekabet edebilirliğini inceleyen Küresel Rekabet Edebilirlik Endeksi'dir. Bir ülkenin üretkenliğini değerlendirmede en önemli göstergeler arasında gösterilmektedir. Bir sonraki aşamada ise, tedarik zinciri yönetimiyle ilgili göstergelere dayalı kümeleme analizi gerçekleştirilmiştir K-Means kümeleme algoritması çalışmada kullanılmıştır. K-means algoritması, Python programlama dili kullanılarak kodlanmıştır. 2018 yılına ait veri setleri kullanılarak küme analizleri yapılmıştır. Çalışmanın son bölümünde ise kümeler arasındaki farklılıklar ve sunulan araştırma önerileri fikirleri tartışılmıştır. Bu çalışmanın araştırma amacı, göstergelere dayalı olarak merkez noktalardaki değişimi, kümeler arasındaki veri setlerine dayalı değişimi ve her veri seti kombinasyonuna dayalı olarak ülkelerin gruplandırılmasını analiz etmektir.

Anahtar Kelimeler: Kümeleme Analizi, K-Means, Lojistik Performans Endeksi, Çevresel Performans Endeksi, Küresel Rekabet Edebilirlik Endeksi.

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[1] Dr.Öğr.Üyesi, İstanbul Gelişim Üniversitesi İİSBF, Lojistik Yönetimi, Türkiye, meyildirim@gelisim.edu.tr, ORCID: 0000-0003-0424-9834

Introduction

Supply chain management (SCM) has gained importance in organizing investment, production, and trade in national economies due to globalization and the COVID-19 pandemic. Governments worldwide are working to improve supply chain policies to enhance competitiveness, reliability, efficiency, and sustainability. More indexes and indicators have been used to track countries' progress. Supply chain management interacts significantly with indexes and indicators measuring countries' development and progress.

For this analysis, we take the unionist approach of Larson and Halldorsson (2004) on the interaction between supply chain management and logistics. This viewpoint considers logistics a component of SCM (Larson & Halldorsson, 2004,p.17). Logistics has been regarded as one of the vital value-adding activities, in addition to supporting the successful completion of domestic and international trade operations. Logistic performance refers to how the previously scheduled logistics activities meet the qualitative and quantitative goals established at the end of the planned period. Performance is typically thought of as a complicated concept that justifies the use of several indicators. The level of logistic performance was defined as the extent to which organizational goals are met (Daugherty et al., 1996, p.25). Scholars have identified many techniques for measuring countries' logistics efficiency, including Logistics Performance Index (LPI) and Agility Emerging Markets Logistics Index (AEMLI). In many studies, LPI prioritizes AEMLI, with LPI often covering 160 countries and AEMLI covering 50 countries. LPI aggregates six critical performance indicators into a single metric. The World Bank produced the most recent current rating in 2018 and computed it for 160 nations (Beysenbaev & Dus, 2020,p.35). LPI's main objective is to compare a country's logistics performance and identify potential problems and opportunities for logistics operations. (Rezaei et al., 2018,p.158). However, LPI is one of the most dependable indicators of a country's logistics operations performance. LPI has two significant drawbacks, which must be highlighted. The first disadvantage is that international freight firms' experience may not reflect the overall logistical conditions in underdeveloped nations. Conventional operators conduct the majority of logistics activities in these countries. International and conventional operators' engagements with government bodies and service levels could diverge. The next drawback of LPI exists in island and landlocked countries. The transit challenges in these nations may be reflected in their low LPI score. It should be noted that transit difficulties in these countries cannot be resolved only by national reforms (Arvis et al., 2018,p.61). LPI is based on a scale of 1 to 5, where one is low and five is high. The LPI is the average of the six LP sub-indexes in arithmetic terms. Customs, logistics infrastructure, international shipments, logistics quality and competence, tracking and tracing, and timeliness are sub-indices (Magazzino et al., 2021,p.4-10).

Sustainability and environmental issues have risen to the top of the list of factors that have acquired importance and appeal in assessing a country's overall performance, which has a direct cause-effect relationship with supply chain management operations. The supply chain has a largely negative influence on the environment. Supply chain operations have been identified as the primary cause of environmental harm. Operations involving the supply chain are credited with causing 80% of greenhouse emissions and 90% of all environmental harm. Supply chain activities adversely impact various factors, including air quality (Jæger et al., 2021,p.1234). The sustainability of these countries has been threatened by escalating environmental deterioration. Governments have been under increasing pressure to limit environmental harm. Water, air, and soil pollution not only impacts the local community but is also thought to be the primary driver of global warming and shifting biodiversity. Building a sustainable operational supply chain management ecosystem has become essential to the survival of these countries. The environmental impact of logistics is receiving increasing attention from all quarters (Islam et al., 2021,p.129-147). Supply chain management activities rely heavily on energy derived from fossil fuels, resulting in significant greenhouse emissions, which most governments have targets to minimize (Khan, 2019,p.13217). One of the primary indicators used to track a nation's progress toward environmental policy goals is the Environmental Performance Index (EPI). The primary justification for EPI's widespread use as an indicator in research is that it enables a thorough assessment of the nation's overall environmental quality, taking into account the majority of environmental impact factors, including heavy metals, air pollution, climate, and energy (Wang et al., 2021,p.5), The 2018 EPI assesses 180 nations based on 24 performance metrics divided into ten categories. The Yale Center for Environmental Law and Policy, Yale University, the Columbia University Center for International Earth Science Information Network, and the World Economic Forum collaborated to create the 2018 Environmental Performance Index (2018 Environmental Performance Index, 2022). The analysis used data from 2018.

