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Enhancing the Logistics Performance

A textual big data approach

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1 Introduction

The proficiency of logistics is an important determinant in a country's economic growth and increased competitiveness. Logistics is one of the most important factors for increasing national competitiveness (Hayaloğlu, 2015). Hence, every country aims at developing logistics as its key economic sector. A country with inefficient logistics sees increase in costs and reduction of a global integration (Gani, 2017). Assessment of the logistics efficiency requires various indicators that characterize its efficiency and productivity (Lambert & Burduroglu, 2000). Macroeconomic criteria and indices depicting the logistics efficiency have different procedural approaches in measuring pointers. Among them, ranking logistics models of the leading countries according to the rating of the Logistics Performance Index (LPI) by the World Bank, established in 2007, has become widely used in research. This indicator allows to determine the main differences between the analyzed countries (Marti et al., 2014). The countries' rankings have been continuously changing based on the actions taken by them to advance their logistic performance indicators. Therefore, the studies carried out before this research need constant enhancement and identification of their changes in order to improve logistics. This helps in detecting recent trends and determining methods to improve the logistic components, beneficial mechanisms or instruments to use and how to incorporate government and companies in improving logistic activities.

As robust factors weighing in logistics assessment, there is a growing need to break from the traditional approach to evaluate the logistic performance. Despite LPI being widely known and used for the logistics performance assessment, it has a complex procedure, which is linked to high effort and expenditure. A crucial complexity is the methodology used in collecting the data for assessment. LPI uses surveys with many experts from freight forwarding and express carrier companies as a prime source to find a weighted average of the country scores on six components (Arvis et al., 2018). These components include the efficiency of the clearance process, trade and infrastructure quality, ease of shipment, competence and logistics quality, efficiency of tracking consignments and timely delivery of shipment. This is a time consuming and costly methodology in terms of acquiring large data and analyzing them as nearly 900 respondents answered the latest survey in 2018 regarding 160 countries (Arvis et al., 2018). Based on the result of the LPI policymakers determine priorities to enhance trade facilitation and therefore trying to improve their logistics performance. However, for some countries like Sweden or Bahrain not many respondents have evaluated their logistics performance making improvement decisions more difficult (Ojala & Çelebi, 2015). This obstacle has to be overcome to secure policymakers and countries a reliable information.

A fundamental intention is to find an approximation for a current logistic performance assessment, which is more time-effective and less cost-intensive. Additionally new inputs for the LPI are aimed to be included to supplement the current LPI methodology. With more and more logistics literature and reports from different kind of experts being developed, it could be possible to develop a methodology that structures this large data for assessing a country's

logistic performance. This looks achievable with the current techniques in textual big data analytics.

Big data is an uprising topic, especially since the last decade. It was first acknowledged an increased amount of research data within libraries in 1944 (Press, 2013). Since then the amount of information data is continuously growing (Bounie & Gille, 2012). Driven by cloud computing and the Internet of Things (IoT) trend the data currently keeps growing exponentially (Patgiri & Ahmed, 2016). It offers huge possibilities to companies and institutions using all the information in it. Thus, new models and tools are being developed to handle the volume of data (Gokalp et al., 2016).

Data is mainly characterized by the three "V's" - its variety, velocity and volume (Sagiroglu & Sinanc, 2013). Some researchers such as Miloslavskaya & Tolstoy (2016) also include the variability, visibility and value as key characteristics of data. As part of its variety data can be generally categorized as structured, semi-structured and unstructured (Miloslavskaya & Tolstoy, 2016). Structured data is typically already processed by internal operations and systems within a company. Whereas unstructured data is typically unorganized and undefined, making it hard for machines analyzing them. Semi-structured data has some degree of standards and typical characteristics that form a pattern, therefore making it possible to be processed by machines further.

Most of the big data, to be precise 95%, is unstructured, for example postings in social media or mails (Gandomi & Haider, 2015). Process and analyze this kind of data can bring huge benefits to companies, institutions as well as countries. As there is such a huge amount of data like images, audio, video and text, machine learning and big data techniques are good opportunities to use them in academic research. Logistic research has just begun using these approaches in their studies. Still, most of the used approaches are regarding concrete topics or are focusing more on the operational view of logistics. In contrast, this paper aims to focus on a general overview of logistics, especially the country performance. An inspiration for this is the LPI measuring a country's logistics performance. With the latest techniques in big data analytics, there is a possibility to enhance the current LPI decision factors.

To dive further into this direction, the following research question is formulated:

How can textual big data analysis with the approach of text mining be used to enhance the LPI to assess countries' logistic performance?

To fulfill this question this research aims to give an overview of the current state of the art using (textual) big data for country logistic performance analysis. This paper is further addressing general problems of the LPI. In consequence of that it is aimed to give implications how text analytics may enhance the LPI. Lastly, this paper intends to emphasize the use of big data approaches, especially in logistics.

The focus is on analyzing texts, although having the opportunity to evaluate images, audio and videos is given with the state of the art in research. Finding a pattern within texts is a part of textual big data analysis. Multiple methods and tools can be applied to investigate texts. It offers a cheap and fast way to look into free accessible, mainly unstructured, data. The following research is inspired by Kinra's (2019) textual big data approach to assess a country's logistic performance. It is using his research to answer the research question. Therefore, the paper aims to find a proposal to analyze relevant information of a country logistic performance convenient for assessment and potential ranking.

