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Clustering Countries on Logistics Performance and Carbon Dioxide (CO_2) Emission Efficiency: An Empirical Analysis

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Abstract: *The logistics industry is among the industries that affect carbon dioxide emissions. The logistics activities of the countries produce CO_2 emissions. For this reason, there is a significant relationship between the logistics performance of countries and their CO_2 emissions. In this study, it is aimed to make a cluster analysis by considering the CO_2 emission per capita efficiency of the countries and their logistics performance. The empirical study was completed in three stages. In the first stage, hierarchical clustering analysis was conducted with the logistics performances of the countries and the CO_2 emission per capita. In the second stage, the CO_2 emission per capita efficiency based on the logistics performance sub-indicators of the countries were determined by data envelopment analysis. In the third stage, non-hierarchical clustering analysis was performed with the variables of logistics performances and CO_2 emission per capita efficiency of the countries. 2018 logistics performance index (LPI) and CO_2 emission per capita data of 150 countries were used. According to the research findings, there are differences in the findings of hierarchical clustering analysis and non-hierarchical clustering analysis. In the conclusion part of the study, the differences between the clusters were explained and suggestions were developed for the researchers.*

Keywords: Logistics Performance, Carbon Dioxide (CO_2) Emission, Hierarchical Clustering Analysis, Non-Hierarchical Clustering Analysis, Data Envelopment Analysis

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1. Introduction

Today, rapid technology development and increasing industrialization lead to an increase in environmental pollution. Environmental pollution brings with it the problem of global warming. The biggest factor causing global warming is the emission of carbon dioxide gas (CO_2) (Adams & Acheampong, 2019). Although there have been efforts to use renewable energy recently, logistics activities are mainly based on energies obtained from fossil fuels (Khan, 2019). For this reason, the logistics industry is among the industries that affect the CO_2emission, which is the natural result of fossil fuel energy use. Antoni et al. (2015) state that the amount of CO_2 emissions created by logistics activities (transportation, storage, handling etc.) ranks second after the amount of CO_2 emissions created by energy production. As in all industries, it is seen that studies to reduce CO_2 emissions in the logistics industry are discussed in the literature (Jamali & Rasti-Barzoki, 2019).

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To achieve minimum CO_2 emissions in logistics activities, which are among the indispensable elements of global trade, and especially in transportation activities, the efficiency of logistics performance should be maximized. Thus, it can be ensured that the CO_2 emissions arising from logistics activities are reduced to an acceptable level. Jiang et al (2020) suggest that strong logistics and transportation strategies can be developed by determining the CO_2 efficiency level based on logistics activities. Yang et al. (2019) explained that by considering the CO_2 emission performance from a logistics perspective, the CO_2 emission efficiency of the cities can be calculated, so that the logistics and CO_2 emission strategies of the cities can be created. Guo et al (2016), on the other hand, explain that there is a significant relationship between countries' Gross domestic product (GDP), logistics volumes and CO_2 emissions. It has also been clearly demonstrated that CO_2 emissions will increase with the increase in logistics volume and GDP. At this point, it becomes clear that logistics activity volumes should be considered for countries to reach effective CO_2 emission values.

Considering the CO_2 emissions in 2018, the top five countries in the world are China (10313460 kt.), United States (4981300 kt.), India (2434520 kt.), Russian Federation (1607550 kt.) and Japan (1106150 kt.). When the ranking is examined, it is understood that the CO_2 emissions of developed and developing countries are high. In least developed countries (LDCs), however, CO_2 emissions are at a lower level. In terms of CO_2 emissions per capita in 2018, the scores of LDCs are higher. This indicates that countries with different perspectives on CO_2 emissions can take place in different rankings and different classifications. In this study, it is aimed to make a classification based on the relationship between logistics performance and CO_2 emissions per capita. At this point, it is goaled to make country classifications based on these two variables, considering the logistics performances and CO_2 emissions per capita of the countries. In line with this aim and goal, 3 basic research questions belonging to our research are developed. These are as follows:

(1) Can a successful classification be made considering the logistics performances of the countries and the per capita CO_2 emissions?

(2) Can a successful classification be made when considering the per capita CO_2 emission efficiency values based on the logistics performances of the countries and their logistics performance?

(3) Are there differences between country classifications?

In this study, it is aimed to evaluate the CO_2 emissions of the countries by considering their logistics activities. For this reason, the logistics performance indicators of the countries were determined as input variables and CO_2 emissions as output variables. With this model structure, it tests whether CO_2 emissions are at the desired point or not for the logistics activities of the countries. Of course, there are many factors that affect CO_2 emissions. However, an evaluation of the research was made by considering logistics. To answer the research questions identified above, this empirical research is handled. In the second section, the conceptual framework and literature review of the logistics performance and CO_2 emissions, which are discussed within the scope of the research, are included. In the third section, namely the methodology section, hierarchical clustering analysis, non-hierarchical clustering analysis and data envelopment analysis (DEA), which are planned to be applied in the research, are explained. In the fourth section, the variables, sample area and findings of the empirical study are explained. In the fifth section, the results, implications, and suggestions are given.

2. Conceptual Framework and Literature Review

2.1. Logistics Performance

Logistics activities are among the main activities that play an active role in the national and international trade activities of countries. Logistics activities, which have a complementary role in the successful realization of trade activities, also create added value. On the other hand, failure in the implementation of logistics activities negatively affects trade activities. At this point, the concept of logistics performance emerges. Logistics performance is the degree to which the previously planned logistics activities reach the qualitative and quantitative targets determined at the end of the planned period (Bakan & Şekkeli, 2016). It is relatively easy to identify logistics performance at the individual and organizational level.

However, efforts to determine the logistics performance of countries should be large-scale. In this context, the logistics performance index (LPI) was developed by *World Bank* to determine the logistics performance scores of countries (Arvis et al., 2018). The logistics performance index, which was published for the first time in 2007, was published regularly at intervals of two years between 2010 and 2018. In the literature, the relationships between the logistics performances of countries and other variables have been examined. There are studies examining the relationships between logistics performance and competitiveness (Ekici et al., 2016), logistics performance and international trade (Marti et al., 2014a), logistics performance and GDP (Civelek et al., 2015), logistics performance and corruption perception (Uca et al., 2016), logistics performance and environment (Liu et al., 2018), logistics performance and CO_2 emission (Karaduman et al., 2020), logistics performance and green transportation (Lu et al., 2019). This shows that LPI data is used effectively in academic studies.