Countries' competitiveness and wealth are critical to monitoring their SCM performance. SCM operations significantly impact the competitiveness of countries. Country clustering studies that take competitiveness indices into account become even more significant. Global Competitiveness Index (GCI) is a comprehensive index for assessing national competitiveness that considers national competitiveness's microeconomic and macroeconomic underpinnings. World Economic Forum (WEF) started to publish Global Competitiveness Index (GCI) in 2004. The performance of countries is monitored by the 12 competitiveness pillars that make up the GCI (Sala-i-Martin et al., 2007,p.1). The research aims to contribute to the literature on country-based supply chain management performance rankings. Comparing supply chain performance across countries is not an intensively researched topic, and it is believed that this study contributes to the literature to some extent by providing in-depth insight into this area.

Benchmarking the performance of countries' supply networks is not an extensively researched matter. We could not discover any previously published research in which cluster analysis was done for the majority of countries in worldwide based on the three most significant supply chain-related indices, namely the LPI, the GCI, and the EPI, in this study's literature review. From this point of view, the present study can be seen as filling an essential gap in related literature. Once the research topic and research questions had been determined, the first stage of the research involved conducting a relevant literature review, which was then submitted under the heading Literature Review. The initial step is to cluster each dataset separately. In the second step, the data sets generated by the pair-wise aggregated indices are clustered and analyzed. All related indicators are merged into a single dataset in the final stage. The final cluster analysis is performed. The analysis result has been submitted in the Results and Discussions section.

Literature Review

One of the most critical topics in the logistics literature is efficiency evaluation. A relatively lower number of studies are undertaken on the macro level of the logistics industry. One of the macro-level study topics is the analysis of the LPI. A data envelopment analysis study to calculate a synthetic logistics performance index found that income and geography were the significant factors behind LPI scores (Martí et al., 2017, p.188). Research on the link between LPI and Gross Domestic Product(GDP) per capita shows a significant relationship between logistics skills and performance(Limcharoen et al., 2017, p.4882). The research on the influence of LPI on international commerce found that improvements in LPI competitiveness result in considerable increases in international trade volume, particularly in several African, South American, and Eastern European countries (Martí et al., 2014). A significant number of studies examine the relationships between logistical performance and the competitiveness of countries. In studies of the moderator effect of GCI on the LPI, improvement in LPI components' timeliness, tracking and tracing, and international shipments can lead to a higher GCI score (Çemberci et al., 2015, p.374). The effects of the selected GCI strategic subfactors on the LPI for Africa, Asia, and the EU countries have been investigated. Infrastructure, human factors, and institutions comprise the three primary clusters into which selected subfactors are divided. The human factor plays a more significant role in progressively improving LPI in Europe, while the necessary infrastructure remains paramount in Asia. All three factors influence Africa's logistics development (Sergi et al., 2021, p.1). The primary GCI pillars that substantially influence a country's logistics performance are business sophistication, financial market development, infrastructure, market efficiency, higher education, and training (Kabak et al., 2020, p.1). Ekici et al. revealed the relationship between competitiveness and LPI indicators (Ekici et al., 2016, p.117). Their subsequent study, published in 2019, examined the cause-and-effect linkages between the GCI pillars and the LPI indicator. The result indicated that technical readiness, higher education and training, innovation, market size, and infrastructure could improve the country's logistics performance (Ekici et al., 2019, p.197). Research examining the relationship between country logistics performance, competitiveness, and wealth showed a mediator effect of LPI on the relationship between GCI and GDP (Civelek et al., 2015, p.368; d'Aleo, 2015, p.1). GCI and LPI studies showed that institutions, ICT adoption, and innovation have an impact on logistics performance in the Visegrád Group countries (Kálmán & Tóth, 2021, p.170). Railroad and port infrastructure have been identified as crucial factors influencing countries' ability to undertake logistics in other research (Erkan, 2014, p.1237). Studies demonstrate that transportation infrastructure investments positively affect foreign trade, particularly in middle-income countries (Korinek & Sourdin, 2011, p.4). Sustainability is becoming an increasingly prominent and concentrated research area. A substantial amount of research on the environmental effects of the logistics industry has been conducted. One of the most commonly explored subjects is the relationship between greenhouse emissions and logistical performance. The findings of these studies revealed a significant and positive relationship between LPI scores and CO_2 emissions per capita (Karaduman et al., 2020, p.449; Magazzino et al., 2021, p.9; Polat et al., 2022, p.221). According to the research on the relationship between carbon emissions, logistics, and GDP, a direct correlation between carbon emissions and both logistics and GDP has been shown (Guo et al., 2016, p. 24758). A study of the role of the logistics industry in the economies of Southeast Asian countries concluded that logistics has a significant impact on GDP growth and greenhouse gas emissions (Nguyen, 2021, p.1681). EPI and LPI have been among the main indexes used to study logistics' effect on the environment. An index combining LPI and EPI has examined countries' logistics performance and environmental quality. Using the hybrid index, they concluded that increasing logistical efficiency and higher national income levels would increase emissions and environmental degradation (Kim & Min, 2011, p.1169). In the MENA research, the LPI and EPI hybrid index showed that economic development weakens environmental performance (El-Nakib & Elzarka, 2014, p.10). Using LPI and EPI for research can be challenging since the most recent data for LPI dates back to 2018, and the current index values are not yet available. LPI updates are expected to increase the number of studies on this subject.