The following section describes the used textual analysis methodology. Next, the results of the textual analysis are presented and complemented by literature. In the end implications for literature is given and a visualization for further research is described.

1.1 Way of Argumentation

In order to gain a comprehensive understanding on the LPI, the study starts by providing the theoretical background with an literature review (chapter 2). Having a theoretical background in mind, a methodology is explained (chapter 3). Next, the results of the textual analysis are presented and complemented by literature (chapter 4). Based on the results implications for further research are presented (chapter 5), followed by the limitations in chapter 6. The last chapter summarizes the findings from this study.

2 Literature review

Logistics and trade include many policies that are crucial to a country's business competitiveness. Until 2005, the policymakers did not have sufficient information to make comparisons and recognize trade barriers. In this context, the literature has focused on the assessment of trade facilitation measures. An approach to this assessment is through the LPI published by the World Bank.

LPI analyses the country differences and provides an overview of customs procedures, logistics costs and infrastructure quality required for land and sea transport. LPI, thus, became a key instrument explaining the relationship between trade and transport expeditions. LPI has helped in increasing awareness amongst policymakers, established reforms and promoted trade in different countries (Banco Interamericano de Desarrollo, 2010).

In general, a lot of authors have focused on trade facilitation and have used LPI as an explanatory variable for trade. For example, Wilson et al. (2005) defined trade facilitation using port efficiency, customs, regulations and use of e-commerce using a gravity model on a sample of 75 countries. Mejia et al. (2006) analyzed the effect of changes in trade facilitation of Mexican industrial good flows and suggests the trade reform to boost exports by 22.4%.

Using LPI, Korinek & Sourdin (2011) confirmed the influence of logistics performance on trade, especially where improvements in infrastructure are concerned. They see this to be influential in middle-income countries and more specifically for exporters. They also point out that administrative enhancements have a higher impact on importing countries.

Marti et al. (2014) used LPI as a proxy for trade facilitation and concluded with the relationship between complex goods and logistics. They came to the conclusion that the more complex goods are in terms of transport, the higher the logistics influence is. Their study uses LPI to analyze the relationship between bilateral exports and logistics.

Hollweg & Wong (2009) study the regulatory restrictions in logistics for the Association of Southeast Asian Nations (ASEAN). They find that the regulatory restrictions and LPI are negatively correlated which points out that the countries with fewer legal barriers have a better logistics score. The trade restrictions lead to increased time and costs, ultimately reducing competitiveness.

Some authors also link LPI to other developmental aspects. Guner & Coskun (2012) study the relationship between the logistics development measured by the LPI and other socio-economic factors by focusing on 26 OECD members. Min & Kim (2010) use Data Envelopment Analysis (DEA) to combine the LPI and environmental development index to create a new hybrid index called the "Green LPI". The authors point to the fact that the LPI does not take environmental damage into consideration. This is important to consider as occasionally higher logistics efficiency is achieved at the cost of more emissions of pollutants.

However, policymakers face certain misinterpretations that arise due to the direct relationship of LPI to the levels of income. LPI ranks developed countries such as the USA, Germany and Singapore to a leading position owing to their high income. At the same time, China, India, and Vietnam are ranked higher, than other developed nations like Portugal, Greece, and Iceland, due to low-cost production. Using this ranking and LPI, Hoekman and Nicita (2008, 2010) conclude that tariff and non-tariff barriers still hold significance for trade in low-income countries.

Also, different researchers have found the importance of certain LPI components higher than the other. These researchers have either tried to use a new index using LPI components (Felipe and Kumar, 2012) or use regression models on a single component (Hertel & Mirza, 2009; Puertas et al., 2013). Noticeably, in the above researches, it was concluded by the authors that infrastructure was the most important component as opposed to customs efficiency. This leads to confusion for policymakers as different countries can have different components essential for them. From a managerial point of view, this makes decision-making ambiguous as the LPI does not give a country-specific view.

3 Methodology

This paper uses Kinra's (2019) prototype performance classification tool which is developed from a text corpus of country logistics assessments. The text corpus was taken from the Council of Supply Chain Management Professionals (CSCMP) as it contains large positive and descriptive assessments on the analyzed countries. These assessments are emphasized to foster future development plans for a country. Henceforth, they needed to be scrutinized further to get more insightful knowledge.

The author developed the tool using the data collected from 21 text documents, describing the logistics systems of 20 countries from 2006-2014, tokenizing the text corpus using Natural Language Toolkit (NLTK) and Python programming language along with techniques such as word frequency. Taking forward Kinra's research, text mining was conducted on his data and the results were analyzed from it.

3.1 Text mining

Text mining, having evolved within the last 20 years, is a comparatively new area in terms of interdisciplinary research field. It is strongly associated with fields such as Natural Language Processing (NLP), knowledge management, and machine learning (Tonkin & Tourte, 2016). NLP is a subfield of linguistics and artificial intelligence and deals with how to program computers to process and analyze large amounts of data. Due to the strong incorporation, different authors have given a wide range of terms for defining text mining.

Miner et al. (2012) define seven practical areas of text mining: search and information retrieval, document clustering, document classification, web mining, information extraction, concept extraction and NLP. Each of these areas offers a range of techniques to be applied on the textual data. However, the basic element to be processed is the textual document (Feldman & Sanger, 2007).