LPI has a total of 6 sub-indicators. These sub-indicators are "customs, logistics infrastructure, international shipments, logistics quality and competence, tracking and tracing, timeliness". *Customs* points to the success of the operation of customs, which are accepted as transit points in international trade (Martí et al., 2017). The fact that customs are fast and reliable also allows logistics activities to be carried out quickly and reliably. *Logistics infrastructure* points to the basic infrastructure that the country needs to carry out its logistics activities (Göçer et al., 2021). It is expected that the logistics performance of countries with a strong logistics infrastructure will also be high. *International shipments* points to material shipment successes based on import and export activities of countries. Logistics quality and competence refers to the capabilities and total quality of countries in performing logistics activities. There is a significant relationship between logistics capabilities and logistics performance (Limcharoen et al., 2017). *Tracking and tracing* refers to the level of traceability of logistics activities. Logistics activities based on simultaneous information flow and supported by information technologies contribute to the formation of high logistics performance. *Timeliness*, on the other hand, is explained as the success of logistics activities at the desired time. All logistics performance indicators directly contribute to the formation of the general logistics performance scores of the countries.

In the literature, there are different studies that consider LPI overall scores and sub-indicators. In these studies, it is seen that the relationships between different methods and different variables are examined. Studies using LPI scores as data sets are presented in Table 1. Studies in the literature mainly focus on gravity model, regression analysis, panel data analysis, structural equation model. In addition, although there are studies dealing with cluster analysis applications, it is seen that they are not sufficient. In this research, it is aimed to apply cluster analysis and DEA analysis based on the hybrid approach based on the LPI scores of the countries. At the same time, CO_2 emission per capita from an environmental perspective is another variable of the research.

Table 1. LPI Literature Review

Authors	**Variables**	**Methodology**	**Years**	**Findings**
Korinek & Sourdin (2011)	LPI, Global Competitiveness Index (GCI), Enabling Trade Index (ETI)	Gravity model	2010	The low logistic performance creates an obstacle to trade.
Guner & Coskun (2012)	LPI, Socioeconomic factors	Regression analysis	2010	The relationships between LPI and Gross Domestic Product, Gross Domestic Product and Human Development Index are significant.
Marti et al. (2014b)	LPI, International trade	Gravity model	2007-2010	LPI as a good proxy of trade facilitation.
Marti et al. (2014a)	LPI, Trade	Gravity model	2007-2012	All LPI sub-dimensions significantly affect trade flow.
Puertas et al. (2014)	LPI, exports	Gravity model	2007-2012	Logistics is more important in importing countries than in exporting countries.

Table 1. LPI Literature Review (Continue)

Authors	Variables	Methodology	Years	Findings
Erkan (2014)	LPI, GCI	Linear regression analysis	2014	Quality of railroad and port infrastructure significantly affected LPI
Çemberci et al. (2015)	LPI, GCI	Hierarchical regression analysis	2012	GCI moderates the impact of International Transportation, Tracking and Tracing, and Timeliness sub-dimensions on overall LPI.
Civelek et al. (2015)	LPI, GCI, GDP	Hierarchical regression analyses	2007-2014	LPI has a mediating effect.
Uca et al. (2016)	LPI, Corruption Perception Index (CPI), Foreign Trade Volume (FTV)	Hierarchical regression analysis	2007-2014	LPI has a mediating effect in the relationship between CPI and FTV.
Roy et al. (2018)	LPI, per capita GDP	Clustering analysis, multivariate adaptive regression spline regression model	2014	Clustering of countries was made.
Wang & Choi (2018)	LPI, Export volume and import volume	Panel data analysis	2010-2014	As LPI increases, both export and import volumes increase.
Ekici et al. (2019)	LPI, GCI	Regression Analysis	2010-2016	Some GCI sub-dimensions significantly affect LPI.
Kabak et al. (2020)	LPI, GCI	Bayesian Net and Partial Least Square method	2010-2016	Some GCI sub-dimensions significantly affect LPI.
Bugarcic et al. (2020)	LPI, Trade volume	Gravity model		LPI has significant effects on trade volume.
Çelebi et al (2021)	LPI, GDP, Foreign Direct Investment and Patents	Structural equation model	2007-2012	Foreign Direct Investment and Patents have a mediating effect.
Sergi et al. (2021)	LPI, GCI	ANOVA method	2018	Human factor, Infrastructure and Institutes are of critical importance for countries.

2.2. Logistics Performance and CO_2 Emission

CO_2 emissions, which are among the causes of climate change at the global level, are increasing day by day with industrialization. During the industrialization period, manufacturing, construction, and logistics industries are among the main industry areas that affect CO_2 emissions (Xu & Ning, 2020). In addition, the biggest factor causing CO_2 emission in the world since 1990 is the electricity and heat generation industry. Transportation, which is the cornerstone of the logistics industry, comes in second place (Karaduman et al., 2020). Among the environmental outcomes of transportation activities, the one with the worst impact is greenhouse gas (GHG) emissions. CO_2 emission is the most dangerous emission for the environment and global warming among GHG emissions. For this reason, pressures on the logistics industry to reduce CO_2 emissions in the world are increasing (Li & Chen, 2019). In the face of these pressures, both engineering efforts to prevent CO_2 emission in application areas and scientific-based academic efforts are triggered. Mckinnon (2010) examined the relationship between CO_2 and storage in order to achieve minimum CO_2 emissions in the total of logistics activities. It has been suggested in the study that the number of warehouses should be determined and established as a result of the CO_2 emission relationship based on transportation, warehouse and inventory strategies. Here, it is understood that it is of great importance to evaluate the effect on CO_2 emissions by considering all the different fields of activity within the logistics industry. Therefore, it is seen in the literature that studies on the relationship between the total logistics performance of countries and CO_2 emissions are increasing.