Companies are also changing how their supply chains operate following the sustainability concept, which is defined as satisfying present requirements without harming the ability of future generations to satisfy their own needs. All processes that have evolved in supply chain management, including but not limited to raw material supply, manufacturing, distribution, usage, end-of-life processes, and waste, must be reorganized following economic, social, and environmental sustainability principles in the sustainable supply chain. (Bílgín, 2021, p. 123-141). The advancement of an organization's overall performance is significantly facilitated by sustainable supply chain management. Academic studies provided compelling evidence that sustainability efforts have the potential to have a direct impact on the supply chain's operations, including manufacturing, shipping, and purchasing(Aylak, 2022, p. 105–108). Environmental education, internal environmental management, investment recovery, green purchasing, manufacturing, distribution, packaging, and marketing have all been identified as critical components of green supply chain management. The analysis of Turkish manufacturing firms to investigate the impact of these dimensions on economic, environmental, and social performance revealed that, except for green purchasing, all green supply chain management dimensions showed at least one relationship with the above state performance measures(Yildiz Çankaya & Sezen, 2019, p. 98). The correlation between sustainable development governance, organizational knowledge, sustainable organizational development, and corporate sustainability was established in a linked academic study on corporate sustainability management and performance. These are the primary factors influencing corporate environmental and sustainability management(Lăzăroiu et al., 2020, p. 1–2). The direct impact of green logistics management methods on environmental, social, market, and financial performance has been researched. The research findings indicated the need for additional resources on green logistics management practice areas such as, but not limited to, sustainable energy, recycling, sustainable transportation and distribution, sustainable warehousing, and green product packaging in order to achieve environmental goals, which would result in increased financial and market performance of firms(Agyabeng-Mensah et al., 2020, p. 11).

Methodology

Cluster analysis was developed in the 1930's as a branch of multivariate statistical analysis. The technique did not gain traction until the release of Sokal and Sneath's book on numerical taxonomy in biology in 1963. The cluster analysis usage has been extended in several disciplines (Blashfield, 1976, p.377). The primary objective of clustering analysis is to generate clusters to maximize intraclass similarity while decreasing interclass similarity. The degree of similarity within a group and diversity between groups mainly determine the effectiveness of clusters (Phanich et al., 2010, p.2). The cluster analysis algorithms can be categorized as hierarchical and non-hierarchical based on their algorithm structure. Agglomerate and divisive are the two subcategories of the hierarchical category. The key subcategories of non-hierarchical methods are partitioning, density-based, grid-based, and others (Ma & Chow, 2004, p.503). The algorithms of the hierarchical class gather the most two similar objects in a cluster (Revelle, 1979,p.58-60). Non-hierarchical clustering techniques directly cluster the data. Algorithms in this group generally alter centers until all points are associated with the centers.

Non-hierarchical classification is more efficient than hierarchical classification in terms of computing time. In the non-hierarchical category, partitioning is the most common type. The partitioning method often relocates the cluster's center until all points are within a certain distance from their respective centers. The most popular example of a partitioning methodology is the K-Means algorithm (Taşkın & Emel, 2010, p.400). Implementation ease and simplicity, speed of convergence, and adaptation to sparse data are the significant reasons influencing the algorithm's widespread use among other cluster algorithms (Oyelade et al., 2010, p.293). K-means clustering is one of the unsupervised machine learning techniques used to cluster data into k classes, where k denotes the number of categories the analyst has pre-specified. The K-Means algorithm divides data into k number of groups so that objects within the same cluster are as similar as possible and objects from other clusters are as distinct as possible. The centers in K-Means clustering represent each cluster. The center is the mean of the points assigned to the cluster (Kassambara, 2017, p.36). The grouping is accomplished by minimizing the sum of squares of distances between the data and the cluster centroid (Teknomo, 2006, p.1). The centroid coordinates are assigned at random in the start phase of the K-Means classification process. The distances from data to centroid points have been calculated as the first steps of the algorithm. In the second step, data is assigned to the cluster where it is closest to the cluster's center point. The primary purpose of the algorithm mentioned above is to find cluster divisions that minimize the Within-Cluster Sum of Squares (WCCS), for which a formula is provided in Equation 1, where cluster centers are defined as points c_i (Miniak-Górecka et al., 2022, p. 3).

$$WCCS = \sum_{i=1}^{k} \sum_{x_j \in c_i} \left\| x_j - c_i \right\| \text{ in where} \qquad (1)$$

$$c_i = \text{mean}(x_j \in c_i)$$

Coordinate averages are taken from the data assigned to the related clusters, and the corresponding average is assigned as the new center point of the cluster. The distances of each data to the new center points are calculated. Data are assigned to one cluster with a minimum distance to the cluster center points. This process can be repeated a predetermined number of times, or no change in center points has been recorded (Demir et al., 2018, p.51).

The analyst should determine the number of clusters before starting the algorithm. At this stage, researchers predominantly use the elbow method to determine the optimal k value. One of the critical metrics for choosing the ideal number of clusters is the elbow point.

In the elbow method, inertia is the sum of the squares' distances from each data point to its nearest center. In a graph where inertia and cluster numbers are plotted, the elbow point is where inertia decreases linearly after a certain level of cluster numbers (Chen et al., 2021, p.285). The Elbow Method selects the best possible value of k depending on the distance between the data points and their allocated clusters using the sum of squared distance (SSE). In Equation 2, the SSE formula is as follows(Nikmah et al., 2023, p. 23).

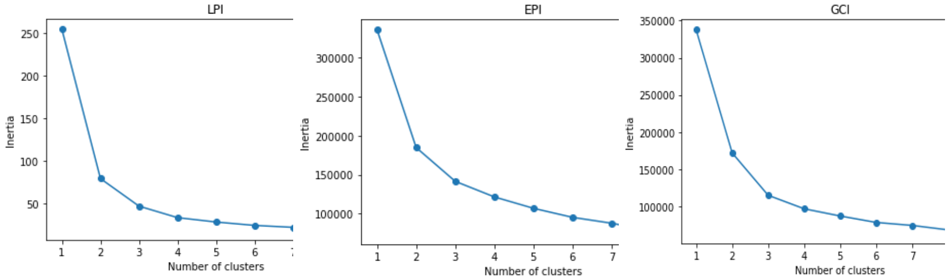
$$SSE = \sum_{i=1}^{k} \sum_{x \in C_i} dist^2(m_i, x) \tag{2}$$

