A FLEXIBLE WEIGHT APPROACH FOR THE LOGISTICS PERFORMANCE INDEX METHODOLOGY

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ETHICAL DECLARATION

I hereby declare that I am the sole author of this thesis and that I have conducted my work in accordance with academic rules and ethical behaviour at every stage from the planning of the thesis to its defence. I confirm that I have cited all ideas, information and findings that are not specific to my study, as required by the code of ethical behaviour, and that all statements not cited are my own.

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ABSTRACT

A FLEXIBLE WEIGHT APPROACH FOR THE LOGISTICS PERFORMANCE INDEX METHODOLOGY

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Master's Program in Logistics Management

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The World Bank (WB) conducts a survey among market experts and all related parties and transforms the results of this survey into an index periodically in order to provide countries insight on their and other countries' logistics performance. The surveyees evaluate countries according to 6 criteria and WB transforms these evaluations into scores for each criterion and calculates the index by aggregating these scores. During aggregation, WB uses a fixed weight set for all countries. This fixed weight set (common weight) used in the LPI methodology may favor some countries and disfavor others. In this study, we develop a lexicographic mathematical model which lets countries choose the weights that will provide them their best position within a reasonable range around the fixed LPI weights. As the level of weight flexibility increases, we observe that more countries improve their position and the countries experiencing the greatest improvements generally belong to less developed and developing countries. Developed countries tend to maintain their positions. Afterwards we make cluster analysis with the optimal weights countries choose using *k-means* clustering method and evaluate the trends among the countries choosing similar weights. We observe that the developing and less developed countries tend to gather in clusters where mean weight of infrastructure is higher.

Keywords: LPI, lexicographic model, weight flexibility, common weight, *k-means* clustering.

ÖZET

LOJİSTİK PERFORMANS ENDEKS METODOLOJİSİNE ESNEK AĞIRLIK YAKLAŞIMI

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Dünya Bankası sektör uzmanları ve ilgili paydaşlara periyodik aralıklarla bir anket sunmakta ve bu anketin sonuçlarını Lojistik Performans Endeksi (LPI) adını verdiği, ülkelerin kendilerinin ve diğer ülkelerin lojistik performanslarını değerlendirmek için baz alabilecekleri bir endekse dönüştürmektedir. Bu ankette ülkeler için 6 değerlendirme kriteri vardır ve Dünya Bankası bu kriterlerin puanlarını ağırlıklı ortalama yöntemiyle tek bir puana dönüştürmektedir. Bunun için kullandığı ağırlık yöntemi sabit ağırlık yöntemidir ancak bu yöntem bazı ülkeler için avantajlı diğer ülkeler için dezavantajlı olmaktadır. Ülkelerin, Dünya Bankasının sabit ağırlık kümesine makul bir yakınlıkta olmak şartıyla kendilerini diğer ülkeler arasındaki en iyi pozisyona getirecek ağırlıkları seçmelerine izin veren bir matematik model geliştirdik. Bu modeli çeşitli yakınlık seviyeleri için çalıştırdık ve gördük ki sabit ağırlık kümesini esnettikçe (yakınlık aralığı arttıkça) pozisyonunu geliştiren ülke sayısı da artmaktadır. Pozisyonunu geliştiren bu ülkeler çoğunlukla az gelişmiş ve gelişmekte olan ülkelerdir. Gelişmiş ülkelerin daha durağan kaldığı gözlenmiştir.

Daha sonra, ülkelerin bu seçtikleri ağırlıkları kullanarak *k-ortalamalar* yöntemiyle kümeleme çalışması yaptık ve benzer eğilim gösteren ülkeleri tartıştık. Gördük ki az gelişmiş ve gelişmekte olan ülkeler, lojistik alt yapısına daha çok ağırlık veren kümelerde toplanmaktadır.

Anahtar Kelime: Dünya Bankası, LPI, matematik model, sabit ağırlık, *k-ortalamalar* kümeleme

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CHAPTER1: INTRODUCTION

The Logistics Performance Index (LPI) is a benchmarking tool developed and delivered by the World Bank first in 2007 to provide countries information and insight on their performance in international trade highlighting their weaknesses and strengths (World Bank, 2023). The World Bank issued LPI in 2007, 2010, 2012, 2014, 2016, 2018 and finally in 2023.

The World Bank conducts a survey among trade experts and trade related parties in order to highlight logistics performance of the countries and finds an aggregate score for each country as the result of the survey. In 2023 edition of the World Bank LPI Report, besides the scores acquired from the survey, real time shipment tracking data is included in the report in order to reflect the real-world situation more properly but is not included in the calculation of LPI yet (Arvis et al., 2023).

The index is based on data acquired from a survey conducted among various actors that play role in international trade; forwarders, customs experts, shipping agencies, etc. and is composed of six fundamental indicators:

- efficiency of customs and border management clearance,
- quality of trade and transport infrastructure,
- ease of arranging competitively priced international shipments,
- competence and quality of logistics,
- ability to track and trace consignments,
- timeliness of shipments in reaching destination within the scheduled or expected delivery time.

The surveyees evaluate the country in terms of these six indicators and the surveyor turns their answers into scores for each indicator. The World Bank uses an aggregation method to evaluate the overall logistics performance by assigning weights to each indicator. These weights used in calculation of final LPI are the same for each country implying that these six factors have the same level of importance for all the countries. However in reality this may not be the case. Vivek et al. (2018) mentions diverse economic strength of the countries and the heterogenous structure of data. Hollweg and Wong (2009) suggest the economic environment and features of legislation are different in each country and this distinction affects international good flows in other words logistics significantly. Therefore, each country having a distinct structure of economy and legislation may give different levels of importance to the indicators.

The aim of our study is to emphasize and demonstrate that fixed weight methodology of LPI hinders the potential of some countries and in order to highlight their real potential we provide countries a room to develop their LPI score by providing some degree of flexibility around the original weights of The World Bank. This allows them to give more weight to the areas in which they have more comparative advantage. At the same time we can highlight their weak and strong areas in the international trade operations using the results we obtain. Besides, using the optimal weights each country prefers after we provide weight flexibility, we can utilize cluster analysis of these optimal weights to understand why some countries choose the same weights.

Therefore our study has two main research questions:

1) If we let the countries choose their optimal weights by providing them some degree of flexibility according to the original World Bank LPI weights, how will the rankings change and to what extent?
2) What kind of similarities do the countries choosing similar weights have in common?

We develop a mixed integer linear programming model so that each country chooses the weights that will place it in its best position among other countries provided that these weights move in a reasonable range with respect to the original LPI weights. We test our model with four different levels of flexibility and we discuss the findings. As level of flexibility increases the number of countries improving their position increases. The majority of the countries that improve their position most are developing and the least developed countries. The top and worst scoring countries tend to maintain their positions. After we apply *k-means clustering analysis* to the optimal weights that the countries choose at different flexibility levels, some group of countries always take place in the same clusters with each other. There is a group of developing and less developed countries that take place in clusters where the mean weight of infrastructure is higher than the other indicators. They prioritize infrastructure to improve their situation.

The rest of the thesis is organized as follows; Chapter 2 provides a general review of literature. Chapter 3 discusses the available data and methodology. Chapter 4 presents the computational tests and the results. Chapter 5 provides conclusion of the discussions.

CHAPTER 2: LITERATURE REVIEW

In line with our research questions and methodology, we examine the literature in three sections: country and region assessments of LPI, common weight discussions and clustering.

2.1 Country and Region Assessments of LPI

Marti, Martin and Garcia (2014) investigate the relation between various factors and bilateral trade within a group of countries and report that Logistics Performance Index is a significant factor that facilitates international trade. Accordingly, LPI scores and rankings have remarkable importance for all the countries and international trade partners of these countries. Therefore, a significant number of studies focus on country and region assessments.

The World Bank calculates LPI Index via linear aggregation by assigning weights to six indicators. This multicriteria structure makes LPI evaluations very suitable for the utilization of Multi Criteria Decision Making (MCDM) methods.

Rezai, Van Roekel and Tavasszy (2019) discuss that the weight set of the World Bank are similar for each indicator though there are small differences and it does not seem logical for a country to give the same importance to each indicator. They use Best-Worst Method to determine relative importance of the indicators and find that infrastructure is the most important indicator with a weight of 0.24 and tracking and tracing is the least important one with a weight of 0.10. Ulutaş and Karaköy (2019) find similar results in terms of the most and least important indicators. They develop an integrated MCDM method by combining Criteria Importance Through Intercriteria Correlation (CRITIC), Step-wise Weight Assessment Ratio Analysis (SWARA) and Proximity Indexed Value (PIV) methods to evaluate LPI rankings of European Union Countries. They report infrastructure to be the most important indicator with a weight of 0.25 and tracking and tracing the least with a weight of 0.10.

Marti, Martin and Puertas (2017) make use of a Data Envelopment Analysis (DEA) model in order to evaluate logistics performance of countries using The World Bank Logistics Performance Index. They report that the rankings of countries are affected by two attributes of countries: region and income.

Işık, Aydın and Koşaroglu (2020) use a combination of Statistical Variance (SV) and Multi-attributive Border Approximation Area Comparison (MABAC) methods to evaluate LPI rankings of 11 Central and Eastern European Countries.