3.2 Word frequency

Word frequency analysis automatically identifies the frequently occurring words from a text corpus by using the term document matrix. The tokens are analyzed using NLTK to create term document matrix which in turn is used to generate word cloud (most frequent words) for a given document. These word clouds are the simplest way of visualizing the most frequently occurring words in a given document. The word clouds gave an overview of major components influencing a country's logistics performance. Further, these word counts were analyzed using Tableau to create graphs and draw conclusions regarding ways to complement the current LPI in assessing countries' logistics performance.

3.3 Methodology approach

For Kinra's framework, text extraction was performed on the global perspective documents. The size of these documents varies from 20 to 60 pages. The extracted text was tokenized with NLTK and Python programming language. The text was further cleaned and processed using NLTK. Furthermore, word frequency analysis is used along with Tableau to draw analysis on the findings by Kinra. By comparing the results of the word frequency of each country patterns were searched after visualizing them in Tableau. Additionally, these results were discussed with further literature that shaped up the analysis, which is presented in the following section.

4 Analysis

Throughout the research, it was found that no textual big data techniques have been applied to assess countries' logistics performance. Research has shown some application of big data methods, like some authors used to solve liner shipping problems (Brouer et al., 2018; Jafarzadeh & Schjølberg 2018; Kim et al. 2017), for concrete business cases but none for assessing country logistic performance. However, research shows that several authors have detected limitations in the current LPI methodology. These are further addressed with a textual big data approach.

The LPI is measuring input and output indicators to rank countries according to their logistics performance (Arvis et al., 2018). This indicator is not considering input-output ratios and ranks countries according to absolute components. By assessing so, the LPI is not taking other, external circumstances into account (Markovits-Somogyi & Bokor, 2014). In contrast, literature is showing that this is a problem as input (components) enable the performance, whereas the output (components) present the results (Charan et al., 2008). Therefore, these two sections needed to be assessed separately. Takele & Buvik (2019) showed additionally the influence of the input components on the output components of the LPI. In general several researchers put emphasis on the importance of input components for a country's logistic performance. Memedovic et al. (2008) called the input components like infrastructures and quality of logistic services a logistics capability of a country. These logistics capabilities have an impact on performances, productivity as well as competitiveness and can be directly influenced by countries. Moreover, Su & Ke (2015) pointed out the findings of the research by the Institute of Transportation (IOT), Ministry of Transportation and Communications in Taiwan, that the components infrastructure, customs and service quality are the leading contributors to the country's logistic performance (IOT, 2014). The IOT proposed to policy makers that focussing the improvements of these components is going to improve the performance of the other lagging components, tracking & tracing, international shipments and timeliness, as well. Thus, just the input components of a country should be taken into consideration to assess a country's logistic performance ability.

In general, input and output components can be assessed through text mining. Kinra (2015, 2019) is providing an in-depth framework for the assessment of country's logistic performance with decision factors on the basis of environmental complexity. As this framework only considers input components it can be used for further detailed assessments. The decision factors provide information and can be seen as information measures. Using the decision factors for text mining either a supervised or unsupervised approach can be conducted for the assessment of a country's logistic performance due to the grouped factors into categories.

By assessing a country's logistic performance with the decision factors provided by Kinra (2015, 2019) an alternative approach has been presented to measure performance. This approach complements the LPI by analyzing input components and adding more input variables

into the assessment. Through this the assessment is able to consider country-specific actions for their development, which is not included currently in the LPI, thus complementing it.

As this approach is distinguishing input and output components, also highlighting the relationship between these two sectors, it is implicating literature as well as research to distinguish it too. Research should especially help and clarify the inputs and outputs. An approach of how an identification can be done is the previously presented complexity framework using input decision factors by Kinra (2015). A similar framework is possible to be made for output components.

Through the emphasis on the input and output relationship it is needed to understand that bad inputs (capabilities) correlate highly with poor output performance. This leads to a need of a relative comparison or ranking of country's logistic performance. It is also highlighted by Markovits-Somogyi & Bokor (2014) that the LPI is an absolute assessment and to consider country-specific external circumstances as well as abilities a relative assessment has to be conducted. If the output performance of a country with bad capabilities, e.g. infrastructure, is still good, it is going to be easily recognized and investigated by research. In addition, a standardized measurement for a country's potential is necessary to be included in the assessment.

In order to increase the comparability of the LPI, some researchers recommend weighting the individual components in order to get a more realistic insight (Rezaei et al., 2018). Currently, LPI weighs all the six components equally and thus, all components have the same influence on a country's score (Arvis et al., 2018). This is a problem because Rezaei et al. (2018) and Ulutas & Karaköy (2019) already say that the components should be treated with different levels of importance. Also (Saltelli & Homma, 1992) shows that the improvement of different enablers has a different impact on the results. For the LPI, this would mean that a change in the input components infrastructure, customs and service quality has a varying degree of influence on the output components and thus on the overall logistic quality. As a result, an incorrect weighting of the components leads to an incorrect evaluation of the importance level. This, ultimately, leads policymakers to set the wrong focus and use an incorrect basis for optimal decision making.

Therefore, researchers have used different approaches to determine the weights of LPI components. Rezaei et al. (2018) use a subjective point of view to identify the weights. The Best Worst Method was used to assign the weights. Managers from 107 countries from all six continents responded to the questionnaire. The weighting of the individual components is shown in Table I in the appendix I.