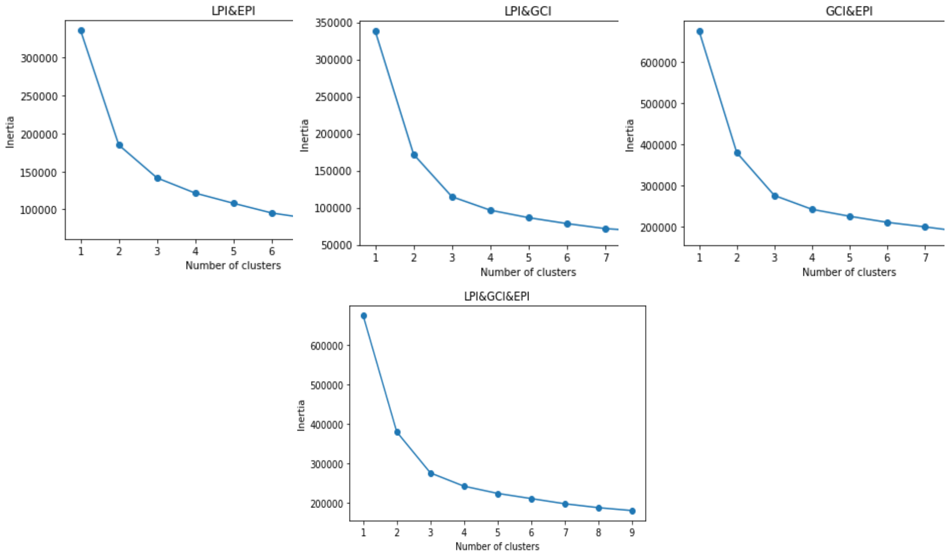
where k is the number of created clusters,C_i represents cluster i, m_i represents the center of cluster i, and $dist^2(m_i,x)$ represents the distance between data point x and the center of cluster m_i.

This study focused on the LPI, EPI, and GCI among the leading supply chain-related indexes. Customs, infrastructure, International shipments, Logistics Quality & Competence, Tracking & Tracing, and Timeliness are all LPI indicators chosen to be included in the research. GCI dataset consists of all 12 indicators of the GCI: Institutions, Infrastructure, ICT Adoption, Macroeconomic Stability, Health, Skills, Product Market, Labor Market, Financial System, Market Size, Business Dynamism, and Innovation Capability. In EPI, indicator selection is based on issue categories. Air Quality, Water & Sanitation, Heavy Metals, Climate & Energy, and Air Pollution are selected indicators to be included in the EPI dataset, and countries are clustered using non-hierarchical clustering analysis based on specified datasets.

The datasets for LPI, EPI, GCI, LPI&EPI, LPI&GCI, EPI&GCI, and LPI&EPI&GCI for 216 countries have been obtained for 2018. Countries are clustered using non-hierarchical clustering analysis based on specified datasets. Using Python 3.9, we performed the k-means cluster analysis method described above. The K-means clustering algorithm's ideal value for K is determined using the elbow method. Elbow plots were charted between inertia and k values ranging from 1 to 9 for each dataset in the figure below.

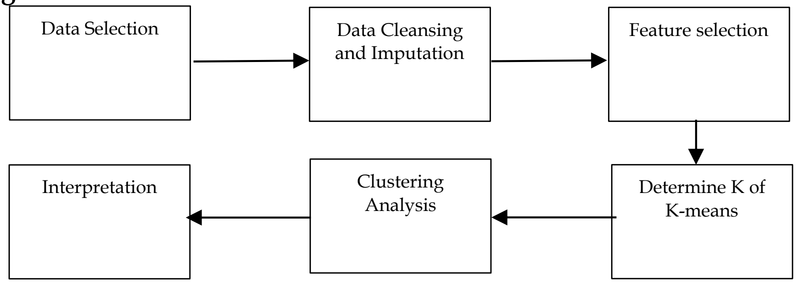
Figure 1. Prediction for Number of Clusters k Value Using Elbow Method





The above graphs clearly show that there has been a significant decrease in the number of clusters from 2 to 3, so the K value for all datasets has been determined as 3 in this study. Each clustering analysis divided the countries into C1, C2, and C3 groups. The basic steps of the analysis are summarized in Figure 2.

Figure 2. Flowchart of Research



Results and Discussions

The relationship between supply chain activities of countries and supply chain-related indicators has been the subject of numerous studies in the literature (Ekici et al., 2019; Liu et al., 2018; Magazzino et al., 2021; Mariano et al., 2017). It is seen that clustering analysis studies are carried out for their countries only in a limited number of the studies (Bazani et al., 2020; Kálmán & Tóth, 2021; Roy et al., 2018). Cluster analysis with many indicators drawn from various indicators has not been an intensive research area. Six individual cluster evaluations, namely LPI, EPI, GCI, LPI&EPI, LPI&GCI, EPI&GCI, and LPI&EPI&GCI have been conducted.

Each clustering analysis divided the countries into C1, C2, and C3 groups. The indicator's central points have been calculated for each data set, and changes in centroid have been analyzed. The data sets' center points have been set as the reference value for each cluster C1 to C3, and the center points of other data sets have been submitted as the percentage deviation from the anchor point. A deviation from the anchor point is one of the most critical indicators when interpreting the effect of adding an index or indexes to the datasets.

Countries are categorized as the top (C1), middle (C2), and low (C3) performers in the classification based on the LPI, GCI, LPI-GCI, GCI-EPI, and LPI-GCI-EPI data sets. The top performer countries are ranked as C1 in EPI and LPI-EPI datasets. Except for Air Pollution and Climate&Energy, the C3 class has the lowest center points in all categories. Countries in the C3 category are classified as middle performers in these categories. Because the lowest and middle-level center points of the Air Pollution and Climate&Energy categories are so close to each other, they should be considered during the evaluation phase. Each indicator center point value supports this situation, which have been submitted in Table 5.