Besides Multiple Criteria Decision Making Methods, there are studies using different methods to evaluate importance of LPI indicators such as Hasan et al. (2025) which incorporate LPI indicators in a network structure and use Network Analysis to determine their relative importance. They report that quality of logistics, infrastructure and tracking are the most important indicators.

2.2 Common Weight Discussions

According to Köksalan et al. (2009), given a set of alternatives, sorting is assigning each alternative into ordered classes. On the other hand, ranking is ordering the alternatives according to preferences within this set of alternatives. In this sense, our model that is developed to introduce weight flexibility, sorts the countries rather than ranking them. The World Bank used to report a full ranking of the countries by evaluating Total LPI scores using an aggregate function with criteria weights. In the 2023 LPI Report, The World Bank made a change in its methodology and rounded the results to the first decimal. Though it still uses the same aggregate function with the same criteria and the same criteria weights, the reported results resemble sorting rather than ranking. This can be considered to be done on purpose to change the reporting to a kind of sorting rather than a ranking of the countries. This is in line with the discussions regarding the cons of the use of precise ranking in case of not that much precise information as is also discussed in Köksalan et al. (2010) in the case of the ranking of MBA programmes. The authors state that in case of subjective or imprecise data, some kind of sorting which they call flexible ranking is a more appropriate method than ranking. The World Bank also uses subjective data since they gather data via a survey reflecting expert opinions.

The World Bank adopts a common weight approach in the calculation of the Logistics Performance Index. In other words, the same weight set is used for every country in the calculation. Doyle and Green (1994) state using a common weight set disadvantages especially the participants that are good in specific areas. On the other hand, there are also studies that support common weights (i.e. fixed weights) to be used in ranking and sorting problems. Karsak and Uçar (2024) and Karsak and Ahiska

(2005) emphasize the strength of common weight methodology in Data Envelopment Analysis as increasing discriminating power and providing full ranking compared to the full flexible weights of the classical Data Envelopment Analysis. Regarding the disadvantages of classical DEA, Dyson and Thanassoulis (1988) state that this can result in focusing on certain attributes and neglecting others and suggest imposing weight restrictions on the classical DEA. Moreover, as stated in Özpeynirci and Köksalan (2007) "reducing the weight space with additional information increases the discrimination power of DEA." As declared in Köksalan et al. (2010) models with a reasonable amount of weight restrictions can increase the discriminating power of classical DEA and diminish unfairness inherent in common weight DEA models which impose full weight restriction by fixing the weights by favoring some of the participants and disfavoring the others.

2.3 Clustering

Clustering is grouping objects that have similar features in the same group in order to assess and evaluate similar patterns and differences (Güzeller, 2016). In the literature there exist mainly two groups of cluster analysis: hierarchical and non-hierarchical. Hierarchical cluster analysis is generally used when you want to form clusters that are related with each other. Non-hierarchical analysis is used generally when you want to highlight the differences between the clusters. *k-means* clustering is categorized as non-hierarchical analysis and forms disjoint groups by partitioning the data into a specific number of clusters (Güzeller, 2016). To determine this specific cluster number silhouette analysis can be used. Silhouette Analysis was first developed and used by Peter Rousseeuw in 1986 and has been widely accepted and used to decide cluster numbers by then. Rousseeuw (1986) introduces the term silhouette which is a representation of the tightness and separation of a cluster and the average of these silhouettes shows how well a clustering is done.

Vivek et al. (2018) make use of Clustering Analysis to derive extended insights from the LPI Data. They use k-means algorithm taking cluster numbers as 5 to group countries in the LPI index firstly according to Gross Domestic Product (GDP) Per Capita then secondly according to LPI Scores. Then they put these clusters in a regression model to highlight the relation between LPI, its indicators and income. Ulkhag (2023) uses three different cluster analysis methods (k-means, Classification of Real Alternatives [CLARA] and k-metoid) to analyze 2018 LPI scores and divide the data into three clusters. Pehlivan et al. (2024) use Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to evaluate LPI scores and rankings of 19 G20 countries and compare their findings with the 2023 LPI rankings. They also apply cluster analysis to the indicator scores for each country using Ward's Method and they find 3 clusters.

There are several studies that apply clustering analysis to overall LPI scores or indicator scores and evaluate accordingly. Our study differs from them by applying cluster analysis to the optimal weights chosen by countries to achieve their best ranking under a model where different flexibility levels are introduced. This will enable us to observe and evaluate similar behaviour of countries and highlight their priorities.

CHAPTER 3: METHODOLOGY

We develop a mathematical model that allows countries to improve their rankings by making slight changes in the weight set of World Bank LPI. Afterwards we modify this model in a lexicographic way so that the weights the countries choose are close to the original weights. Then we make cluster analysis by using these optimal weights the countries chose. Finally we compare the country groups we obtain from clustering analysis with other available data sets to highlight and evaluate similar trends.

We use World Bank LPI Data 2023 in our model and in our clustering analysis. We also use additional Income Group, Region and Border Data Sets for further analysis. Income Group and Region Data are from (World Bank, 2022) and the Border Data is from (World population Review, 2020).

3.1 Mathematical Model

In order to introduce weight flexibility to the standard LPI score calculation, we use the interval weight based technique described in Köksalan et al. (2010). We develop a similar mixed integer programming model. Since in the LPI Report released in 2023 by the World Bank they changed the LPI score calculation methodology by rounding the results to the first decimal, we also included rounding to the first decimal in our model below:

<u>Sets</u>

K: The Set of Countries, $K = \{1,\ldots,k,\ldots, n\}$

J: The Set of Criteria , $J=\{1,\ldots,j ,\ldots, q\}$

<u>Parameters</u>

n: Number of Countries,

q: Number of Criteria

M: A large number

i: The country of focus

u_{jk}: LPI score of the country k for criterion j

p_j: Normalized weights given to each criterion by LPI (the original LPI weights)

α: The parameter to introduce weight flexibility

<u>Decision Variables</u>

ut_k: The total scores of country k

$utint_k$: The positive variable used for rounding

w_j: Weight for each criterion j

y_k: Binary variable; is 1 if ut_i is greater or equal to ut_k , 0 otherwise for every k which is not equal to i

We set each country $i \in$ K as the country of focus and solve model P_α^i and store the results separately. For each α there is a $(w_j^i)_\alpha^*$ which represents the optimal weight country i (the country under consideration) chooses for criterion j.

The objective function of our model minimizes the ranking of the country of focus. Constraint (2) ensures that sum of weights of all criteria equals 1. Constraint set (3) and (4) introduce weight flexibility to the model. Constraint sets (5) and (6) are lower and upper limits of the utint$_k$ respectively. Constraint set (7) relates $utint_k$ to ut_k. Constraint set (8) determines the value of the binary variable by comparing utility levels. Constraint sets (9)-(12) define the decision variables of the model.

Model $P_\alpha^{\ i}$

Minimize $\quad n - \sum_{k=1, k\neq i}^{n} y_k \qquad (1)$

Subject to

$$\sum_{j=1}^{q} w_j = 1 \qquad (2)$$

$$w_j \leq (1+\alpha)p_j \qquad \forall j \qquad (3)$$

$$w_j \geq (1-\alpha)p_j \qquad \forall j \qquad (4)$$

$$uint_k \geq 10 \times \left(\left(\sum_{j=1}^{q} u_{jk} w_j \right) - 0.05 \right) \qquad \forall k \qquad (5)$$

$$uint_k \leq 10 \times \left(\left(\sum_{j=1}^{q} u_{jk} w_j \right) + 0.05 \right) \qquad \forall k \qquad (6)$$

$$uint_k = 10 \times ut_k \qquad \forall k \qquad (7)$$

$$ut_i \geq ut_k - M \times (1 - y_k) \qquad \forall k \neq i \qquad (8)$$

$$y_k \in \{0, 1\} \qquad \forall k \qquad (9)$$

$$ut_k \geq 0 \qquad \forall k \qquad (10)$$

$$uint_k \in \{0, 1, 2, \ldots\} \qquad \forall k \qquad (11)$$

$$w_j \geq 0 \qquad \forall j \qquad (12)$$

The weights obtained as the result of our model may be one of the several alternative optimal solutions that end with the same objective function, i.e. there are other weight sets satisfying the constraints and providing the same optimal objective function value. In this phase of the study we modify our model in such a way that it provides us the optimal weights with the least possible total deviation from the original LPI weights for each country and also with the least maximum deviation in order to have weights that might end up in better clustering.

We modify our objective function as "Minimizes the ranking of the country of focus and also minimizes the maximum deviation and the deviation of the weight set from the original weight set" and add two new decision variables as *devmax* (maximum deviation for each criterion) and dev_j (the deviation between the original LPI weight and the optimal weight for each criterion). The modified model is now a multi objective model having a lexicographic structure with the modifications below.

Model PL_α^i

$$\text{Minimize} \quad \left(n - \sum_{k=1,k\neq i}^{n} y_k\right) + 0.1 \times devmax + 0.001 \times \sum_{j=1}^{q} dev_j \qquad (1)$$

Subject to (2)-(12)

$$dev_j \geq w_j - p_j \qquad \forall j \qquad (13)$$

$$dev_j \geq p_j - w_j \qquad \forall j \qquad (14)$$

$$devmax \geq dev_j \qquad \forall j \qquad (15)$$

$$dev_j \geq 0 \qquad \forall j \qquad (16)$$

$$devmax \geq 0 \qquad \forall j \qquad (17)$$

(2)-(12) are the same as in the model P_α^i. Constraint sets (13) and (14) relate dev_j and w_j. Constraint set (15) relates *devmax* to dev_j. Constraint sets (16) and (17) define the new decision variables. Please note that we used notation w_j in the equations not w_j^i because we run and solve the models P_α^i and PL_α^i for each i at each α separately. After each running of the model, we obtain only one set of w_j.