Ulutas & Karaköy (2019) also examined the weighting of LPI components and formed three approaches to assess the ratios. Similar to Rezaei et al. (2018) a subjective approach was conducted by these researchers. They used the Step-wise Weight Assessment Ratio Analysis

(SWARA) method to obtain subjective data by expert judgements from three managers. On the other hand also an objective approach to determining weights was applied by using the Criteria Importance Through Intercriteria Correlation (CRITIC) method with a decision matrix. In addition to the objective and subjective determination of the weights Ulutas & Karaköy (2019) formed a combined view using the proximity indexed value (PIV) method, which is based on the objective and subjective approach. An overview of the weights is shown in Table I in the appendix.

To be able to determine weights for the LPI components with the text mining analysis used in this paper, the keywords of the individual decision factors must be assigned to the LPI components (see appendix II part B). Since only input variables are taken into account in the text analysis, only the input components are considered for the comparison. In order to achieve a comparability of the weights, the keywords were assigned to the input components, based on the methodology of the LPI. The LPI questionnaire (Arvis et al., 2018) was used for this purpose. For example, airports are allocated to the input component infrastructure. The average number of keyword counts per component is used to determine the weights and is related to the total sum of average values. A detailed explanation of this method is attached in the appendix II part B.

In order to make a comparison with the weighting of the other authors, only the inputs are considered as they are the important enablers for logistic performance. The calculated weights can be found in Table II in the appendix I and the detailed calculation is within appendix part A. The text analysis is a combined approach from a subjective and objective point of view, since the reports present both objective facts (e.g. statistics, figures, etc.) and the subjective opinion (e.g. evaluation, future development) of the experts.

In the following illustration, the weights of the above mentioned approaches are shown side by side in a bar chart. The red solid line represents an equal weighting as it is currently used in the LPI. The values of the weighting are shown on the vertical axis and the input components customs, infrastructure and service quality are assigned to each weighting approach of the authors on the horizontal axis. It can be stated that the SWARA method by Ulutas & Karaköy (2019) with three managers and the survey by Rezaei et al. (2018) with 107 respondents show similar results, as represented by the yellow and green bars. This can also be seen for the two results received from the combination of subjective and objective perspective by Ulutas & Karaköy (2019). The text analysis based on decision factors, used here, is represented by the purple and dark blue coloured bars.

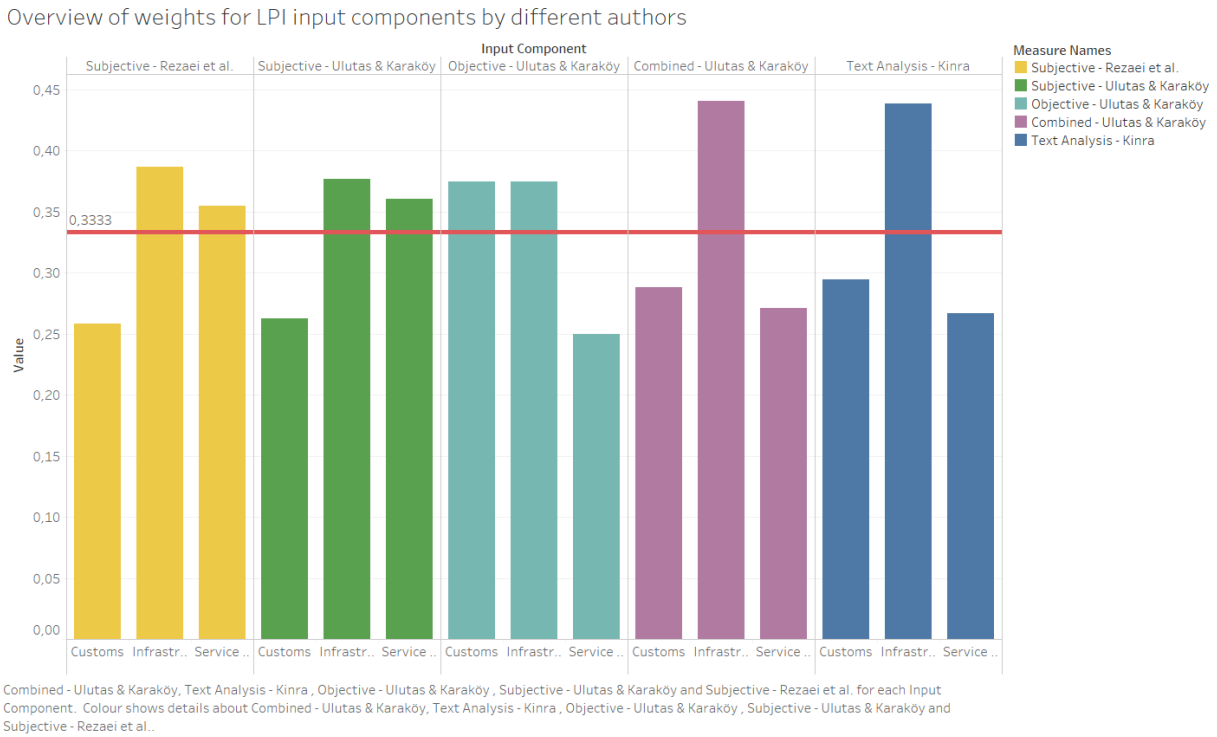

Figure 1: Overview of weights for LPI input components

From this comparison, it can be stated that the results of the researchers are robust and that the text mining comes to similar results when weighting the LPI input components. A text analytics approach can thus be considered for determining the weights of the LPI components.

To compare the actual weighting of the individual component in the illustration below the value of the weights are shown on the vertical axis and the weights of the researchers are assigned to the components customs, infrastructure and service quality on the horizontal axis. The red line represents a reference point to the evenly distributed weights from the LPI. For each component, an average value is also calculated, which is represented by the gray horizontal lines.