The LPI index, which considers all the logistics activities of the countries, provides information on the use of the logistics capabilities of the countries and successful logistics outputs. For this reason, studies examining the relationships between LPI scores, and CO_2 emission scores of countries make explanations about the relationship between logistics and CO_2 at the national level. Karaduman et al. (2020) examined the relationship between the logistics performance of the Balkan countries and the per capita CO_2 emission values using panel data analysis method. In this study, LPI scores and per capita CO_2 emission scores for 2007, 2010, 2012, 2014 and 2016 were used. As a result of the research, it was concluded that there is a positive and significant relationship between the LPI scores of the Balkan countries and the CO_2 emissions per capita. Mariano et al. (2017) applied DEA analysis to improve the low carbon logistics performance index of 104 countries. In the research, the low carbon logistics performance scores of the countries were determined by Malmquist and Window analysis. In addition, CO_2 emissions of countries were used as input variables, sub-factors of LPI and GDP were used as output variables in the study. Liu et al. (2018) determined the relationship between the LPI scores of the countries and the CO_2 emission values in the sample area of 42 Asian countries with the system-generalized method of moment regression analysis. In the research, it was concluded that there is a significant relationship between the logistics performance of the countries and their environmental degradation. Magazzino et al (2021), examining the LPI scores and CO_2 emissions of 25 countries with the best logistics performance scores, found that there is a high level of positive correlation between the success of logistics performance and the CO_2 emissions of countries. Rashidi and Cullinane (2019) have determined the CO_2 emission efficiency levels based on energy use of 22 OECD countries through DEA analysis and conceptualized them as “sustainable operational logistics performance (SOLP)”. Kim and Min (2011) determined the green logistics performance indexes of countries based on LPI and environmental performance index. Environmental performance index has considered the values of environmental health and ecosystem vitality. It is seen that CO_2 emission values are used within the scope of ecosystem vitality values. As a result of the research, the green logistics performance index helps to explain the environmental impact of the countries' logistics competitiveness. Nguyen (2021) analyzed the relationship between LPI and CO_2 emissions of countries in the sample area of Southeast Asian countries by regression analysis. As a result, LPI has a significant effect on CO_2 emissions. Studies on LPI and CO_2 emissions in the literature are presented in Table 2.

Table 2. LPI-CO_2 Literature Review

Authors	Variables	Methodology	Years	Findings
Kim & Min (2011)	LPI, EPI (including CO_2), Green LPI	A series of simple regression analyses	2010	Green LPI scores has been determined.
Mariano et al. (2017)	LPI, CO_2	DEA	2007-2012	The Low carbon logistics performance index (LCLPI) has been developed.
Liu et al. (2018)	LPI, CO_2	The system-generalized method of moment (GMM) panel regression model	2007-2016	It has been proposed to develop policies to reduce CO_2 emissions in Asian countries.
Rashidi & Cullinane (2019)	LPI, Energy use, kt of CO_2e, SOLP	DEA	2007-2016	Sustainable operational logistics performance (SOLP) has been enhanced. LPI and SOLP were compared.
Karaduman et al. (2020)	LPI, CO_2	Regression analyses	2007-2016	There is a positive significant relationship between LPI and CO_2.
Magazzino et al. (2021)	LPI, CO_2, GDP, employment, capital, education, innovation, infrastructure	Panel data analysis	2007-2018	LPI has a significant effect on CO_2 emissions.
Nguyen (2021)	LPI, GDP, CO_2 emission, health expenditure, Foreign direct investment, Trade openness	Feasible generalized least square model (FGLS)	2007-2018	LPI has a significant effect on CO_2 emissions.

3. Methodology

3.1. Cluster Analysis

Cluster analysis, which was first developed by Tryon in 1939, is among the multivariate statistical analyzes (Tryon, 1939). The main purpose of cluster analysis is the clustering of data. For this purpose, it is aimed to ensure maximum homogeneity within clusters and minimum heterogeneity between clusters. Cluster analysis classifies data according to their similarity or distance. Similarity and distance measures used in cluster analysis are as follows: “Euclidean distance, Squared Euclidean distance, Minkowski Distance, Manhattan City-Block Distance, Scaled Euclidean Distance, Mahalanobis Distance, Hotellin T^2 Distance, Canberra Distance”. In this study, the Squared Euclidean distance calculation method, which is the most widely used distance criterion, was applied. Squared Euclidean distance calculation is shown in Equation (1) (Çilingirtürk, 2011). With this calculation, the similarity between the two vectors is observed.

$$d_{ik} = d(x_i, y_k) = \sum_{i=1}^{n} \left(x_{ji} - y_{jk}\right)^2, i \neq k = \overline{1,n} \quad (1)$$

The important issue in cluster analysis is to determine the number of clusters. This is more important for hierarchical cluster analysis. Because the main purpose of this method is to determine the number of clusters. For this, dendrogram diagram or distance coefficients are used. If the number of clusters is unknown in the use cases of both methods, the appropriate number of clusters is determined by applying hierarchical cluster analysis first, and then non-hierarchical cluster analysis can be evaluated according to this number of clusters. Apart from these, there are methods used to determine the number of clusters. However, in this study, other cluster number determination calculations were not mentioned because the number of clusters was determined by non-hierarchical clustering analysis.

Hierarchical Cluster Analysis: It is a clustering analysis used when the number of clusters is unknown.

In this method, the units of the clusters and the total number of clusters are calculated by the distances of the data from each other. The advantages of hierarchical clustering analysis can be listed as easy calculation of distance and similarity criteria, ease and flexibility in applying to different attributes (Kalaycı, 2010). In hierarchical cluster analysis, N observations are defined as n clusters. The two clusters with the least distance are matched. By reducing the number of clusters by one, the distance matrix is created again. These operations are repeated n-1 times. There are different methods in hierarchical cluster analysis. These are “single connection (nearest neighborhood) technique, full correlation (farthest neighborhood) technique, average connection technique, central (centroid) technique, median connection technique, and ward technique”. Ward's method, which is the most suitable method to obtain a homogeneous cluster at the maximum level, was applied in this study. This method is also known as the least variance technique. Equation (2) is used for the calculation of the Ward method.

$$ESS = \sum_{i=1}^{n} x_i^2 - {}^{1}\!/_{n} \left(\sum_{i=1}^{n} x_i\right)^2 \quad (2)$$

Here “n” is the number of observations, x_i is the score of the “i”th observation. In this method, much better results are obtained in applications with more than 50 observations. Since each cluster is an observation, the sum of squares of the error is zero. Then, the two subsets are combined, and the process continues. In this method, data loss is minimized. In Ward's method, the squared Euclidean criterion, one of the distance criteria, is generally used (Alpar, 2003).