3.2 Clustering Methodology

In order to acquire further information from our findings and evaluate them more we decided to apply cluster analysis to the optimal indicator weights to find groups of countries which show similar behaviour.

The data we want to cluster is defined as compositional data in the literature since it sums up to a constant (Wang et al., 2021) and for the distance measures relating this kind of data Aitchison (1984) and Aitchison (1986) propose to make log transformations in order to make data available for analysis and state that the results without transformation will be misleading. Therefore, we take logarithm of the optimal weights of the countries for the α value in consideration using centered log ratio method and use *k-means* clustering algorithm to determine the closeness of these weights to each other and assign each country to a cluster accordingly.

Let $\left(w^i\right)_\alpha^* = \left[\left(w_j^i\right)_\alpha^*\right]$ denote the optimal weight vector calculated for country i for a given α value. By aggregating these individual vectors for all 139 countries, we construct the optimal weight matrix w_α^* as follows:

$$w_\alpha^* = [(w^1)_\alpha^*, (w^2)_\alpha^*, \dots, (w^{139})_\alpha^*]$$

To identify structural similarities between countries based on these weights, we define a clustering function

$$C_\alpha = f(\mathrm{w}_\alpha^*)$$

The function f integrates two critical components (i) the Centered Log-Ratio transformation and (ii) the k-means algorithm, which partitions the data. The resulting output

$$C_\alpha = [C_\alpha^1, C_\alpha^2, \dots, C_\alpha^{139}]$$

assigns each country i to a specific cluster C_α^{i} based on its optimized weight profile for the given α value.

CHAPTER 4: COMPUTATIONAL TESTS AND RESULTS

In this chapter we present the results of the computational tests with α=0.05, α=0.10, α=0.15, α=0.20 on the mathematical model and the findings we obtain after conducting cluster analysis to the optimal weights countries choose. Below we present an example for a small sample of 5 countries for the sake of comprehensibility.

Table 1. Rankings for a sample of five countries

Country	LPI	α=0	α=0.05	α=0.10	α=0.15	α=0.20
Netherlands	1	1	1	1	1	1
United A. Emirates	2	1	1	1	1	1
Australia	3	3	3	3	3	3
Italy	3	4	3	3	3	3
Estonia	5	5	5	5	4	3

As α increases, the rankings of the countries either improve or stay the same. Australia, Italy and Estonia can't advance beyond rank 3. Because Netherlands and United Arap Emirates outperform Australia, Italy, and Estonia in every criterion (i.e., Netherlands and United Arap Emirates dominate these countries). However, Netherlands and the United Arap Emirates do not dominate each other. Similarly, Australia, Italy, and Estonia do not dominate one another; thus, by choosing different weights, each achieves a 3rd place ranking, with the United Arap Emirates and Netherlands consistently occupying the top two positions.

4.1 Results of Computational Tests on the Mathematical Model

We use Gams Studio51 to solve the developed model. For this purpose, we use LPI 2023 data provided by the World Bank. Firstly, we used the same weights used for calculation in the 2023 LPI Report and afterwards we introduced weight flexibility to the model. We ran the model with alpha values 0.05, 0.10, 0.15, 0.20 to introduce +/-%5, +/-%10, +/-%15 and +/-%20 weight flexibility and compared obtained rankings with the rankings of the original LPI findings. In order to verify that our model is not producing random results we used Spearman's Rank Correlation Test. We calculated Spearman's Rank Correlation Coefficient using Excel to see the correlation between the original and the obtained rankings and found very high Rank Correlation indicating that in general our findings are consistent with the original LPI rankings though there are significant differences in the rankings of some of the countries. Table 2 below shows Spearman's Rank Correlation Coefficient measures between the original LPI rankings and between the rankings of the developed model for various α values.

Table 2. Correlation with original LPI rankings

α=0	α=0.05	α=0.10	α=0.15	α=0.20
0.996982	0.997303	0.996179	0.993981	0.991709

Spearman's Rank Correlation Coefficient for α=0 must be equal to 1 in theory. However in practice this is not the case. Because the World Bank calculates LPI scores, rounds the results to the first decimal and reports these rounded scores. We, on the contrary, do the rounding within the model. In order to estimate the exact scores we could have used the score estimation model developed in Köksalan et al. (2010). Instead we decided to proceed with the data in hand since the value of Spearman's Rank Correlation Coefficient is very close to 1.

Table 3 shows the rankings provided by the LPI (original World Bank calculation), by our model before weight flexibility is introduced (α=0), after weight flexibility is introduced (α=0.05, α=0.10, α=0.15 and α=0.20).

As the weight flexibility of the developed model increases, we observe rank improvements even among some of the countries from the top 20 scorers like Austria, Belgium, Hong Kong, Japan and Korea. However, even for α=0.20 there are countries maintaining their positions and most of them are the countries from top 20 scorers like Singapore, Finland, Denmark, Germany, Canada and France. The rankings of Türkiye remain almost stable with improvement of 1 rank for α values of 0.10, 0.15 and 0.20. The highest improvement belongs to Algeria, Mongolia, Mauritania, Grenada, Bangladesh, Ukraine and Cuba. Please note that most of these countries are the countries that take place in the bottom parts of the World Bank's LPI rankings and all of them are developing or least developed countries except Grenada and Cuba.

Table 3. Rankings of countries

Country	LPI	α=0	α=0.05	α=0.10	α=0.15	α=0.20
Singapore	1	1	1	1	1	1
Finland	2	2	2	2	2	2
Denmark	3	3	3	3	3	3

Table 3. (continued) Rankings of countries

Country	LPI	α=0	α=0.05	α=0.10	α=0.15	α=0.20
Germany	3	3	3	3	3	3
Netherlands	3	7	5	3	3	3
Switzerland	3	3	3	2	2	2
Austria	7	7	5	5	4	4
Belgium	7	7	5	5	3	3
Canada	7	3	3	3	3	3
Hong Kong	7	7	5	5	4	4
Sweden	7	7	5	5	4	4
United A. Emirates	7	7	5	5	4	4
France	13	13	13	13	13	13
Japan	13	13	13	13	13	7
Spain	13	13	13	13	13	12
Taiwan	13	13	13	13	13	13
Korea	17	17	16	16	16	14
United States	17	17	16	16	16	13
Australia	19	17	16	16	16	15
China	19	20	19	19	19	19
Greece	19	20	19	19	19	19
Italy	19	20	19	19	19	19
Norway	19	20	19	19	19	19
South Africa	19	20	19	19	19	19
United Kingdom	19	20	19	19	19	19
Estonia	26	27	25	25	20	19
Iceland	26	27	25	25	25	25
Ireland	26	27	25	25	25	25
Israel	26	20	19	19	19	19
Luxembourg	26	27	25	25	25	25
Malaysia	26	27	25	25	25	25
New Zealand	26	27	25	25	25	20
Poland	26	27	25	25	25	25
Bahrain	34	34	34	34	34	33
Latvia	34	34	34	34	27	27
Qatar	34	34	34	34	34	27
Thailand	34	34	34	34	34	33
India	38	38	38	37	37	37
Lithuania	38	38	38	37	37	37
Portugal	38	38	38	37	37	37
Saudi Arabia	38	38	38	37	37	37
Türkiye	38	38	38	37	37	37
Croatia	43	44	43	43	42	41
Czech Republic	43	44	43	43	38	38
Malta	43	38	38	37	37	37
Oman	43	44	43	43	42	41

Table 3. (continued) Rankings of countries

Country	LPI	α=0	α=0.05	α=0.10	α=0.15	α=0.20
Philippines	43	44	43	43	43	42
Slovak Republic	43	44	43	43	42	41
Slovenia	43	44	43	43	37	37
Vietnam	43	50	43	43	43	41
Brazil	51	50	50	49	48	48
Bulgaria	51	50	50	49	48	48
Cyprus	51	56	50	50	49	49
Hungary	51	50	50	49	43	43
Kuwait	51	50	50	49	48	48
Romania	51	50	50	43	43	43
Botswana	57	56	56	56	50	49
Egypt	57	56	56	56	55	54
North Macedonia	57	56	56	51	49	49
Panama	57	56	56	56	55	54
BosniaHerzegovina	61	65	61	60	60	60
Chile	61	61	61	60	60	60
Indonesia	61	61	61	60	60	60
Peru	61	65	61	60	60	60
Uruguay	61	61	61	60	60	60
Antigua & Barbuda	66	65	65	64	63	62
Benin	66	71	71	66	65	64
Colombia	66	61	61	60	60	60
Costa Rica	66	65	65	64	63	62
Honduras	66	71	71	71	65	64
Mexico	66	65	61	60	60	60
Namibia	66	65	65	64	63	62
Argentina	73	71	71	71	70	70
Montenegro	73	71	65	65	65	64
Rwanda	73	71	71	71	68	66
Serbia	73	78	71	71	71	71
Solomon Islands	73	71	71	71	70	68
Sri Lanka	73	71	71	71	70	70
Bahamas	79	78	78	78	71	70
Belarus	79	78	78	78	77	77
Djibouti	79	78	71	71	71	70
El Salvador	79	78	78	78	78	78
Georgia	79	78	78	78	77	77
Kazakhstan	79	78	78	78	77	77
Papua New Guinea	79	78	78	72	72	72
Paraguay	79	78	78	78	78	77
Ukraine	79	87	78	78	78	78
Bangladesh	88	97	87	87	86	85
Congo Rep	88	87	87	85	85	84