The relevant results have been submitted at hereunder tables

Table 1. Cluster-Based Central Points: LPI indicators

Class	Dataset	Customs	Infra-structure	International Shipments	Logistics Quality and Competence	Tracking and Tracing	Timeliness
C1	LPI	3.62	3.86	3.61	3.85	3.90	4.12
	LPI-EPI	-8.2%	-9.7%	-7.3%	-8.8%	-8.7%	-6.7%
	LPI-GCI	-2.6%	-3.1%	-3.2%	-3.2%	-3.2%	-2.5%
	LPI-GCI-EPI	-2.6%	-3.1%	-3.2%	-3.2%	-3.2%	-2.5%
C2	LPI	2.81	2.90	3.00	2.99	3.08	3.43
	LPI-EPI	-7.0%	-8.3%	-6.2%	-8.3%	-7.5%	-5.5%
	LPI-GCI	-7.0%	-8.3%	-5.8%	-7.9%	-7.2%	-5.2%
	LPI-GCI-EPI	-4.6%	-6.0%	-4.0%	-6.0%	-5.5%	-3.4%
C3	LPI	2.29	2.26	2.53	2.40	2.49	2.88
	LPI-EPI	1.9%	3.5%	3.9%	4.6%	4.3%	1.6%
	LPI-GCI	-2.1%	-1.9%	0.4%	0.3%	-0.3%	-2.7%
	LPI-GCI-EPI	0.0%	1.4%	2.2%	2.7%	2.2%	-0.1%

Center points of C1 and C2 segments attained the highest values in the LPI data set. On C3, the LPI-EPI dataset showed the highest value of center points. Among the LPI indicators on LPI dataset, the highest center point belongs to Timeliness for all classes. International shipments with the lowest center point in the C1 class should be considered one of the significant fields in which high-performing countries on the LPI should focus more on improvement. The maximum center point change on LPI indicators in the C1 class occurred at -9.7% on the Infrastructure indicator, which uses LPI-EPI datasets. On C2, the greatest change occurred on the Infrastructure indicator with -8.3%. Among the other datasets, the LPI-EPI dataset displayed the highest average center point decrease, with 8.2% on C1 and 7.1% on C2. For the same dataset on C3, a 3.3% increase has occurred. LPI-EPI dataset showed no center point chance for EPI indicators in all classes, as shown in Table 3. The status is an important indicator to examine in class C1 and C2 countries on LPI-EPI and LPI and EPI datasets.

Table 2. Cluster-Based Central Points: GCI Indicators

Class	Data set	Institutions	Infrastructure	ICT Adoption	Macroeconomic Stability	Health	Skills
C1	GCI	70.59	83.55	73.97	98.24	94.30	77.49
	GCI-EPI	0.4%	0.4%	0.2%	-0.1%	0.8%	1.0%
	GCI-LPI	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	LPI-GCI-EPI	0.5%	0.7%	0.0%	-0.2%	1.2%	1.0%
C2	GCI	52.48	66.92	53.48	78.35	79.89	62.14
	GCI-EPI	1.2%	1.3%	5.0%	-0.2%	2.2%	2.0%
	GCI-LPI	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	LPI-GCI-EPI	2.7%	1.9%	6.6%	2.5%	2.5%	2.7%
C3	GCI	44.75	43.98	28.54	63.33	48.93	41.53
	GCI-EPI	3.0%	6.8%	2.1%	6.9%	4.1%	3.6%
	GCI-LPI	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	LPI-GCI-EPI	-1.0%	1.4%	2.4%	-3.5%	2.7%	1.7%

Class	Data set	Product Market	Labor Market	Financial System	Market Size	Business Dynamism	Innovation Capability
C1	GCI	66.00	69.82	78.92	67.34	72.98	68.37
	GCI-EPI	-0.2%	0.6%	-0.3%	-2.2%	0.6%	1.8%
	GCI-LPI	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	LPI-GCI-EPI	-0.2%	0.7%	0.3%	-1.1%	0.8%	2.6%
C2	GCI	55.22	57.25	59.30	55.28	58.10	36.96
	GCI-EPI	0.7%	0.6%	1.4%	1.9%	0.4%	2.4%
	GCI-LPI	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	LPI-GCI-EPI	1.7%	1.6%	2.0%	0.9%	1.8%	3.3%
C3	GCI	48.70	51.77	48.20	40.93	48.32	27.78
	GCI-EPI	2.8%	1.8%	4.4%	6.7%	3.9%	5.1%
	GCI-LPI	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	LPI-GCI-EPI	-0.7%	-0.7%	0.3%	2.8%	-1.0%	1.0%

As a result, the overall mean values of the central points in the GCI dataset for C1, C2, and C3 are 76.79, 59.61, and 44.73, respectively. The standard deviation values in the same order are calculated as 10.02, 11.07, and 9.26. 77.01, 76.80, and 77.21 are the mean values of the class C1 center points for GCI-EPI, GCI-LPI, and LPI-GCI-EPI. The corresponding value's standard deviations are calculated as 10.14, 10.01, and 10.09. This is an essential factor to be considered because GCI indicators exhibit minimal variation in all classes. For C1, in an analysis of the LPI-GCI-EPI dataset, the maximum change was found in a class on the Innovation capability indicator with a value of 2,6%. The Class C2 maximum change, being 6.6%, was found on the ICT Adoption indicator on analyzing LPI-GCI-EPI datasets. Based on the analysis of Class C3, the maximum difference value was calculated using the GCI-EPI dataset as the macroeconomic stability indicator. Since the overall mean value for the percentage change is only 1.07%, and the standard deviation for the percentage change is 0,002, the stated figures could be considered outliner values.