Non-Hierarchical Cluster Analysis: It is a cluster analysis used when the number of clusters is known. In this method, the number of iterations and the convergence criterion are important. It is preferred that the number of iterations is at most 10 and that the convergence criterion has the smallest value between 0 and 1. Thus, the reliability level of the analysis can be increased (Kalaycı, 2010). In addition, in this method, data sets with a sample number of more than 1000 can be easily analyzed. However, this is not possible in hierarchical cluster analysis. In non-hierarchical cluster analysis, k-means method and maximum likelihood methods are available. In this method, the number of clusters must be at least 2 and at most “n”. Since averaging is used, only quantitative data can be used in this method. The main purpose of this method is to maximize the similarities of the observations in the same cluster and to minimize the similarities between the clusters (Han et al., 2011). In this method, "k" random cluster centers are determined to form clusters. Cluster averages of all data are calculated and assigned to the nearest cluster center. Cluster means are recalculated after each assignment. If the cluster center averages are the same as the previous transaction, the transaction ends. The K-means calculation is shown in equation (3).

$$E = \sum_{j=1}^{k} \sum_{i_l \in c_j} \left| i_l - w_j \right|^2$$
$$w_j = i_l,\ j \in \{1, \dots, k\}, l \in \{1, \dots, n\} \tag{3}$$

3.2. Data Envelopment Analysis

Data Envelopment Analysis, which has been widely preferred among the analysis methods recently, was first introduced to the literature by Charnes et al. (1978). DEA is a non-parametric mathematical programming method that aims to provide information about the relative efficiency of decision-making units (DMU). The purpose of this method is to determine the relative efficiency between decision making units. The most basic feature that distinguishes DEA from other analysis methods is that the inputs and outputs used in the model can be established from different units (Johnes & Johnes, 1993). DEA is based on the total factor productivity principle obtained from decision units that produce "m" inputs and "s" outputs. Total factor productivity calculation is as shown in Equation (4) (Charnes & Cooper, 1962).

$$Total\ Factor\ Efficiency = \frac{\sum_{r=1}^{s} u_{rk} Y_{rk}}{\sum_{r=1}^{m} v_{rk} X_{rk}} \tag{4}$$

The mathematical expressions used in Equation (4) are as follows:

Y_{rk} $(r = 1, \dots, s)$ It is the amount of output produced by the decision unit.

X_{ik} $(i = 1, \dots, m)$ It is the amount of input used by the decision unit.

u_{rk} $(r = 1, \dots, s)$ It is the weight coefficient that the decision unit gives to the outputs.

v_{ik} $(i = 1, \dots, m)$ It is the weight coefficient that the decision unit gives to the inputs.

Different DEA models are found in the literature. In this research, the output-oriented Banker, Charnes, Cooper (BCC) model was applied. The reason why this model is preferred is that the analysis is carried out by evaluating whether the decision-making unit works in increasing, decreasing or constant regions according to the scale. Output-oriented BCC model calculation is as shown in Equation (5), dual calculation is as shown in Equation (6) (Banker et al. 1984).

$$\min q_k = \sum_{i=1}^{m} v_i x_{ik} - v_k$$
$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} - v_k \geq 0 \quad j = 1, \dots, n \tag{5}$$
$$\sum_{r=1}^{s} u_r y_{rk} = 0\ u_r, v_i \geq \varepsilon;\ \ r = 1, \dots, s;\ \ i = 1, \dots, m;\ v_k$$

$$Max\ \varphi_k$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- - x_{ik} \leq 0$$
$$\sum_{r=1}^{s} \lambda_j y_{rj} - s_r^+ - \varphi_k y_{rk} \leq 0 \tag{6}$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$r = 1, \dots, s;\ \ i = 1, \dots, m; j = 1, \dots, n$$

The indices and parameters of our empirical study are as follows:

<u>*Indices:*</u>

i	Logistics performance	*i = 1,2…,m (m=6)*
r	CO_2 emissions per capita	*r = 1,2…,s (s=1)*
j	Countries	*j = 1,2…,n (n=150)*

<u>*Parameters:*</u>

v_i : "i" weight given to logistic performance input.

u_r : "r" weight given to CO_2 emissions per capita output.

x_{ik} : "k" score of the "i" logistics performance input of the decision unit.

y_{rk} : "k" score of the "r" CO_2 emissions per capita output of the decision unit.

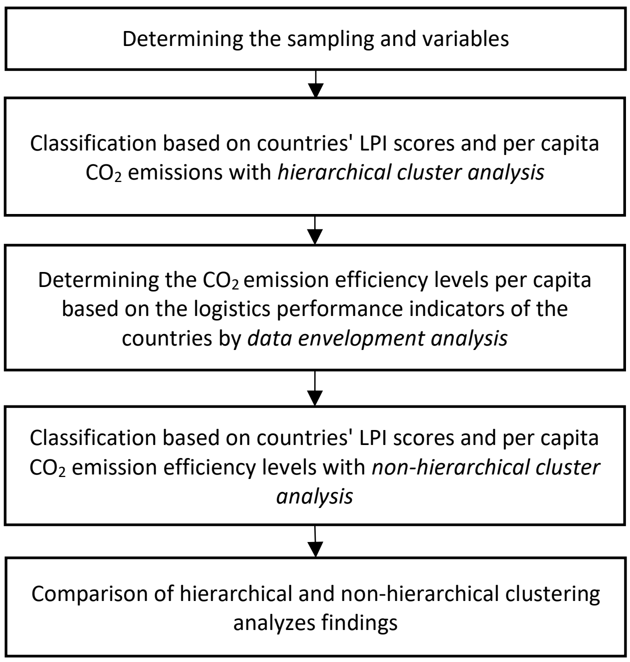
$v_i x_{ij}$: "j" country's weighted input score.