Table 3. (continued) Rankings of countries

Country	LPI	α=0	α=0.05	α=0.10	α=0.15	α=0.20
Dominican Rep	88	87	87	85	78	78
Guatemala	88	87	87	85	85	84
Guinea Bissau	88	87	87	85	85	84
Mali	88	87	87	85	85	85
Nigeria	88	87	87	86	85	85
Russian Federation	88	87	87	85	85	84
Uzbekistan	88	87	87	85	85	84
Albania	97	97	96	95	94	92
Algeria	97	113	96	95	94	92
Armenia	97	97	96	95	94	92
Bhutan	97	97	96	95	94	93
CentralAfrican Rep	97	97	96	95	94	92
Congo Dem Rep	97	97	96	95	94	92
Ghana	97	97	96	95	94	92
Grenada	97	97	87	86	85	85
Guinea	97	97	96	95	94	92
Jamaica	97	97	96	88	87	87
Mauritius	97	87	87	86	85	85
Moldova	97	97	96	95	87	87
Mongolia	97	113	96	96	94	94
Nicaragua	97	97	96	95	94	93
Tajikistan	97	97	96	95	94	92
Togo	97	97	96	95	94	88
Trinidad &Tobago	97	97	96	95	94	92
Zimbabwe	97	97	96	95	94	92
Bolivia	115	113	111	111	109	108
Cambodia	115	113	111	111	109	99
Gabon	115	113	111	111	109	108
Guyana	115	113	111	111	109	108
Iraq	115	113	111	111	109	108
Lao PDR	115	113	111	111	109	108
Liberia	115	113	111	111	109	108
Sudan	115	113	111	111	110	109
Burkina Faso	123	124	124	123	121	121
Fiji	123	124	124	123	121	121
Gambia	123	124	124	114	113	111
Iran	123	113	111	111	109	108
Kırgız Republic	123	124	124	123	121	121
Madagascar	123	131	131	131	125	124
Mauritania	123	124	112	111	111	111
Syrian Arab Rep	123	124	124	123	121	121
Venezuela	123	124	124	123	121	121
Cuba	133	131	124	124	123	122

Table 3. (continued) Rankings of countries

Country	LPI	α=0	α=0.05	α=0.10	α=0.15	α=0.20
Yemen	133	131	131	131	131	131
Angola	135	134	131	131	131	131
Cameroon	135	134	133	133	133	132
Haiti	135	134	133	133	131	131
Somalia	138	137	137	137	137	137
Afghanistan	139	137	137	137	137	137
Libya	139	137	137	137	137	137

Table 4 shows the number of countries which improved, declined or maintained their rankings as we introduce weight flexibility to the developed model. As the level of flexibility increases (i.e. α increases), the number of countries that improve their rankings increases.

Table 4. Changes in country rankings

	α=0.05	α=0.10	α=0.15	α=0.20
IMPROVED	70	107	121	127
DECLINED	_	_	_	_
NO CHANGE	69	32	18	12

Figure 1 to Figure 6 show the distribution of optimal weights for different α values for each indicator. In Figure 1, the bottom of the box represents the data in the first quartile, the line crossing the box horizontally represents median of the data which is also called second quartile. The x sign indicates mean of the data. The top of the boxes represents the data in the third quartile of the data. Inside of the box represents interquartile range (IQR) and illustrates how much disperse or compact the data is. The dots outside the whiskers represent the outliers (very high or very low values). For α=0.05 the interquartile range is very small indicating that the data is very compact. On the other hand there are outliers both above and below the whiskers indicating the presence of values extremely high and extremely low. As α increases we observe that the IQR increases on the other hand the first quartile values remain stable.

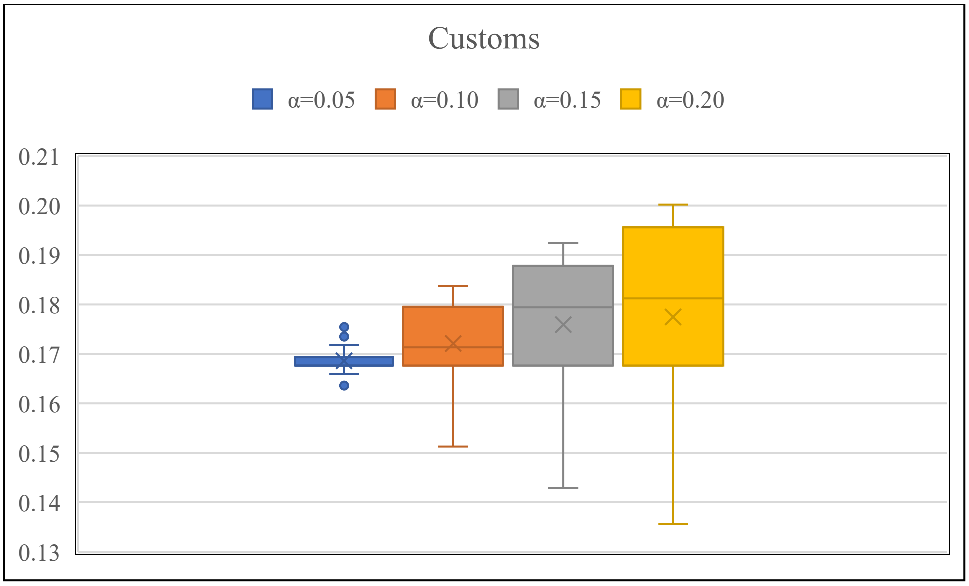

Figure 1. Box and whisker plot of the weights assigned to customs

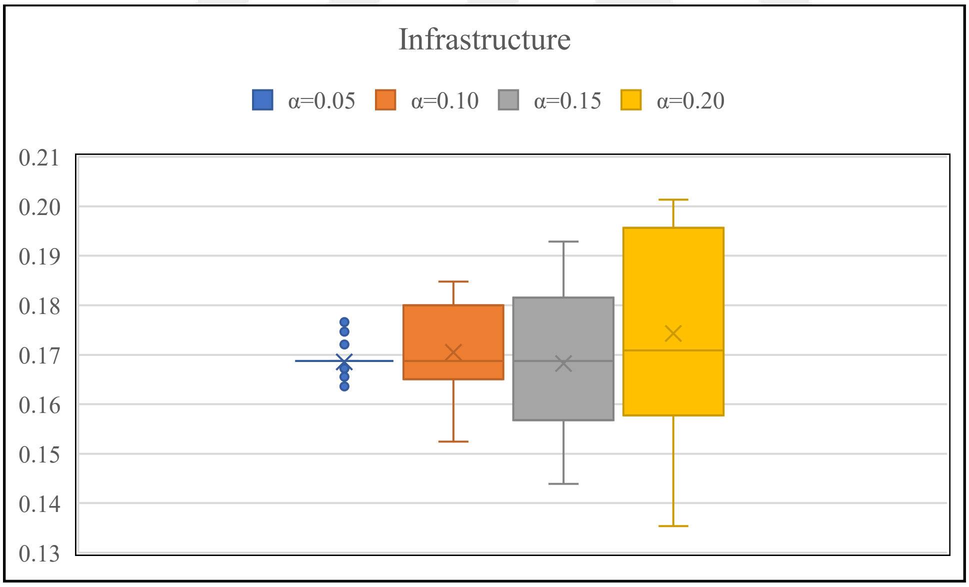

Figure 2. Box and whisker plot of the weights assigned to infrastructure

In Figure 2 for α=0.05 we can hardly observe a box but a line and some outliers. Almost all of the countries choose the same weight for this level of flexibility except some countries which choose extremely high and extremely low weights. As α increases the IQR also increases indicating the dispersion of data increases. On the other hand median and mean stay almost the same.