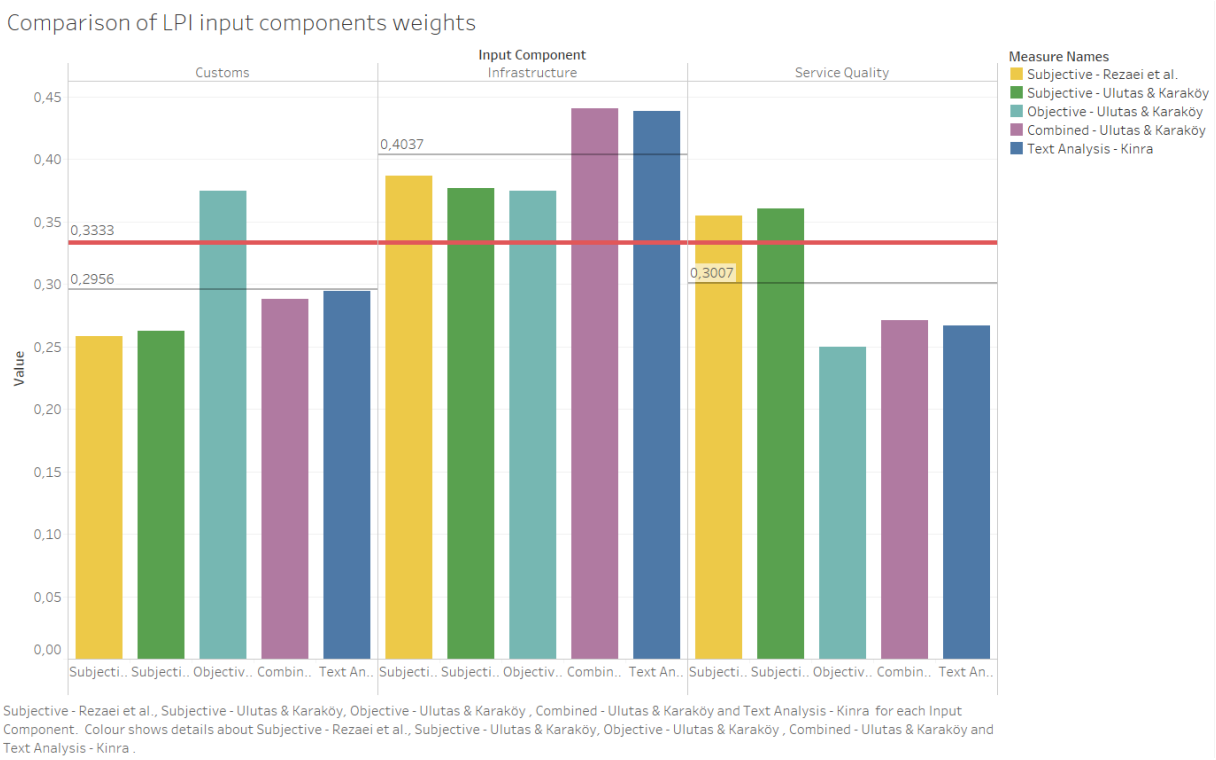

Figure 2: Comparison of input component weights

This illustration clearly shows that there is a deviation from the red straight line and therefore from the equal weighting as used in the LPI for the individual components. From this it can be deduced that the components in the LPI should be weighted. It should be noted that the input component infrastructure has the highest weighting for all approaches and is therefore the most important input component.

Due to the fact that the text mining approach assigns a weighting to the components, it surpasses the LPI because the importance level of the components is taken into account. On the other hand, this approach can complement the LPI with the determined weights. Accordingly, the weights for the individual input components can be used to calculate the scores of the ranking. Anyway, as different approaches have already shown, the LPI components should be weighted to show a realistic impact on the country's logistics performance. Also, infrastructure is the most important of the three input components. The comparison has also shown that the weights are robust and the text mining approach comes to similar results (see Figure 3), this approach should be used instead of time consuming and resource intensive expert surveys.