Table 3. Cluster-Based Central Points: EPI indicators

Class	Data set	Air Quality	Water and Sanitation	Heavy Metals	Climate and Energy	Air Pollution
C1	EPI	82.15	86.83	80.24	60.19	68.62
	EPI-GCI	6.0%	5.9%	3.1%	0.8%	2.5%
	EPI-LPI	0.0%	0.0%	0.0%	0.0%	0.0%
	EPI-GCI-LPI	6.3%	7.2%	2.8%	2.2%	3.2%
C2	EPI	75.19	58.00	52.54	45.83	41.09
	EPI-GCI	-3.5%	4.8%	7.3%	6.8%	12.1%

	EPI-LPI	0.0%	0.0%	0.0%	0.0%	0.0%
	EPI-GCI-LPI	-4.1%	5.8%	10.1%	6.4%	13.1%
C3	EPI	46.13	16.54	34.70	48.76	42.88
	EPI-GCI	1.6%	-11.8%	-1.1%	-1.5%	-1.3%
	EPI-LPI	0.0%	0.0%	0.0%	0.0%	0.0%
	EPI-GCI-LPI	6.8%	-2.8%	-2.0%	-1.6%	-1.9%

The EPI-LPI datasets provided the most critical indicator in the preceding table. It is emphasized that countries that want to improve their EPI-LPI performance should prioritize EPI indicators.

Evaluating the difference in the highest and lowest performer classes' central points is crucial. The magnitude of the difference in the clusters' center points is an essential indicator in determining the place and weight of the relevant factor in the classification evaluation. Increasing magnitude requires a more precise evaluation of indicators in determining classification conclusions.

Table 4. Dataset-Based Central Points Difference: LPI Indicators

Dataset	Classes	Customs	Infrastructure	International Shipments	Logistics Quality and Competence	Tracking and Tracing	Timeliness
LPI	C1-C3	1,33	1,60	1,08	1,45	1,41	1,24
	C1-C2	0,81	0,96	0,60	0,86	0,83	0,68
	C2-C3	0,52	0,64	0,48	0,59	0,58	0,56
LPI-EPI	C1-C3	0,99	1,15	0,72	1,00	0,96	0,92
	C1-C2	0,92	1,08	0,67	0,98	0,92	0,76
	C2-C3	0,28	0,32	0,19	0,23	0,24	0,32
LPI-GCI	C1-C3	1,29	1,52	0,95	1,32	1,29	1,21
	C1-C2	0,92	1,08	0,67	0,98	0,92	0,76
	C2-C3	0,37	0,44	0,29	0,34	0,37	0,45
LPI-GCI-EPI	C1-C3	1,26	1,47	0,90	1,29	1,26	1,14
	C1-C2	0,86	1,04	0,60	0,95	0,90	0,70
	C2-C3	0,39	0,43	0,30	0,34	0,36	0,44

The most significant difference between the top-performing and the lowest-performing countries in the LPI dataset is in infrastructure, which is the most central message of the table as mentioned earlier. When the LPI data set's C1-C2 and C2-C3 values are examined, it has been reported that the primary indicator is that the way to improve logistics performance is primarily through infrastructure investments.

Table 5. Dataset-Based Central Points Difference: GCI Indicators

Dataset	Classes	Institutions	Infrastructure	ICT Adoption	Macroeconomic Stability	Health	Skills
	C1-C3	25,84	39,58	45,44	34,92	45,37	35,96
	C1-C2	18,10	16,63	20,50	19,90	14,40	15,35
GCI	C2-C3	7,74	22,94	24,94	15,02	30,97	20,61
	C1-C3	24,78	36,94	44,96	30,40	44,15	35,24
	C1-C2	17,78	16,09	17,94	19,97	13,46	14,92
GCI-EPI	C2-C3	7,00	20,85	27,02	10,43	30,69	20,32
	C1-C3	25,84	39,58	45,44	34,92	45,37	35,96
	C1-C2	18,10	16,63	20,50	19,90	14,40	15,35
GCI-LPI	C2-C3	7,74	22,94	24,94	15,02	30,97	20,61
	C1-C3	25,29	36,55	44,16	32,69	43,09	34,50
LPI-GCI-	C1-C2	17,02	15,95	16,98	17,75	13,54	14,45
EPI	C2-C3	8,27	20,60	27,18	14,93	29,55	20,05

Dataset	Classes	Product Market	Labor Market	Financial System	Market Size	Business Dynamism	Innovation Capability
GCI	C1-C3	17,30	18,05	30,72	26,41	24,66	40,59
	C1-C2	10,79	12,57	19,63	12,06	14,88	31,41
	C2-C3	6,51	5,48	11,09	14,35	9,78	9,17
GCI-EPI	C1-C3	15,80	17,53	28,41	22,22	23,18	40,41
	C1-C2	10,23	12,67	18,60	9,55	15,04	31,78
	C2-C3	5,56	4,87	9,81	12,67	8,13	8,63
GCI-LPI	C1-C3	17,30	18,05	30,72	26,41	24,66	40,59
	C1-C2	10,79	12,57	19,63	12,06	14,88	31,41
	C2-C3	6,51	5,48	11,09	14,35	9,78	9,17
LPI-GCI-EPI	C1-C3	16,18	17,93	28,66	21,73	23,83	40,67
	C1-C2	9,71	12,12	18,68	10,88	14,40	31,97
	C2-C3	6,47	5,81	9,99	10,86	9,43	8,70

As shown in the above table, ICT adoption accounts for most of the variance between the highest-performing and lowest-performing clusters. This distinction emphasizes the importance of the pertinent indicator for validity across all datasets. Another topic to observe is the product and labor markets, where there is minimal interest difference. Regardless of their class, it is crucial to understand that the countries must take the necessary steps to improve the performance of these two fields. This is evident when the values of the related fields in Table 2 are evaluated.