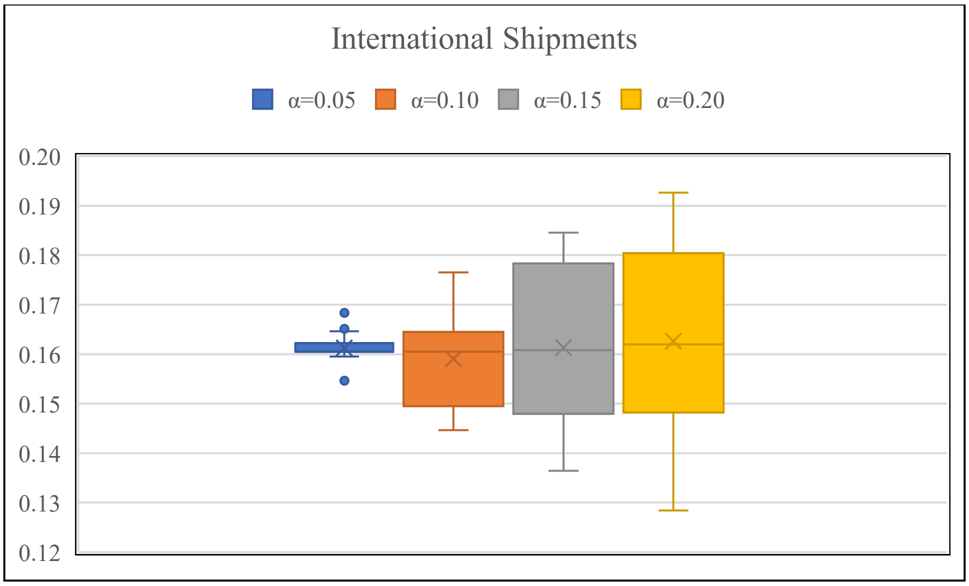

Figure 3. Box and whisker plot of the weights assigned to international shipments

In Figure 3 for α=0.05 we observe that weights are compact though there are a few out outliers. As α increases the IQR also increases indicating the dispersion of data increases. On the other hand median and mean stay almost the same. For α=0.10 the majority of the weights tend to decrease whereas for α=0.15 and α=0.20 the weights are dispersed in both directions; up and down.

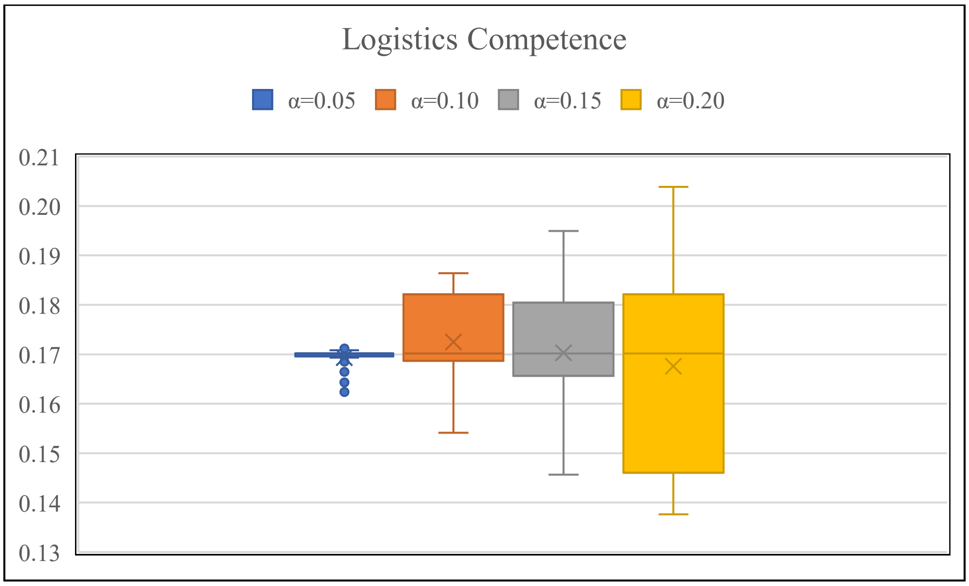

Figure 4. Box and whisker plot of the weights assigned to logistics competence

In Figure 4, the line for α=0.05 indicates almost all the countries choose the same weights except some outliers which choose extremely small weights. For α=0.10 and α=0.15 the trend is upwards, however as α increases to 0.20 the weights move in both directions.

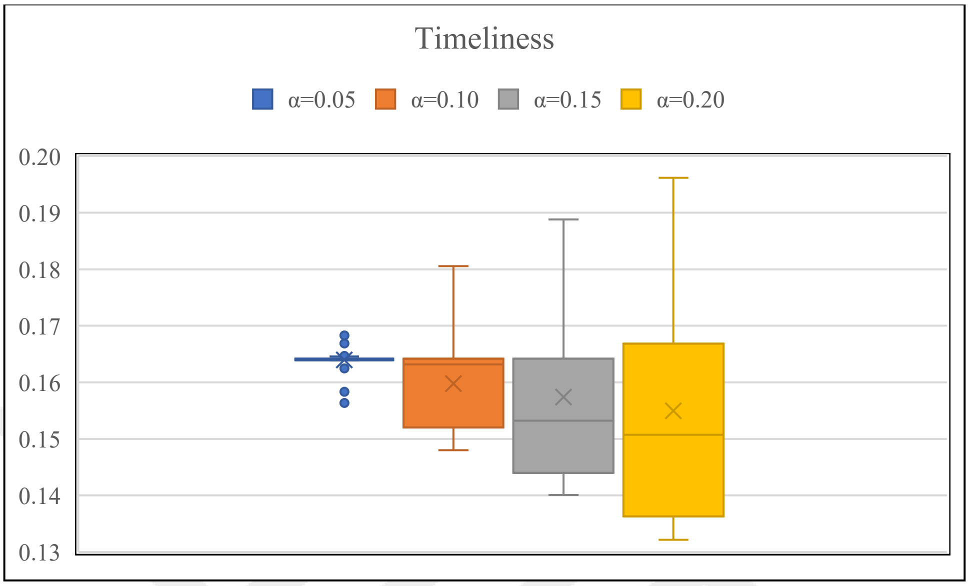

Figure 5. Box and whisker plot of the weights assigned to timeliness

In Figure 5 as α increases IQR increases, on the other hand the median and the mean tend to decrease. The minimum value of the weights decreases. As flexibility increases the mean and the first quartile decreases rapidly.

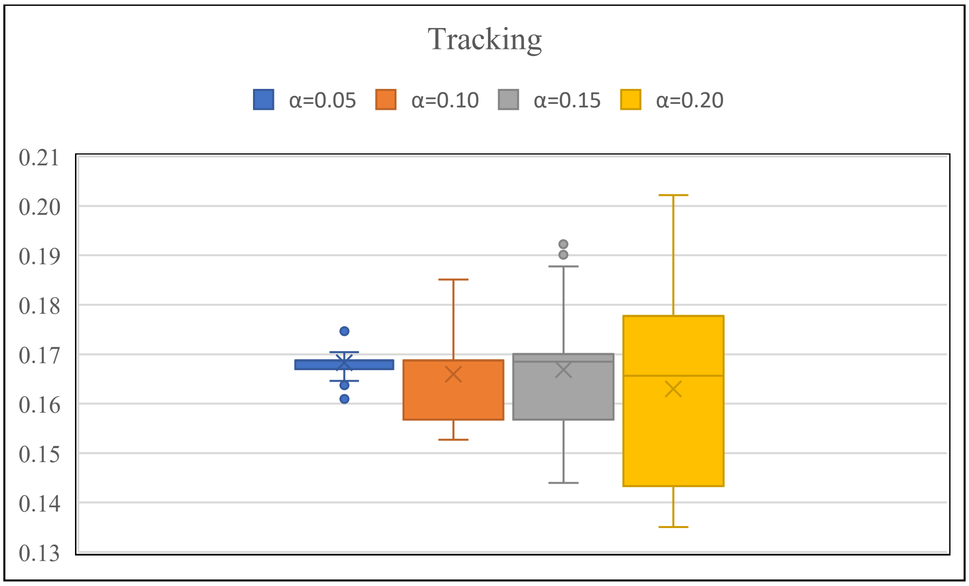

Figure 6. Box and whisker plot of the weights assigned to tracking

An interesting situation occurs in Figure 6; for α=0.10 we do not observe horizontal line within the box, median value and the third quartile value are the same. Because majority of the countries choose the same optimal weight for tracking. This optimal weight is the same as original LPI weight for tracking. Also for α=0.15 we observe that the median value and the third quartile value are very close to each other. Also there are notable outliers at α=0.15; Cuba, Hungary, Rwanda, Moldova, Estonia, Gambia, Latvia and Sudan assign very high weights to tracking compared to the mean. As α increases to 0.20 the median value, the mean value and the first quartile value decrease on the other hand the third quartile value increases. The weights move in both directions, i.e. some countries decrease the weights they assign to tracking whereas some increase the weights.

We observe that as α increases the interquartile range of the data generally increases indicating a higher dispersion as we expect since flexibility increases. On the contrary, the interquartile range of logistics competence and the tracking indicators exhibit a stable structure as α increases from 0.10 to 0.15 and interquartile of international shipments remains almost the same as α increases from 0.15 to 0.20. We observe the outliers only in case of α=0.05 for all the indicators except tracking.

When we look at the outliers, we observe that Cameroon and Haiti, assign very high rates to customs, infrastructure and international shipments, Bolivia, Cambodia, Gabon, Guyana, Iraq, LaoPDR, Liberia, Sudan and Iran assign very high weights to customs, infrastructure and tracking compared to other countries in order to obtain their best rankings when α=0.05. When α=0.15 Cuba, Hungary, Rwanda, Moldova, Estonia, Gambia, Latvia and Sudan assign very high weights to tracking to obtain their best rankings.

4.2 Results of Clustering using Flexible Weights Model

We use *k-means* cluster analysis to the log transformed(centered-log-ratio) data because the indicator weights for each country in our model sum up to 1 which makes our data compositional data by definition. Then to identify the appropriate number of clusters we calculate and draw Silhouette Graphs for the weights found by the model with different values of alpha and use Phyton 3.0 and Excel for this purpose.