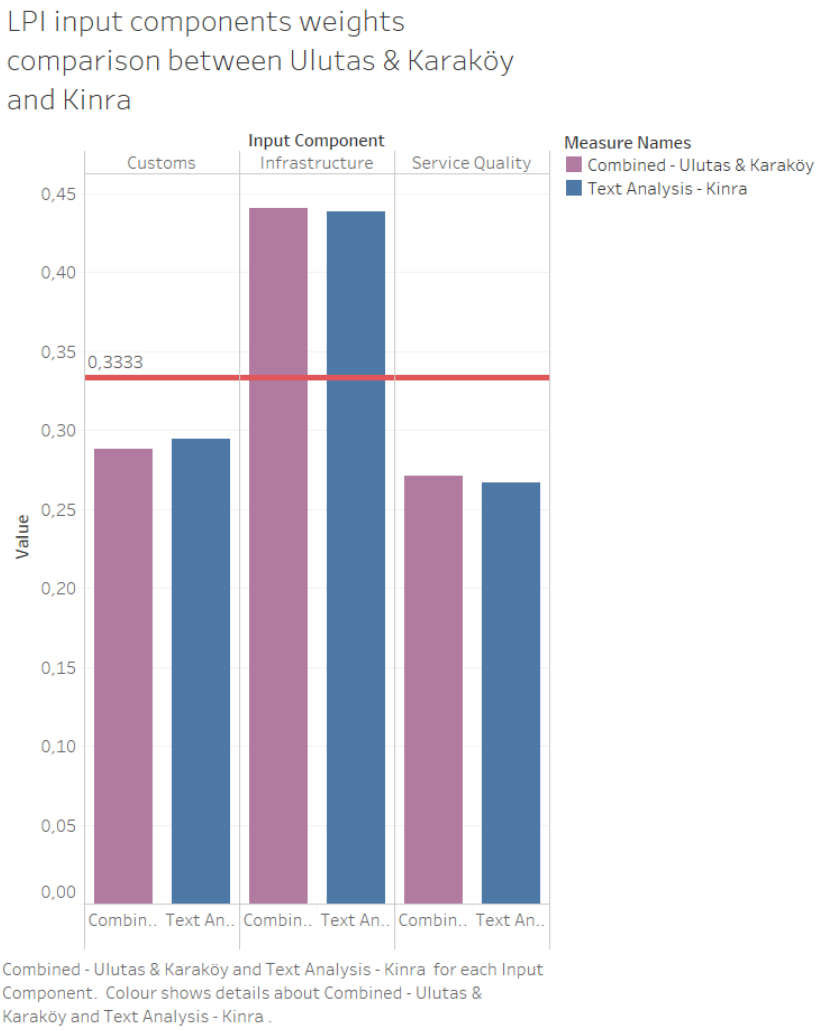

Figure 3: Comparison of the two combined approaches

In line with the input-output relationship mentioned above, the weighted approach is an alternative way of ranking countries. Compared to LPI, the focus is more on the decision factors that a country can influence directly, taking into account the different influence of enablers on the results. The appendix I contains Table III, which shows the original LPI ranking of countries from 2010 compared with the ranking based only on weighted input components. The weights from the text mining approach were used for the calculation (see appendix II part C). It may be noted that the score and ranking of the countries does not change significantly. Germany, for example, achieved a score of 4.11 in 2010, whereas the adjusted score is 4.19. The rank remained unchanged. For Mexico, the score falls by 0.19 and the country's ranking rises from 50th to 49th place. This demonstrates that if the weighted input components are taken into account only, the score and rank do not change dramatically.

In the weighted approach with exclusive consideration of the input components, the importance of the components in general is considered, but for specific countries that are, for example landlocked, certain importance levels are different from the general values. For this reason,

country-specific factors are considered in the following section. Weighting these factors within the LPI components does not provide a comparable basis between different countries, since country-specific weighting can affect the score to different degrees. Therefore, the general weights determined in the previous section provide a reasonable basis for ranking the countries. However, for making country-specific decisions, an alternative approach is pursued here using the decision factors, which takes into account the special circumstances of countries, such as landlocked.

The LPI and its components helped countries, governments, and corporations in knowing their business partners more closely and anticipate adjustments that could affect their competitiveness. However, more details of a country's logistics environment needed in-depth focus. The Domestic LPI took care of dwelling into those environments.

The Domestic LPI examines in detail the logistics environments of 100 countries. This is achieved by surveyed logistics professionals assessing the logistics environments in their own countries. This evaluation focuses on detailed information regarding countries' logistics environments, core processes, logistics institutions, and data on time and distance. This approach targets logistics restraints within countries such as ports or borders. The following four factors are considered by the Domestic LPI to measure performance: infrastructure, services, border procedures & time, and supply chain reliability (Arvis et al., 2014).

However, literature points out that it is unreasonable to compare the LPI of countries with different socio-economic conditions (Yu & Hsiao, 2016) . Other environmental factors need to be considered to elaborate country-specific logistics development (Guner & Coskun 2012). Zofío & Prieto (2001) stresses on considering economic aspects under environmental or political issues irrespective of a country being a member of the Organization for Economic Co-operation and Development (OECD). Thus, it might lead to erroneous LPI scores when all countries are pooled into one group or a single set of variables are applied to evaluate LPI over economically and socially different countries.

Another set of potential differences can arise when different variables such as income and geographical area come into the picture. Marti et al. (2017) suggest that the logistics performance depends largely on income and geographical area. High-income countries, which are highly dominated by the European Union (EU), are in the group of best performers. Low-income countries, in general, occupy the last places in the logistics ranking. Such countries generally lack behind due to little development or geographical obstacles like market access. However, some countries with similar income levels but better geographical conditions fare well in the logistics performance ranking – such as India and Vietnam. Henceforth, the importance of geographical area cannot be denied in measuring the logistics performance.

Furthermore, given the different logistics challenges faced by different countries, the same progressive strategies cannot be applied equally to all countries. This difference has been

pointed out by Marti et al. (2017) as they study the progressively narrowing gap of highest and lowest-ranked countries over subsequent LPI rankings. The findings reveal that the LPI of Somalia currently represents 25% of Germany (the highest-ranked) which has massively increased.

At the same time, the gap between countries ranked high in the LPI is continuously narrowing. The reasons for this narrowing gap and improving logistics performance range from improvement in infrastructure to foster trade in low and middle-income countries to customs clearance. Apparently, different countries need different solutions to improve their logistics performance. Hence, the policymakers cannot rely on the same progressive strategies and need a better tool to complement a robust local decision-making strategy.