$u_r y_{rj}$: "j" country's weighted output score.

4. Empirical Analysis

There are many studies in the literature that deal with the relationship between the logistics activities of countries and CO_2 emissions (Mariano et al., 2017; Liu et al., 2018; Magazzino et al., 2021). In this empirical study, it is aimed to make determinations based on the relationship between the logistics performance levels of countries and their CO_2 emissions per capita. A total of 3 different methods were applied and the research was completed in three stages. In the first stage, hierarchical clustering analysis was performed by considering the logistics performance scores of the countries and the CO_2 emissions per capita. In the second stage, CO_2 emission per capita efficiency levels based on the logistics performances of the countries were determined by DEA. In the third stage of the research, non-hierarchical clustering analysis was performed by considering the logistics performance scores of the countries and the CO_2 emission efficiency scores based on the logistics performance. The empirical analysis flowchart is shown in Figure 1.

Figure 1. Empirical Analysis Flow Chart



4.1. Variables and Sampling

With this empirical research, it is aimed to explain the relationship between the logistics performance of the countries and their CO_2 emissions and to classify the countries when this relationship is considered. In addition, two variables were used in both hierarchical and non-hierarchical cluster analysis. The "LPI overall" and "CO_2 emissions per capita" variables of the countries are the variables used in the hierarchical clustering analysis. In the non-hierarchical cluster analysis, the "LPI overall" and " CO_2 emission per capita efficiency level" variables of the countries were used. DEA analysis was conducted to determine the CO_2 emission per capita efficiency levels.

In the DEA analysis, the LPI indicators of the countries (Customs, Logistics Infrastructure, International Shipments, Logistics quality and competence, Tracking and tracing, Timeliness) were determined as input variables, and CO_2 emissions per capita was determined as output variable. Thus, the CO_2 emission per capita efficiency level of the countries was determined by considering the logistics performances of the countries. At the last stage of the empirical analysis, the differences between hierarchical clustering analysis findings and non-hierarchical clustering analysis findings were determined.

The sample area of the study consists of 150 countries located in different geographies of the world. In the literature, it is seen that countries with low carbon consumption are preferred in studies dealing with the relationship between LPI and CO_2, and the highest possible sample unit is preferred to increase the flexibility of DEA analysis findings (Mariano et al., 2015; Mariano et al., 2017). In this study, both low-carbon and high-carbon emitting countries were selected to determine the sample area. The main reason for this approach is that the countries are not grouped before the cluster analysis. At the same time, it is aimed to represent the universe by keeping the number of sample units as high as possible. The sampling area was determined by considering the acquisition of LPI and CO_2 emission per capita data. The period of the data set is 2018. The main reason for determining the year 2018 is that the last reports of LPI scores and per capita CO_2 emission data were announced in 2018. The data on the LPI overall scores and sub-indicators of the countries were obtained from the 2018 data published by the Worldbank (Arvis et al., 2018). CO_2 emissions per capita were obtained from the data set named "CO_2 emissions (kg per 2017 PPP $ of GDP)" with the indicator code "EN.ATM.CO2E.PP.GD.KD" published by Worldbank (2022). The variables of the empirical research and the sample area are shown in Table 3. In addition, the correlation between the variables was determined in the SPSS package program and presented in Table 4. As seen in Table 4, CO_2 emissions per capita efficiency variable has a significant correlation with both LPI Overall and CO_2 emissions per capita variables.

Table 3. Variables and Sampling

Analysis	Variables		Period	Sampling
Hierarchical Clustering Analysis	LPI Overall CO_2 emissions per capita		2018	150 countries
Data Envelopment Analysis	*Inputs*	Customs, Logistics Infrastructure, International Shipments, Logistics quality and competence, Tracking and tracing, Timeliness	2018	150 countries
	Outputs	CO_2 emissions per capita		
Non-Hierarchical Clustering Analysis	LPI Overall CO_2 emissions per capita efficiency		2018	150 countries

Table 4. Correlation of Variables

Variables	Mean	S.D.	LPI Overall	CO_2 emissions per capita	CO_2 emissions per capita efficiency
LPI Overall	2.877067	0.563722	1		
CO_2 emissions per capita	0.206358	0.134669	- 0.014	1	
CO_2 emissions per capita efficiency	0.345405	0.264760	- 0.447*	0.561*	1

Notes: * $p < 0.01$

4.2. Hierarchical Clustering Analysis Findings

A hierarchical clustering analysis was applied to determine which countries are in which clusters, considering the logistics performance and per capita CO_2 emissions of the countries. Since the number of clusters is uncertain, the number of clusters formed by the countries was determined by this analysis and it was determined in which cluster the countries were located. The analysis was applied in the SPSS package program. For hierarchical clustering analysis, Ward's method gives the most accurate clustering results (Hands & Everitt, 1987; Ferreira & Hitchcock, 2009; Tekin, 2018). For this reason, the Wards method was chosen, and the Squared Euclidean distance was preferred for the measurement intervals. The dendrogram diagram obtained as a result of the analysis application is as seen in Appendix 1. When the dendrogram diagram is examined, it is seen that the countries are classified in 3 clusters when the distance cluster junction point of 5 is assumed. There are 95 countries in Cluster 1, 28 countries in Cluster 2, and 27 countries in Cluster 3. Country classification is shown in Appendix 2.

4.3. Data Envelopment Analysis Findings

To determine the per capita CO_2 emission efficiency level based on the logistics performance of the countries, the LPI sub-indicators of the countries were considered as input variables, and the per capita CO_2 emission was accepted as the output variable. The purpose of determining the per capita CO_2 emission efficiency level is to determine what changes will be achieved when the efficiency level of the classification made according to the LPI, and CO_2 emission status of the countries is considered. In the hierarchical clustering analysis stage, the calculations were made by considering the raw values in the CO_2 emissions of the countries. In the non-hierarchical cluster analysis, clusters and cluster elements were determined by considering the CO_2 emission efficiency levels of the countries. For this reason, DEA analysis was applied to determine the CO_2 efficiency levels.