For sake of comparison, we decide on a common *k* value for all the test values of α. Everitt et al. (2011) state that a silhouette value below 0.2 indicates poor performance of grouping and close to 0.5 indicates good performance of clustering. As α increases the same number of clusters give less silhouette values as seen below in Figures 7 to 10, so we decided cluster number as 8 which gives a reasonable silhouette score (approximately 0.40) even for α=0.20.

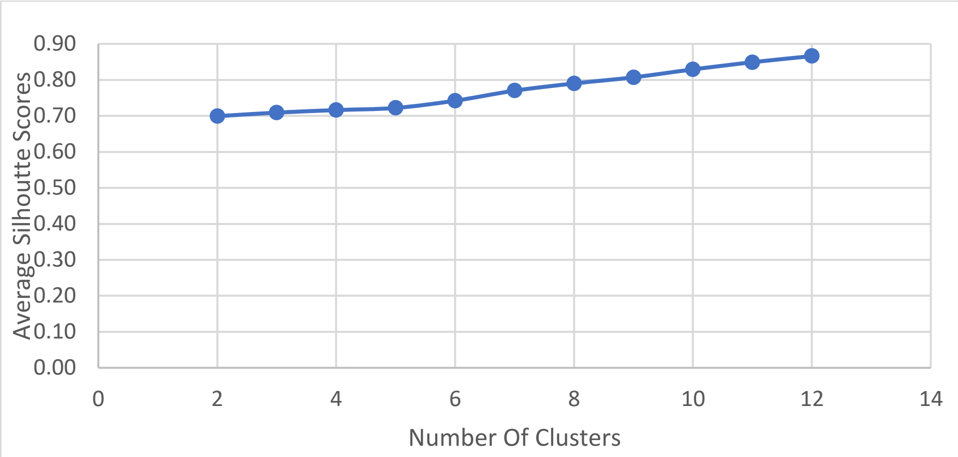

Figure 7. Average silhouette scores for α=0.05

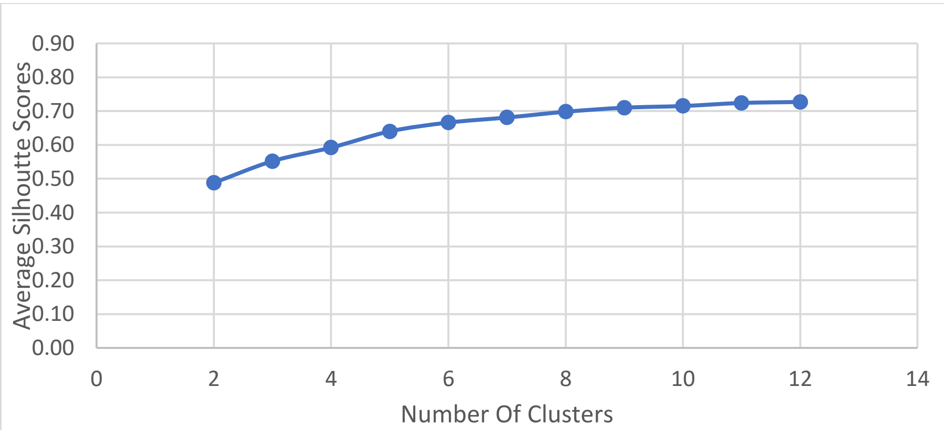

Figure 8. Average silhouette scores for α=0.10

Figure 9. Average silhouette scores for α=0.15

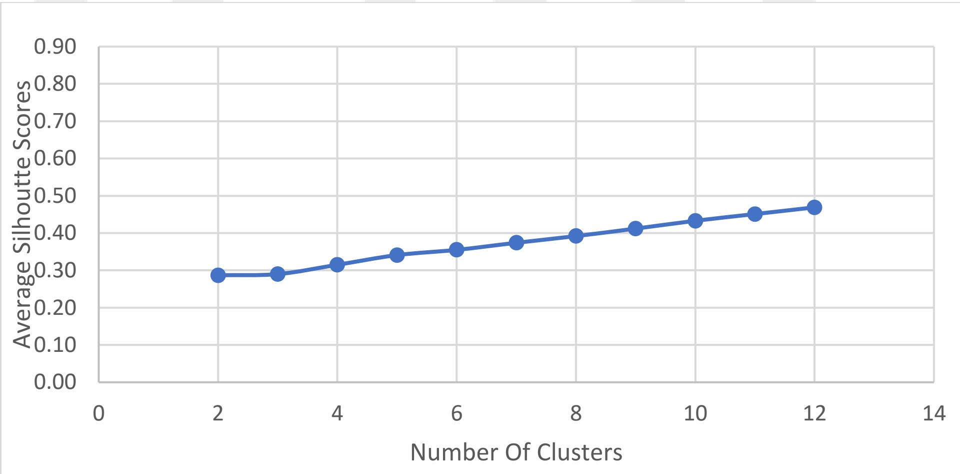

Figure 10. Average silhouette scores for α=0.20

We use 8 clusters for 4 cases: α=0.05, α=0.10, α=0.15 and α=0.20. Below are the results we obtained for the related α values.

a) Clustering Results for α=0.05

Silhouette Score we calculated with 8 number of clusters is 0.790, which shows that the clustering process is successful. The mean values of the weights for 6 indicators of LPI corresponding to best ranks for the countries are given in Table 5. The number of countries and the name of the countries in each cluster are shown in Table 6. Table 7, Table 8 and Table 9 show the Income Group, Borders and Region partitions of the clusters we obtained. For Income Group: H stands for high income countries, UM stands for upper middle income level, LM stands for lower middle income level and L stands for low income level. For Borders: LL stands for Landlocked Countries, O stands for countries that have borders with more than one ocean and S stands for countries that have borders with sea.

Table 5. Mean optimal weights for α=0.05

Cluster	Size	Customs	Infrastructure	International Shipments	Logistics Competence	Timeliness	Tracking
A	2	0.1754340	0.1765780	0.1683300	0.1623630	0.1563610	0.1609340
B	9	0.1734970	0.1746400	0.1546240	0.1643010	0.1582980	0.1746400
C	14	0.1693450	0.1687560	0.1622410	0.1701850	0.1624500	0.1670230
D	7	0.1691150	0.1687560	0.1620100	0.1686830	0.1626810	0.1687560
E	82	0.1675130	0.1686500	0.1605770	0.1701810	0.1642570	0.1688210
F	8	0.1712550	0.1650570	0.1642660	0.1665990	0.1671830	0.1656390
G	11	0.1665400	0.1656490	0.1644420	0.1692880	0.1681010	0.1659810
H	6	0.1718010	0.1645680	0.1655040	0.1701850	0.1641830	0.1637600

In Table 5 there are approximately three groups in terms of infrastructure weights: A-B, C-D-E and F-G-H. The first group has 11 members, the second group has 113 members and the third group has 25 members.

Table 6. Country list of clusters for α=0.05

α=0.05		
CLUSTER	# OF COUNTRIES	COUNTRIES
A	2	Cameroon, Haiti
B	9	Bolivia, Cambodia, Gabon, Guyana, Iraq, LaoPDR, Liberia, Sudan, Iran
C	14	Albania, Armenia, Bhutan, CentralAfricanRepublic, CongoDemRep, Ghana, Guinea, Jamaica, Moldova, Nicaragua, Tajikistan, Togo, TrinidadandTobago, Zimbabwe
D	7	Estonia, Iceland, Ireland, Luxembourg, Malaysia, NewZealand, Poland
E	82	Singapore, Finland, Denmark, Germany, Switzerland, Canada, France, Japan, Spain, Taiwan, Korea, UnitedStates, Australia, Bahrain, Latvia, Qatar, Thailand, India, Lithuania, Portugal, SaudiArabia, Turkiye, Malta, Brazil, Bulgaria, Cyprus, Hungary, Kuwait, Romania, Botswana, Egypt, NorthMacedonia, Panama, BosniaandHerzegovina, Chile, Indonesia, Peru, Uruguay, AntiguaandBarbuda, Benin, Colombia, CostaRica, Honduras, Mexico, Namibia, Argentina, Montenegro, Rwanda, SolomonIslands, SriLanka, Bahamas, Belarus, Djibouti, ElSalvador, Georgia, Kazakhstan, PapuaNewGuinea, Paraguay, Bangladesh, CongoRep, DominicanRepublic, Guatemala, GuineaBissau, Mali, Nigeria, RussianFederation, Uzbekistan, Mauritius, BurkinaFaso, Fiji, Gambia, KırgızRepublic, Madagascar, Mauritania, SyrianArabRepublic, Venezuela, Cuba, Yemen, Angola, Somalia, Afghanistan, Libya
F	8	China, Greece, Italy, Norway, UnitedKingdom, Algeria, Grenada, Mongolia
G	11	SouthAfrica, Israel, Croatia, CzechRepublic, Oman, Philippines, SlovakRepublic, Slovenia, Vietnam, Serbia, Ukraine
H	6	Netherlands, Austria, Belgium, HongKong, Sweden, UnitedArabEmirates

Table 7. Income group distribution of clusters for α=0.05

CLUSTER	INCOME GROUP				TOTAL
	H	UM	LM	L	
A			2		2
B		3	4	2	9
C	1	4	5	4	14
D	6	1			7
E	29	25	17	11	82
F	4	2	2		8
G	6	2	3		11
H	6				6

Clusters A and B, which have the highest mean values for the weight of infrastructure, do not contain any country from the high income group and clusters D and H do not contain any country from the lower middle and low income groups.