The Domestic LPI does not focus on either of the components, income and geographical location, in assessing the logistics performance. Also, the domestic LPI only relies on output components while assessing a country and completely neglects the input components. Thereby, the policymakers have no clear focus to target their policies especially in terms of geographical location. With the increase in literature and text mining techniques, it is possible to get an insight on important country specific conditions. The below graph shows the importance of geographical location for Poland is much higher than what is perceived for other countries:

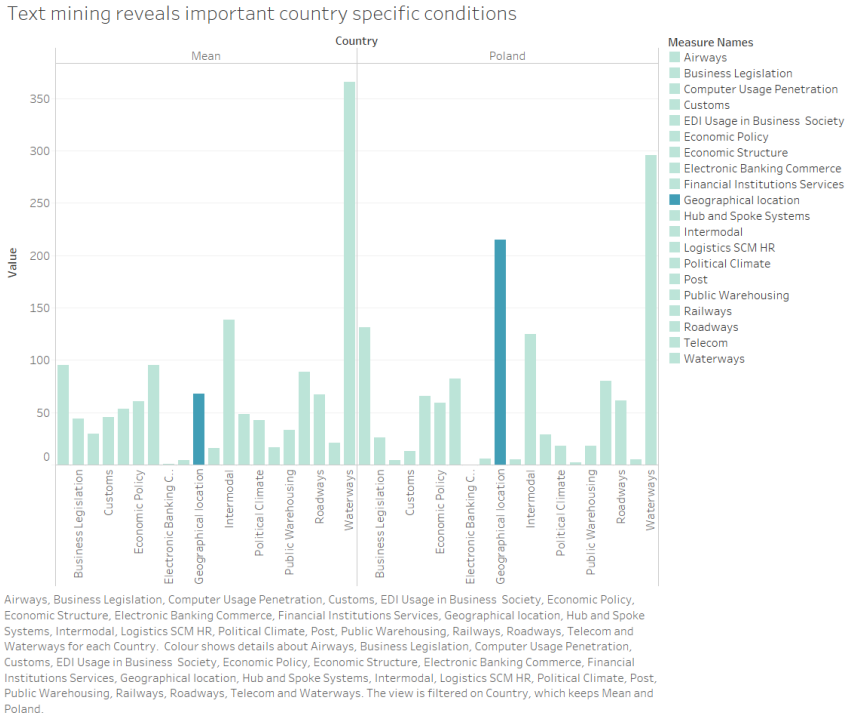

Figure 4: Word frequency analysis to show the importance of Poland

One such literature study is by Szczudlik-Tatar (2013) where the author talks about the geographical importance of Poland while assessing China's interest in the Central Eastern European (CEE) region. As China expanded its railway cargo links to Europe through Chongqing-Xinjiang-Duisburg railway in 2011, there was no stop in Poland even though the trains pass through the country, while the Chengdu-Lódź connection is used only to import products from China and trains return almost empty to Chengdu, without Polish products (Szczudlik-Tatar, 2013).

The author states that strategically Poland could be more beneficial for China in terms of economic opportunities than the Eastern European provinces where there is strong competition from United States and Western European companies. This paves way for Poland to focus its strategies on Western China and become a face of the Polish economic presence in the economic hub of China.

New variables need to be added to the existing domestic LPI to assess a country's logistics environment. Coupling this with the text analytics will help in identifying factors that are crucial for a country e.g. geographical factor. This approach will lead to a more detailed and flexible view inside countries and help policymakers to have a clearer picture of the areas that need to focus on their policies to improve logistics performance.

In current times, the dynamics of countries' performance stretch beyond the usual LPI components. With new emerging trends and complexities, there is a need to extend the decision factors to support local decision-making situations. A similar framework is suggested by Kinra (2019) where new emerging categories like sustainability, complexity, security, etc. are shown as prominent in decision making.

5 Implications for further research

In the previous section problems of the current LPI methodology regarding the input-output relationship, the weighting of components as well as missing and country-specific variables has been addressed. The following visualization aims to provide the perspective of this paper on these topics.

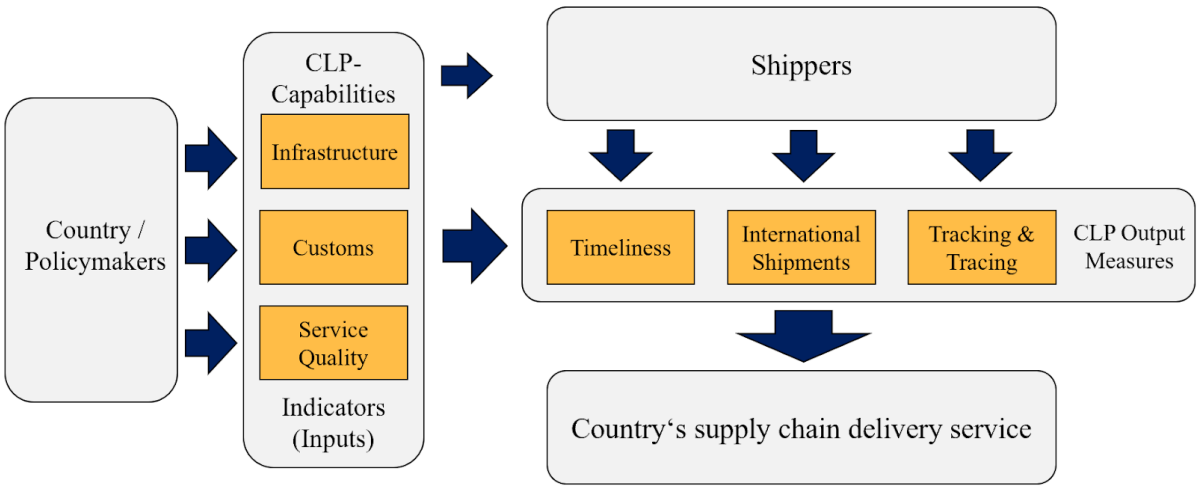

Figure 5: Country Logistics Performance Management Framework (CLPMF)