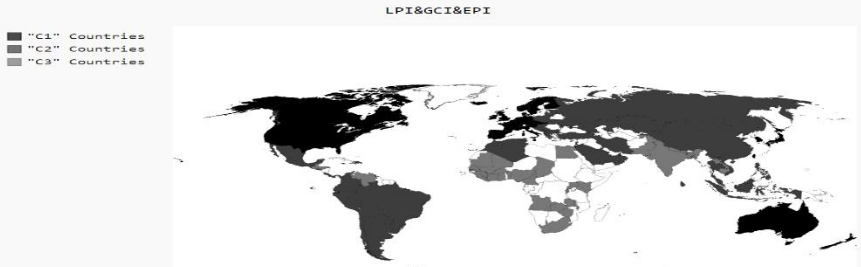
Table 6. Dataset-Based Central Points Difference: EPI Indicators

Dataset	Classes	Air Quality	Water and Sanitation	Heavy Metals	Climate and Energy	Air Pollution
EPI	C1-C3	36.02	70.30	45.54	11.43	25.74
	C1-C2	6.96	28.84	27.70	14.37	27.53
	C2-C3	29.06	41.46	17.84	-2.94	-1.79
EPI-GCI	C1-C3	40.15	77.39	48.38	12.62	27.99
	C1-C2	14.47	31.21	26.34	11.71	24.24
	C2-C3	25.68	46.17	22.04	0.91	3.75
EPI-LPI	C1-C3	36.02	70.30	45.54	11.43	25.74
	C1-C2	6.96	28.84	27.70	14.37	27.53
	C2-C3	29.06	41.46	17.84	-2.94	-1.79
EPI-GCI-LPI	C1-C3	38.04	76.97	48.50	13.57	28.76
	C1-C2	15.20	31.68	24.66	12.76	24.34
	C2-C3	22.84	45.28	23.84	0.80	4.42

In Water & Sanitation compared to other indicators, significant differences exist. The most significant disparity between high- and low-performer countries is in Water & Sanitation. This reveals the seriousness of the relevant situation, which remains the case for all data sets and other group differences. One factor that should be emphasized is the importance of providing international assistance to improve the performance of middle and low-income countries in this field.

Based on the calculation results, clustering map was generated using Python Pygal. The map is submitted in Figure 2

Figure 2. Clusters of Countries Based on LPI; GCI and EPI



An analysis of cluster information based on continents and sub-regions, least developed countries status, and developed economies would lead to essential insights. Information about the location of the countries is taken from the website of The United Nations Statistics Division. As Taiwan is not included in the UN source, the region, and subregion-based cluster analysis results were submitted only for 125 countries in the following table(Standard Country or Area Codes for Statistical Use, 2023; Statistical Annex, 2023)

Table 7. Region And Subregion Based Cluster Analysis Results

		LPI			GCI			EPI		
Region Name	Sub-region Name	C1	C2	C3	C1	C2	C3	C1	C2	C3
Africa	Northern Africa		1	3		4			4	
	Sub-Saharan Africa		5	20		2	23		1	24
Total Africa			6	23		6	23		5	24
Americas	Latin America and the Caribbean		9	11	1	17	2		17	3
	Northern America	2			2			2		
Total Americas		2	9	11	3	17	2	2	17	3
Asia	Central Asia		1	2		3			2	1
	Eastern Asia	3		1	3	1		2	1	1
	South-eastern Asia	1	5	3	2	5	2	1	5	3
	Southern Asia		2	4		4	2		2	4
	Western Asia	2	7	4	3	10		3	10	
Total Asia		6	15	14	8	23	4	6	20	9
Europe	Eastern Europe	2	5	1	1	7		6	2	
	Northern Europe	6	4		8	2		9	1	
	Southern Europe	3	6	3	5	7		11	1	
	Western Europe	7			7			7		
Total Europe		18	15	4	21	16		33	4	
TotalOceania(Australia and New Zealand)		2			2			2		
Total		28	45	52	34	62	29	43	46	36

		LPI-GCI			GCI-EPI			LPI-EPI			LPI-EPI-GCI			
Region Name	Sub-region Name	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	Total
Africa	Northern Africa		4			4			4			3	1	4
	Sub-Saharan Africa		2	23		1	24		1	24		1	24	25
Total Africa			6	23		5	24		5	24		4	25	29
Americas	Latin America	1	17	2		17	3		17	3		16	4	20

	and the Caribbean													
	Northern America	2			2			2			2			2
Total Americas		3	17	2	2	17	3	2	17	3	2	16	4	22
Asia	Central Asia		3			2	1		2	1		2	1	3
	Eastern Asia	3	1		2	2		2	1	1	2	2		4
	South-eastern Asia	2	5	2	1	6	2	1	5	3	1	6	2	9
	Southern Asia		4	2		2	4		2	4		2	4	6
	Western Asia	3	10		2	11		3	10		2	11		13
Total Asia		8	23	4	5	23	7	6	20	9	5	23	7	35
Europe	Eastern Europe	1	7		2	6		6	2		2	6		8
	Northern Europe	8	2		8	2		9	1		7	3		10
	Southern Europe	5	7		5	7		11	1		5	7		12
	Western Europe	7			7			7			7			7
Total Europe		21	16		22	15		33	4		21	16		37
TotalOceania (Australia and New Zealand)		2			2			2			2			2
Total		34	62	29	31	60	34	43	46	36	30	59	36	125

For all datasets for which the analysis was completed, the most important information conveyed by Figure 1 and Table 7 is that the geographical location of the countries may be an essential relationship between clusters. Based on the map and values for the continent and sub-region, it is evident that most countries nearby are in the same or close cluster. The relationship between geographic location and LPI, EPI, and GCI have been the subject of numerous analyses (Bucher, 2016; Lukáč et al., 2020; Mešić et al., 2022; Sala-i-Martin et al., 2007, 2015).