Table 8. Border group distribution of clusters for α=0.05

CLUSTER	BORDER			TOTAL
	O	S	LL	
A		2		2
B		7	2	9
C	1	7	6	14
D	1	5	1	7
E	15	55	12	82
F	1	6	1	8
G	2	6	3	11
H		5	1	6

Table 9. Cluster distribution of regions for α=0.05

REGIONS	CLUSTER							
	A	B	C	D	E	F	G	H
East Asia and Pacific		2		2	10	2	2	1
Europe and Central Asia			4	5	23	4	6	4
Latin America and the Caribbean	1	2	3		18	1		
Middle East, North Africa, Afghanistan and Pakistan		2			11	1	2	1
North America					2			
South Asia			1		3			
Sub-saharan Africa	1	3	6		15		1	
TOTAL	2	9	14	7	82	8	11	6

b) Clustering Results for α=0.10

Silhouette Score we calculated with 8 number of clusters is 0.698, which shows that the clustering process is successful. The mean values of the weights for 6 indicators of LPI corresponding to best ranks for the countries are given in Table 10. The number of countries and the name of the countries in each cluster are shown in Table 11. Table 12, Table 13 and Table 14 show the Income Group, Borders and Region partitions of the clusters we obtained.

Table 10. Mean optimal weights for α=0.10

Cluster	Size	Customs	Infrastructure	International Shipments	Logistics Competence	Timeliness	Tracking
A	26	0.1811200	0.1820630	0.1472010	0.1834040	0.1506760	0.1555370
B	3	0.1541860	0.1809840	0.1472980	0.1845930	0.1538730	0.1790650
C	11	0.1793770	0.1805200	0.1718430	0.1584210	0.1528480	0.1569920
D	80	0.1688590	0.1684410	0.1609830	0.1688860	0.1642420	0.1685900
E	7	0.1803240	0.1567000	0.1725640	0.1825460	0.1514710	0.1563950
F	7	0.1769060	0.1558710	0.1540940	0.1801900	0.1512980	0.1816410
G	3	0.1552450	0.1550590	0.1468110	0.1838820	0.1778800	0.1811240
H	2	0.1535000	0.1546430	0.1744750	0.1562180	0.1782960	0.1828690

In terms of the mean weights of infrastructure the highest three clusters contain 40 countries and the lowest four contain 19 countries.

Table 11. Country list of clusters for α=0.10

α=0.10		
CLUSTER	# OF COUNTRIES	COUNTRIES
A	26	CongoRep, DominicanRepublic, Guatemala, GuineaBissau, Mali, RussianFederation, Uzbekistan, Albania, Armenia, Bhutan, CentralAfricanRepublic, CongoDemRep, Ghana, Guinea, Mauritius, Moldova, Nicaragua, Tajikistan, Togo, TrinidadandTobago, Zimbabwe, BurkinaFaso, Fiji, KırgızRepublic, SyrianArabRepublic, Venezuela
B	3	Netherlands, Switzerland, Mexico
C	11	Brazil, Bulgaria, Hungary, Kuwait, AntiguaandBarbuda, CostaRica, Namibia, Nigeria, Grenada, Cameroon, Haiti
D	80	Singapore, Finland, Denmark, Germany, Austria, Belgium, Canada, HongKong, Sweden, UnitedArabEmirates, France, Japan, Spain, Taiwan, Korea, UnitedStates, Australia, China, Greece, Italy, Norway, SouthAfrica, UnitedKingdom, Estonia, Iceland, Ireland, Israel, Luxembourg, Malaysia, NewZealand, Poland, Bahrain, Latvia, Qatar, Thailand, Croatia, CzechRepublic, Oman, Philippines, SlovakRepublic, Slovenia, Vietnam, Cyprus, Botswana, Egypt, Panama, Honduras, Argentina, Montenegro, Rwanda, Serbia, SolomonIslands, SriLanka, Bahamas, Belarus, Djibouti, ElSalvador, Georgia, Kazakhstan, Paraguay, Ukraine, Bangladesh, Mongolia, Bolivia, Cambodia, Gabon, Guyana, Iraq, LaoPDR, Liberia, Sudan, Iran, Madagascar, Mauritania, Cuba, Yemen, Angola, Somalia, Afghanistan, Libya
E	7	India, Lithuania, Portugal, SaudiArabia, Turkiye, Malta, Algeria
F	7	BosniaandHerzegovina, Chile, Indonesia, Peru, Uruguay, Benin, Colombia
G	3	NorthMacedonia, PapuaNewGuinea, Jamaica
H	2	Romania, Gambia

Table 12. Income group distribution of clusters for α=0.10

CLUSTER	INCOME GROUP				TOTAL
	H	UM	LM	L	
A	1	8	8	9	26
B	2	1			3
C	3	5	3		11
D	39	17	17	7	80
E	4	1	2		7
F	2	3	2		7
G		2	1		3
H	1			1	2

Table 13. Border group distribution of clusters for α=0.10

CLUSTER	BORDER			TOTAL
	O	S	LL	
A	3	13	10	26
B	1	1	1	3
C	1	9	1	11
D	12	54	14	80
E		7		7
F	3	4		7
G		3		3
H		2		2

Table 14. Cluster distribution of regions for α=0.10

REGIONS	CLUSTER							
	A	B	C	D	E	F	G	H
East Asia and Pacific	1			16		1	1	
Europe and Central Asia	7	2	2	29	3	1	1	1
Latin America and the Caribbean	5	1	5	9		4	1	
Middle East, North Africa, Afghanistan and Pakist	1		1	12	3			
North America				2				
South Asia	1			2	1			
Sub-saharan Africa	11		3	10		1		1
TOTAL	26	3	11	80	7	7	3	2

c) Clustering Results for α=0.15

Silhouette Score we calculated with 8 number of clusters is 0.522, which shows that the clustering process is successful. The mean values of the weights for 6 indicators of LPI corresponding to best ranks for the countries are given in Table 15. The number of countries and the name of the countries in each cluster are shown in Table 16. Table 17, Table 18 and Table 19 show the Income Group, Borders and Region partitions of the clusters we obtained.

Table 15. Mean optimal weights for α=0.15

Cluster	Size	Customs	Infrastructure	International Shipments	Logistics Competence	Timeliness	Tracking
A	9	0.1914030	0.1901700	0.1391070	0.1509090	0.1403930	0.1880180
B	23	0.1866540	0.1842300	0.1447400	0.1783030	0.1472840	0.1587890
C	10	0.1860210	0.1808180	0.1818140	0.1485810	0.1428770	0.1598890
D	5	0.1460200	0.1690850	0.1674210	0.1917780	0.1785340	0.1471630
E	49	0.1674720	0.1675990	0.1616070	0.1677600	0.1661020	0.1694600
F	16	0.1635370	0.1557960	0.1534110	0.1830510	0.1589740	0.1852320
G	20	0.1856650	0.1509330	0.1782930	0.1782950	0.1465960	0.1602180
H	7	0.1871420	0.1507570	0.1786790	0.1498920	0.1843030	0.1492260

Table 16. Country list of clusters for α=0.15

α=0.15		
CLUSTER	# OF COUNTRIES	COUNTRIES
A	9	Bolivia, Cambodia, Gabon, Guyana, Iraq, LaoPDR, Liberia, Sudan, Iran
B	23	Brazil, Bulgaria, Kuwait, Argentina, SolomonIslands, SriLanka, Belarus, Georgia, Kazakhstan, CongoRep, DominicanRepublic, Guatemala, GuineaBissau, Mali, Nigeria, RussianFederation, Uzbekistan, Mauritius, BurkinaFaso, Fiji, KırgızRepublic, SyrianArabRepublic, Venezuela
C	10	Croatia, Oman, SlovakRepublic, Slovenia, Egypt, Panama, AntiguaandBarbuda, CostaRica, Namibia, Grenada
D	5	Belgium, CzechRepublic, Botswana, Bangladesh, Madagascar
E	49	Singapore, Finland, Denmark, Germany, Switzerland, Canada, France, Japan, Spain, Taiwan, Korea, UnitedStates, Australia, China, Greece, Italy, Norway, SouthAfrica, UnitedKingdom, Iceland, Ireland, Israel, Luxembourg, Malaysia, NewZealand, Poland, Bahrain, Qatar, Thailand, Philippines, Vietnam, Hungary, Romania, NorthMacedonia, Montenegro, Serbia, Djibouti, ElSalvador, Paraguay, Ukraine, Jamaica, Mauritania, Cuba, Yemen, Angola, Cameroon, Somalia, Afghanistan, Libya
F	16	Netherlands, Estonia, Latvia, Cyprus, BosniaandHerzegovina, Chile, Indonesia, Peru, Uruguay, Benin, Colombia, Mexico, Rwanda, PapuaNewGuinea, Moldova, Gambia
G	20	India, Lithuania, Portugal, SaudiArabia, Turkiye, Malta, Albania, Algeria, Armenia, Bhutan, CentralAfricanRepublic, CongoDemRep, Ghana, Guinea, Mongolia, Nicaragua, Tajikistan, Togo, TrinidadandTobago, Zimbabwe
H	7	Austria, HongKong, Sweden, UnitedArabEmirates, Honduras, Bahamas, Haiti