Output-oriented BCC model was applied in the empirical study, as explained in the methodology section, to determine the per capita CO_2 emission efficiency level. After the data set, input variables and output variables were created, the model application was made through the OSDEA package program. As a result of the DEA analysis, the efficiency levels of 150 countries are presented in Appendix 3. According to the DEA analysis, there are 15 countries at the full efficiency level of CO_2 emissions per capita in 2018. These are “Afghanistan, Angola, Bhutan, Burundi, Central African Republic, Guinea, Iraq, Lesotho, Libya, Mongolia, Niger, Papua New Guinea, Turkmenistan, Zimbabwe”. All these countries are in Cluster 1 according to the hierarchical cluster analysis. It is also understood that countries with high LPI scores do not have high per capita CO_2 emission efficiency levels. The data presented in Appendix 3 were used in the dataset of non-hierarchical clustering analysis. The main reason for conducting DEA analysis in this empirical study is to determine "per capita CO_2 efficiency" scores. Thus, clusters of LPI and CO_2 emission per capita efficiency levels variables are created. In the study conducted by Mariano et al. (2017), countries with low carbon emissions in terms of logistics were identified as "Japan, Germany, Togo, Benin and the United States", and countries with high carbon emissions were identified as BRICS countries. Compared to the findings of this study, it can be clearly stated that the CO_2 emission efficiency levels of the BRICS countries based on logistics performance are not at the "full efficiency" level in both studies. However, in this study, it is seen that the countries that are at the full efficiency level are in the group of underdeveloped countries. This is explained as low logistics performance causing low CO_2 emissions. Liu et al. (2018) explained that industrial activities in Asian countries increase CO_2 emissions excessively, but there is a decrease in CO_2 emissions after their participation in international trade. In this research, it has been determined that most of the Asian countries have low efficiency level of CO_2 emissions based on their logistics performance. This situation supports that Asian countries have not reached the desired level of efficiency in CO_2 emissions in terms of logistics.

4.4. Non-hierarchical Cluster Analysis Findings

With non-hierarchical clustering analysis, countries are clustered according to their logistics performance and CO_2 emission per capita efficiency variables. The reason why non-hierarchical clustering analysis is preferred is that as a result of hierarchical clustering analysis, there is information that the countries are separated in 3 clusters in total, that is, the number of clusters is known. Non-hierarchical clustering analysis was performed using the SPSS package program using the "k-means cluster analysis" method as explained in the methodology section.

According to the non-hierarchical analysis, the desired 3 clusters were reached in a total of 7 iterations. The minimum distance to the Initial Centers is 1,253. When the final cluster centers values are examined, the LPI is 2.20 for Cluster 1, 3.65 for Cluster 2, and 2.66 for Cluster 3. The CO_2 emission per capita efficiency is 0.91 for Cluster 1, 0.26 for Cluster 2, and 0.26 for Cluster 3. Considering the distances between Clusters, the distance between Cluster 1 and Cluster 2 is 1.589, the distance between Cluster 1 and Cluster 3 is 0.797, and the distance between Cluster 2 and Cluster 3 is 0.987.

ANOVA results of non-hierarchical clustering analysis are shown in Table 5. As seen in Table 5, as a result of non-hierarchical clustering analysis, LPI Overall (F=308.621, Sig. <0.01) and CO_2 emissions per capita efficiency (F=176.870, Sig. <0.01) are significant. In addition, there are 20 countries in Cluster 1, 42 countries in Cluster 2, and 88 countries in Cluster 3. Countries included in the clusters are shown in Appendix 4.

Table 5. ANOVA Results of Non-Hierarchical Cluster Analysis

Variables	Cluster		Error		F	Sig.
	Mean Square	Df	Mean Square	Df		
LPI Overall	19.121	2	0.062	147	308.621	0.000
CO_2 emissions per capita efficiency	3.689	2	0.021	147	176.870	0.000

5. Conclusion, Implication, and Suggestion

It is aimed to classify countries by considering their logistics performance and CO_2 emissions per capita. For this purpose, three basic research questions were developed. To answer the research questions, an empirical application was made by considering the 2018 data of 150 countries. The empirical study was carried out by applying three different methods. The purpose of this is to compare the results of two different classification methods. In addition, another aim is to determine the difference between the direct use of countries' CO_2 emission per capita data and the use of countries' logistics performance-oriented CO_2 emission per capita efficiency levels.

In the first stage of the empirical study, hierarchical clustering analysis was performed with two variables (LPI overall scores and per capita CO_2). According to the hierarchical clustering analysis, the countries were classified in 3 basic clusters. The clusters of countries are as shown in Appendix 2. For Cluster 1, it is seen that the countries are LDCs, and the LPI overall scores are lower than the countries in other clusters. No general inference can be made on CO_2 emissions per capita. This indicates that LPI overall scores are more dominant in classification. For Cluster 2, developing countries are included in this cluster. In addition, these countries have higher LPI scores than Cluster 1. For cluster 3, cluster members are developed countries. In addition, LPI scores are higher than the countries in the other two clusters.

In the second stage of the empirical study, CO_2 emissions per capita were calculated based on the logistics performance of the countries (Appendix 3). According to the DEA analysis, differences were found between the CO_2 emission per capita efficiency and CO_2 emissions per capita of the countries. The efficiency values obtained explain the relationship between the CO_2 emissions per capita of the countries and the logistics performance and reveal the effectiveness of the CO_2 emissions produced by the countries in return for their logistics performance. The new data set (CO_2 emission per capita efficiency) has been used instead of the CO_2 emission per capita in the non-hierarchical clustering analysis.

In the third stage, non-hierarchical clustering analysis was performed. Three cluster are obtained by non-hierarchical clustering analysis (Appendix 4). According to Cluster 1, countries consist of LDCs and LPI scores are low. Cluster 2 includes both developed (Australia, Ireland, New Zealand Switzerland, Slovenia, Austria, Sweden, Israel, Norway, Belgium, Italy, Spain, Canada, Japan, Chile, Czech Republic, Denmark, United States, United Kingdom etc.) and developing countries (Vietnam, China, Thailand, South Africa). LPI scores are also relatively higher than other cluster members. Cluster 3, on the other hand, has a more homogeneous structure. At each economic level, there are countries with different LPI scores and high and low CO_2 emissions (Congo Rep., Rwanda, Chad, Somalia, Malawi, Uganda, Burundi, Sri Lanka, Madagascar etc.). Contrary to the hierarchical cluster analysis, it explains that the logistics performance of the countries is not dominant in the determination of the clusters, and CO_2 emission per capita efficiency of the countries creates changes in the cluster classes. At this point, it can be said that it is not correct to classify countries only according to their CO_2 emission values, and it is necessary to consider the CO_2 emission efficiency levels.