Table 8. Cluster Analysis Results for Least Developed Countries

		LPI		GCI		EPI	LPI-GCI		GCI-EPI	LPI-EPI	LPI-EPI-GCI	
Region Name	Sub-region Name	C2	C3	C2	C3	C3	C2	C3	C3	C3	C3	Total
Africa	Sub-Saharan Africa	1	16		17	17		17	17	17	17	17
Total Africa		1	16		17	17		17	17	17	17	17
Americas	LatinAmerica and the Caribbean		1		1	1		1	1	1	1	1
Total Americas			1		1	1		1	1	1	1	1
Asia	South-eastern Asia		2		2	2		2	2	2	2	2
	Southern Asia		2	1	1	2	1	1	2	2	2	2
Total Asia			4	1	3	4	1	3	4	4	4	4
Total		1	21	1	21	22	1	21	22	22	22	22

Table 9. Cluster Analysis Results on Developed Economies

	LPI		GCI		EPI		LPI-GCI		GCI-EPI		LPI-EPI		LPI-EPI-GCI		
Region / Sub-region	C1	C2	C1	C2	C1	C2	C1	C2	C1	C2	C1	C2	C1	C2	Total

Name															
Americas	2		2		2		2		2		2		2		2
Northern America	2		2		2		2		2		2		2		2
Asia	1	1	1	1	2		1	1	1	1	2		1	1	2
Eastern Asia	1		1		1		1		1		1		1		1
Western Asia		1		1	1			1		1	1			1	1
Europe	18	11	21	8	28	1	21	8	22	7	28	1	21	8	29
Eastern Europe	2	3	1	4	5		1	4	2	3	5		2	3	5
Northern Europe	6	4	8	2	9	1	8	2	8	2	9	1	7	3	10
Southern Europe	3	4	5	2	7		5	2	5	2	7		5	2	7
Western Europe	7		7		7		7		7		7		7		7
Oceania	2		2		2		2		2		2		2		2
Australia and New Zealand	2		2		2		2		2		2		2		2
Total	23	12	26	9	34	1	26	9	27	8	34	1	26	9	35

Above are two tables illustrating the relationship between supply chain indicators performance, country clusters, and economic development levels of countries. Based on all supply chain-related indicators, which are considered based on the highest and lowest sub-segments, it can be seen that the economic development level of the countries is filled in an essential and decisive position.

Conclusion

The purpose of this document is to contribute to the discussion within the literature stream on Supply Chain Management Performance Rankings. This paper offers valuable insights into the performance of the countries' supply chains on a benchmark basis. In this paper, we proposed a three-stage methodological framework for mining supply chain-related indicators derived from multiple indexes, which helps facilitate comprehensive insights into changes in countries' structures and clusters. The first step is to cluster each dataset separately. The main goal is to learn the core characteristics of the clusters created by each data set, as well as the analysis of the countries within the relevant cluster. The second step is to cluster and analyze the datasets generated by the pairwise-aggregated indices. In the final phase, all related indicators are unified under a single dataset, and the final cluster analysis is conducted. Changes in center points based on indicators, the variance based on data sets between clusters, and the grouping of countries according to each combination of data sets is the leading analysis carried out for this research.

The cluster analysis results of 23 indicators retrieved from three significant supply chain-related indexes, LPI, GCI, and EPI, revealed a need for improvement in all indicators. The level of economic development of the countries concerned is an essential and decisive factor in the clustering of countries

Our results demonstrated that geographical zones significantly impact logistics, governance, and environmental performance. Our findings show that high-income countries rank highly in logistics, governance, and environmental performance. America and Northern America have the best performance regions and sub-regions across all datasets. It will take much work for least developed countries to improve their performance and upscale their clusters from low performers.

The study was done on 2018 LPI data, which comprised 160 countries, employed k-means, k-medoids, and clustering big applications techniques (Ulkhaq,2023,p.1010). It can be seen that the findings obtained are highly close to the results of our study.

According to a published LPI cluster analysis study, developed countries predominately comprise the cluster of top-performing countries(Bazani et al., 2020, p. 38). Clearly, the current study's findings lend credence to the previous research.

The research conducted by Civelek etc has demonstrated the statistically significant mediating effect of the LPI on the relationship between GCI and GDP(Civelek et al., 2015, p. 368).

Our findings reveal that the LPI indicators' center points differ in clustering analyses using LPI and LPI & GCI data sets. The related studies have highlighted the significance of further research into the interactions of LPI and GCI.

Comparing Anuşlu & Fırat's research on cluster analysis utilizing the Global Innovation Index, Sustainable Development Goals Index, LPI, and EPI with our LPI&GCI&EPI cluster analysis results, significant similarities in country clusters have been identified. The most significant difference between the two studies is that China is in the second cluster in the current analysis, whereas it is in the third cluster in Anuşlu & Fırat's study(Anuşlu, Fırat,2019, p.150:151). It is crucial to conduct research focused on China and neighboring countries in future studies.

The significance of the research for supply chain management policymakers is that it guides on the relative importance of the relevant aspects and identifies the elements to be prioritized to improve the current position.

In future studies, comparisons and interpretations with clusters based on different indices and indicators can be made. Increasing the number of countries in future studies will give us more detailed information on the subject. Also, in future studies, it will be possible to compare the results by using different clustering techniques.

We conclude that there was a significant link between the indicators included in the supply chain indicators and the country's overall economic performance. The cluster analysis obtained with the indices reviewed is thought to contribute to the literature on supply chain and country progress relationships.

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Benzerlik Taraması	Yapıldı – Ithenticate
Etik Bildirim	itobiad@itobiad.com
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