Table 17. Income group distribution of clusters for α=0.15

CLUSTER	INCOME GROUP				TOTAL
	H	UM	LM	L	
A		3	4	2	9
B	1	11	6	5	23
C	6	3	1		10
D	2	1	1	1	5
E	27	11	8	3	49
F	6	5	3	2	16
G	5	3	8	4	20
H	5		2		7

Table 18. Border group distribution of clusters for α=0.15

CLUSTER	BORDER			TOTAL
	O	S	LL	
A		7	2	9
B	3	14	6	23
C	3	6	1	10
D		3	2	5
E	8	35	6	49
F	4	10	2	16
G	1	13	6	20
H	1	5	1	7

Table 19. Cluster distribution of regions for α=0.15

REGIONS	CLUSTER							
	A	B	C	D	E	F	G	H
East Asia and Pacific	2	2			11	2	1	1
Europe and Central Asia		7	3	2	20	6	6	2
Latin America and the Caribbean	2	5	4		4	5	2	3
Middle East, North Africa, Afghanistan and Pakist	2	2	2		7		3	1
North America					2			
South Asia		1		1			2	
Sub-saharan Africa	3	6	1	2	5	3	6	
TOTAL	9	23	10	5	49	16	20	7

d) Clustering Results for α=0.20

Silhouette Score we calculated with 8 number of clusters is 0.392, which shows not good but acceptable performance of clustering. The mean values of the weights for 6 indicators of LPI corresponding to best ranks for the countries are given in Table 20. The number of countries and the name of the countries in each cluster are shown in Table 21. Table 22, Table 23 and Table 24 show the Income Group, Borders and Region partitions of the clusters we obtained.

Table 20. Mean optimal weights for α=0.20

Cluster	Size	Customs	Infrastructure	International Shipments	Logistics Competence	Timeliness	Tracking
A	27	0.1951170	0.1975620	0.1781280	0.1427080	0.1362350	0.1502510
B	12	0.1463060	0.1881000	0.1417440	0.1795940	0.1610450	0.1832100
C	25	0.1892660	0.1877000	0.1394770	0.1813780	0.1458350	0.1563440
D	6	0.1410080	0.1667780	0.1833850	0.1967890	0.1718110	0.1402280
E	50	0.1686720	0.1611950	0.1613930	0.1722730	0.1645680	0.1718990
F	9	0.1871130	0.1584150	0.1830350	0.1460190	0.1805000	0.1449170
G	6	0.1973910	0.1504140	0.1736310	0.1433310	0.1367000	0.1985340
H	4	0.1911200	0.1399450	0.1878700	0.1966090	0.1443730	0.1400830

Table 21. Country list of clusters for α=0.20

α=0.20		
CLUSTER	# OF COUNTRIES	COUNTRIES
A	27	Spain, Korea, Australia, Slovenia, AntiguaandBarbuda, CostaRica, Namibia, Albania, Algeria, Armenia, Bhutan, CentralAfricanRepublic, CongoDemRep, Ghana, Grenada, Guinea, Tajikistan, TrinidadandTobago, Zimbabwe, Bolivia, Gabon, Guyana, Iraq, LaoPDR, Liberia, Sudan, Iran
B	12	Netherlands, Switzerland, UnitedStates, NewZealand, Qatar, Botswana, Mexico, Rwanda, Jamaica, Nicaragua, Gambia, Cuba
C	25	Japan, Brazil, Bulgaria, Kuwait, Argentina, SriLanka, Belarus, Djibouti, Georgia, Kazakhstan, CongoRep, DominicanRepublic, Guatemala, GuineaBissau, Mali, Nigeria, RussianFederation, Uzbekistan, Mauritius, BurkinaFaso, Fiji, KırgızRepublic, SyrianArabRepublic, Venezuela, Cameroon
D	6	Belgium, Bahrain, Thailand, CzechRepublic, Paraguay, Togo
E	50	Singapore, Finland, Denmark, Germany, Canada, France, Taiwan, China, Greece, Italy, Norway, SouthAfrica, UnitedKingdom, Estonia, Iceland, Ireland, Israel, Luxembourg, Malaysia, Poland, Latvia, India, Lithuania, Portugal, SaudiArabia, Turkiye, Malta, Cyprus, Hungary, Romania, NorthMacedonia, BosniaandHerzegovina, Chile, Indonesia, Peru, Uruguay, Colombia, Serbia, SolomonIslands, ElSalvador, PapuaNewGuinea, Ukraine, Moldova, Cambodia, Mauritania, Yemen, Angola, Somalia, Afghanistan, Libya
F	9	Austria, HongKong, Sweden, UnitedArabEmirates, Philippines, Honduras, Bahamas, Madagascar, Haiti
G	6	Croatia, Oman, SlovakRepublic, Vietnam, Benin, Montenegro
H	4	Egypt, Panama, Bangladesh, Mongolia

Table 22. Income group distribution of clusters for α=0.20

CLUSTER	INCOME GROUP				TOTAL
	H	UM	LM	L	
A	6	8	8	5	27
B	5	4	1	2	12
C	2	11	7	5	25
D	3	2		1	6
E	27	11	9	3	50
F	5		3	1	9
G	3	1	2		6
H	1		3		4

The highest three clusters in terms of the weights of infrastructure contain 64 countries. As α increases the number of countries in the clusters having high weights for infrastructure increases. The number of countries belonging to high income group in each cluster also increases.

Table 23. Border group distribution of clusters for α=0.20

CLUSTER	BORDER			TOTAL
	O	S	LL	
A	2	18	7	27
B	3	6	3	12
C	3	16	6	25
D	1	3	2	6
E	8	37	5	50
F	1	7	1	9
G		5	1	6
H	2	1	1	4

Table 24. Cluster distribution of regions for α=0.20

REGIONS	CLUSTER							
	A	B	C	D	E	F	G	H
East Asia and Pacific	3	1	2	1	8	2	1	1
Europe and Central Asia	5	2	7	2	25	2	3	
Latin America and the Caribbean	6	4	5	1	5	3		1
Middle East, North Africa, Afghanistan and Pakist	3	1	3	1	6	1	1	1
North America		1			1			
South Asia	1		1		1			1
Sub-saharan Africa	9	3	7	1	4	1	1	
TOTAL	27	12	25	6	50	9	6	4

Considering the results of clustering at all 4 levels of flexibility we introduce to our model, we observe that some groups of countries always take place in the same cluster with each other. Developed countries generally take place in clusters where there are not great differences between the mean weights of the indicators. For $\alpha=0.05$ these clusters are E, F and G. For $\alpha=0.10$ Cluster D is the cluster where the mean weights of indicators are more similar and for $\alpha=0.15$ and $\alpha=0.20$ Cluster E contains more similar mean weights of the indicators. On the other hand, developing and the least developed countries take place in clusters where weight of the infrastructure is significantly higher than the weights of other indicators. For example, for the group that contains Bolivia, Gabon, Guyana, Iraq, LaoPDR, Liberia, Sudan and Iran we observe that they take place all together in clusters where the mean weight of infrastructure is higher than at least 4 indicators. This finding is consistent with the results of the whisker box plot of the weights in section 4.1. An interesting grouping occurs where developed countries as Singapore, Finland, Denmark, Germany, Canada, France, Taiwan come together with the least developed and developing countries as El Salvador, Mauritania, Yemen, Angola, Somalia, Afghanistan and Libya. As can be observed they take place all together in clusters where weights do not differ from each other. This is because the most developed and the least developed countries remain almost stable in terms of rankings even in case of $\alpha=0.20$.

CHAPTER 5: CONCLUSION & FURTHER RESEARCH

We work on 2023 LPI data set to develop a mixed integer linear programming model that enables the indicator weights to move within a reasonable range with respect to the original fixed weights of LPI. We observe that by providing even a small level of flexibility to the weights, there is improvement in the rankings of a significant number of countries and as the level of flexibility increases this number increases. In line with our findings in 4.1 and 4.2, we can conclude that developing and less developed countries are more likely to improve their rankings with the increasing flexibility. In contrary, developed countries generally maintain their positions though there are exceptions, this is something we expected. This is probably because they are already using weights that provide them optimal rankings (i.e. the original LPI weights). This finding is consistent with the point of our study that the same weight set used for all countries favors some countries on the expense of disfavoring others.

In this study, we first introduced weight flexibility to every country and then conducted cluster analysis. For further research, clustering can be done in the first place and then the same weight set can be assigned to each cluster applying a modified version of our model. Also, instead of *k-means* clustering one of the convex clustering methods can be used and regarding log transformation of the compositional data, log transformations other than centered log ratio can be used and the results can be compared with our actual results. Also, other data sets can be included to explain optimal weight selection of countries better. Time dimension can be included in the study and further analysis can be done for Türkiye over time. Furthermore, an interactive Decision Support System can be developed that enables the user to observe the rankings of countries with different weights. Regarding the inputs of the model we developed, i.e. the scores of the countries, we can normalize these, for example according to the country sizes or use other attributes for normalization and use afterwards. Also, in our study we used experimental values for α (level of flexibility). Determining a realistic level of flexibility that all the countries will accept can be another research direction.

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