According to the results of the two classifications, three main inferences were made when the countries that changed between the classes were examined.

- "*Saudi Arabia, Bulgaria, Cyprus, Slovak Republic, Indonesia, Mexico, Turkey, Croatia, Brazil, Romania, Lithuania, Colombia, Rwanda*" have high LPI scores. Therefore, in the hierarchical cluster analysis, they were included in the group dominated by developing countries. However, considering the CO_2 efficiency levels, they were included in the class of LCDs as a result of non-hierarchical clustering analysis.
- The LPI scores of "*South Africa, Oman, Vietnam, Estonia, India, Malaysia, Greece, Thailand, Chile, Slovenia, Israel, Hungary, Iceland, Ireland, Panama*" are above the average. For this reason, they were included in the group of countries where developing countries predominate in the hierarchical clustering analysis. However, considering the CO_2 efficiency levels, they were included in the developed countries class as a result of non-hierarchical clustering analysis.
- *"South Africa, Oman, Vietnam, Estonia, India, Malaysia, Greece, Thailand, Chile, Slovenia, Israel, Hungary, Iceland, Ireland, Panama"* have low LPI scores. Therefore, in the hierarchical clustering analysis, they were included in the group of countries where LCDs predominate. However, considering the CO_2 efficiency levels, all these countries formed a new cluster. This indicates that they differ from other countries in terms of their CO_2 emission efficiency.

With this research, it has been determined that there is a significant relationship between the logistics performances of countries and their CO_2 emissions, and that countries can be clustered based on this relationship. As a result of the empirical study, it is suggested that countries should increase the efficiency level of CO_2 emissions per capita, as well as making efforts to improve their logistics performance.

It is recommended that scholars who aim to examine the relationship between logistics performance and CO_2 emissions should use the per capita CO_2 emission efficiency values obtained from this study. In addition, when the LPI and per capita CO_2 data of the World Bank are updated, this research can be improved by considering the new data. New findings can be compared with existing findings. Moreover, cluster analysis based on other variables affecting CO_2 emissions can be performed. Clustering classes and countries can be compared.

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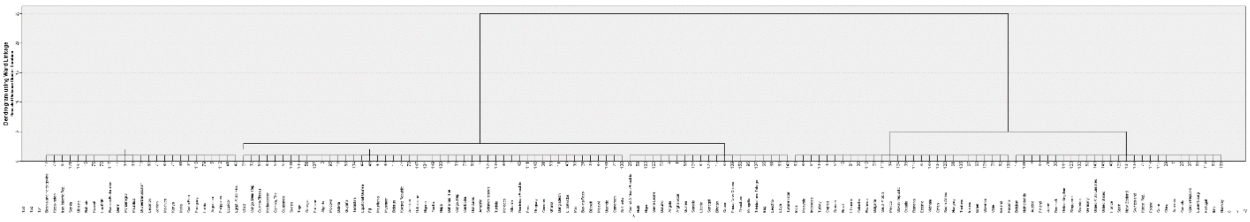
Appendix 1. Dendrogram Diagram



Appendix 2. Hierarchical Cluster Analysis Classes

		Cluster 1		
Afghanistan	Central African	Guinea-Bissau	Malawi	Russian
Albania	Chad	Guyana	Maldives	Senegal
Algeria	Comoros	Haiti	Mali	Serbia
Angola	Congo, Dem. Rep.	Honduras	Malta	Sierra Leone
Argentina	Congo, Rep.	Iran, Islamic Rep.	Mauritania	Solomon Islands
Armenia	Costa Rica	Iraq	Mauritius	Somalia
Bahamas	Djibouti	Jamaica	Moldova	Sri Lanka
Bahrain	Dominican Republic	Jordan	Mongolia	Sudan
Bangladesh	Ecuador	Kazakhstan	Montenegro	Tajikistan
Belarus	Egypt, Arab Rep.	Kenya	Morocco	Togo
Benin	El Salvador	Kuwait	Myanmar	Trinidad
Bhutan	Equatorial Guinea	Kyrgyz Republic	Nepal	Tunisia
Bolivia	Fiji	Lao PDR	Niger	Turkmenistan
Bosnia	Gabon	Latvia	Nigeria	Uganda
Brunei	Gambia	Lebanon	Pakistan	Ukraine
Burkina Faso	Georgia	Lesotho	Papua	Uruguay
Burundi	Ghana	Liberia	Paraguay	Uzbekistan
Cambodia	Guatemala	Libya	Peru	Zambia
Cameroon	Guinea	Madagascar	Philippines	Zimbabwe
		Cluster 2		
Brazil	Cyprus	India	Malaysia	Rwanda
Bulgaria	Estonia	Indonesia	Mexico	Saudi Arabia
Chile	Greece	Ireland	Oman	Slovak Republic
Colombia	Hungary	Israel	Panama	Slovenia
Croatia	Iceland	Lithuania	Romania	South Africa
Thailand	Turkey	Vietnam		
		Cluster 3		
Australia	Czech Republic	Italy	New Zealand	Singapore
Austria	Denmark	Japan	Norway	Spain
Belgium	Finland	Korea, Rep.	Poland	Sweden
Canada	France	Luxembourg	Portugal	Switzerland
China	Germany	Netherlands	Qatar	United Kingdom
Arab Emirates	United States			

Appendix 3. CO_2 Emissions Per Capita Efficiency Scores

Country	Efficiency	Country	Efficiency	Country	Efficiency
Afghanistan	1	Georgia	0.238052463	Netherlands	0.189492276
Albania	0.176377942	Germany	0.193756998	New Zealand	0.185669043
Algeria	0.444440795	Ghana	0.123295482	Niger	1
Angola	1	Greece	0.252775828	Nigeria	0.215841132
Argentina	0.212253706	Guatemala	0.18740072	Norway	0.132331164
Armenia	0.181914899	Guinea	1	Oman	0.646788327
Australia	0.382211243	Guinea-Bissau	0.421731944	Pakistan	0.324767302
Austria	0.156608728	Guyana	0.426068335	Panama	0.094708891
Bahamas	0.203122803	Haiti	0.423042784	Papua	1
Bahrain	0.511440593	Honduras	0.235946067	Paraguay	0.114264526
Bangladesh	0.145067958	Hungary	0.184642641	Peru	0.161262168
Belarus	0.403534562	Iceland	0.132927918	Philippines	0.189637782
Belgium	0.193732624	India	0.334327428	Poland	0.314844474
Benin	0.263853025	Indonesia	0.231972129	Portugal	0.172192334
Bhutan	1	Iran, Islamic	0.691482415	Qatar	0.431487662
Bolivia	0.375898034	Iraq	1	Romania	0.163237979
Bosnia	0.570758405	Ireland	0.1102685	Russian	0.497345984
Brazil	0.168563202	Israel	0.211706289	Rwanda	0.050894998
Brunei	0.333760185	Italy	0.154838125	Saudi Arabia	0.38848627
Bulgaria	0.319264322	Jamaica	0.369961442	Senegal	0.41100971
Burkina Faso	0.130137392	Japan	0.253124459	Serbia	0.452504478
Burundi	1	Jordan	0.299734291	Sierra Leone	0.632759113
Cambodia	0.231519789	Kazakhstan	0.571788905	Singapore	0.103546237
Cameroon	0.14506017	Kenya	0.099917155	Slovak Republic	0.235452485
Canada	0.384564467	Korea, Rep.	0.352883853	Slovenia	0.215973183
Central African	1	Kuwait	0.518699099	Solomon Islands	0.286509939
Chad	0.069076272	Kyrgyz	0.440015375	Somalia	0.378486993
Chile	0.223753626	Lao PDR	0.424364036	South Africa	0.654209661
China	0.588274047	Latvia	0.159536866	Spain	0.166049674
Colombia	0.135400994	Lebanon	0.312013383	Sri Lanka	0.0939849
Comoros	0.138241093	Lesotho	1	Sudan	0.176030155
Congo, Dem.	0.035034645	Liberia	0.662623489	Sweden	0.081839018
Congo, Rep.	0.26280812	Libya	1	Switzerland	0.075504597
Costa Rica	0.096777694	Lithuania	0.141326145	Tajikistan	0.429812124
Croatia	0.174209416	Luxembourg	0.161351863	Thailand	0.248532104
Cyprus	0.251702149	Madagascar	0.117676727	Togo	0.180184791
Czech Republic	0.292340657	Malawi	0.074919259	Trinidad	0.91714692
Denmark	0.124186716	Malaysia	0.333722569	Tunisia	0.33233707
Djibouti	0.127026169	Maldives	0.243981237	Turkey	0.214461916
Dominican	0.161604196	Mali	0.182521113	Turkmenistan	1
Ecuador	0.242335428	Malta	0.089415052	Uganda	0.091072484
Egypt, Arab	0.266554751	Mauritania	0.260622837	Ukraine	0.436159177
El Salvador	0.154643098	Mauritius	0.212743242	United Arab	0.376057812
Equatorial	0.871687842	Mexico	0.227343789	United Kingdom	0.139528478
Estonia	0.41757035	Moldova	0.51737933	United States	0.299669049
Fiji	0.306809877	Mongolia	1	Uruguay	0.099366588
Finland	0.202687669	Montenegro	0.237069267	Uzbekistan	0.709339105
France	0.123520235	Morocco	0.300990095	Vietnam	0.430798664
Gabon	0.309609149	Myanmar	0.301070016	Zambia	0.187470081
Gambia,	0.402364315	Nepal	0.148370142	Zimbabwe	1

Appendix 4. Non-hierarchical Cluster Analysis Classes

		Cluster 1		
Afghanistan	Central African	Iraq	Iraq	Trinidad
Angola	Equatorial Guinea	Lesotho	Lesotho	Turkmenistan
Bhutan	Guinea	Liberia	Liberia	Uzbekistan
Burundi	Haiti	Libya	Libya	Zimbabwe
		Cluster 2		
	Australia	Ireland	New Zealand	Slovenia
	Austria	Israel	Norway	South Africa
	Belgium	Italy	Oman	Spain
	Canada	Japan	Panama	Sweden
	Chile	Korea, Rep.	Poland	Switzerland
	China	Luxembourg	Portugal	Thailand
	Czech Republic	Malaysia	Qatar	United Arab
	Denmark	Netherlands	Singapore	United Kingdom
	United States	Vietnam		
		Cluster 3		
Albania	Chad	Ghana	Madagascar	Philippines
Algeria	Colombia	Guatemala	Malawi	Romania
Argentina	Comoros	Guinea-Bissau	Maldives	Russian
Armenia	Congo, Dem. Rep.	Guyana	Mali	Rwanda
Bahamas,	Congo, Rep.	Honduras	Malta	Saudi Arabia
Bahrain	Costa Rica	Indonesia	Mauritania	Senegal
Bangladesh	Croatia	Iran, Islamic Rep.	Mauritius	Serbia
Belarus	Cyprus	Jamaica	Mexico	Slovak Republic
Benin	Djibouti	Jordan	Moldova	Solomon Islands
Bolivia	Dominican Republic	Kazakhstan	Montenegro	Somalia
Bosnia	Ecuador	Kenya	Morocco	Sri Lanka
Brazil	Egypt, Arab Rep.	Kuwait	Myanmar	Sudan
Brunei	El Salvador	Kyrgyz Republic	Nepal	Tajikistan
Bulgaria	Fiji	Lao PDR	Nigeria	Togo
Burkina Faso	Gabon	Latvia	Pakistan	Tunisia
Cambodia	Gambia	Lebanon	Paraguay	Turkey
Cameroon	Georgia	Lithuania	Peru	Uganda
Ukraine	Uruguay	Zambia		