It is based on the frameworks from Su & Ke (2015) and Arvis et al. (2018) regarding the relationships and interactions between the LPI components, policymakers and shippers. When future research is addressing a country's logistic performance assessment based on the LPI it should consider first of all the differentiation between input and output components. Policymakers are responsible for their country's logistic performance (CLP) capability as emphasized by Memedovic et al. (2008). These country-specific capabilities are the country's infrastructure, customs and service quality, which are all input components of the LPI (Arvis et al., 2018). On the other hand the input components influence the decision on supply chain routes of shippers and freight forwarders depending on the CLP capabilities. How good or bad a country's capability is provided to those firms can be measured by the LPI output components timeliness, international shipments and tracking & tracing. All in all the results can give an overview of a country's supply chain delivery service.

Therefore, it is emphasized that policy makers focus on input components as these are a country's capability, which can be influenced and improved by giving incentives or setting the right conditions to facilitate logistics performance. Actions and regulations should consider the weighting, thus the importance of a component.

For some countries the importance and therefore the weighting of an input component may vary to the general values. This is the case when a country has unique circumstances, which are not common in other countries, for example a landlocked country with many neighbours. Text mining is a suitable approach for those kinds of country-specific conditions. A influencing variable like geographical location or market access can be added in the assessment with less effort making it a flexible and low effort assessment tool.

Nonetheless, the LPI is currently a widely used and appropriate opportunity to compare, rank as well as evaluate a country's logistic performance. To be more robust it should consider to weight components. The comparison can be supplemented by including input-output ratios of

the components as it is enabling a relative comparison. Future research can carry on from that point by comparing input capabilities to the output results.

As pointed out in the previous section assigning weights to components does not change the ranking significantly. It is implicating for other research that their results does not change as long they considered the overall LPI score for grouping countries into like Weingarten et al. (2014) did it to categorize countries having good or bad capabilities. On the other hand it is reasonable that research results change, when researchers used the LPI score to determine the most important or improvable component for a country as this is a more in-depth analysis considering more aspects like comparing components to each other.

In this paper it was shown that with the use of the provided framework by Kinra (2019) an analysis of a country's input components can be made with the use of text mining. It is therefore possible for policymakers to focus on their important and improvement-needed component. For future research it is proposed to provide a framework for the CLP output measures similarly to the approach of Kinra (2019), which was applied for the input components.

With the use of text mining for country's logistic performance measurement weaknesses, opportunities and trends can be detected. As a basis country logistic reports are needed at best continuously and standardized to compare it. This has been done by the CSCMP in their Global Perspectives report. More of these kind of reports will be beneficial for future country's logistics performance assessments and will ease the comparison through standardization.

6 Limitations

This research has some limitations, which have to be considered as they may have an impact on generalization of results. First of all the results are dependent on the data, which was analyzed. In this case the 21 texts regarding 20 countries has been evaluated through text mining based on Kinra (2019). Therefore, the small sample has to be taken into consideration. Consequently, only one landlocked country (Hungary) and no poor country (e.g. from the Sub-Saharan region) was part of the data basis. Taking more countries into the analysis can improve the general applicability of the results as for example the weightings of the input components get more robust.

In general, the LPI questionnaire does not specify clearly to which the decision factors financial institutions & services, business legislation, economic structure and political climate could be assigned. There is no substantial proof in literature that these four decision factors have to be included in the input component infrastructure. Therefore, the weights could change when these decision factors are excluded in the assignment (see appendix III).

Additionally, the results rely on the quality of the analyzed texts. A biased author knowing that a report is taken into the data basis could potentially manipulate or exaggerate, in a positive or negative way, his written report. Thus, a standard and trustworthy institution should be responsible for those reports, like the CSCMP, which is currently not publishing these kinds of reports.

Lastly, this research is aimed at enhancing the current LPI methodology with textual big data techniques. Word frequency as part of text mining itself can neither rank countries nor show direct influences on components. It is moreover a complementation of the current LPI to enhance the robustness of the results.

7 Conclusion

The aim of this paper was to show reasons and possibilities to enhance the current LPI methodology with the use of textual big data approaches. As the LPI is widely known and used for assessing a country's logistic performance many policy makers rely on the results and define on that basis improvements for their logistics. Despite that, literature pointed out some critique of the LPI. First, the LPI is considering input and output components for their assessment. In contrast, performance management literature is emphasizing on the differentiation of inputs, called enablers, and outputs representing the results (Charan et al., 2008). Another problem of the LPI is that it assigns to every component the same weighting, implicating that each component has the same importance level. Some approaches in literature are started to assign different weights for each component. This paper surpasses those approaches as it is generating similar, robust results with less effort conducting the assessment. Lastly, it was highlighted that the LPI and its domestic view lack country-specific circumstances. It is unreasonable to compare the LPI of countries with different socio-economic conditions (Yu & Hsiao, 2016). Moreover it was stated that other country-specific variables such as the geographic location influence the logistics performance of a country.

Taking these critics into account a word frequency analysis has been conducted using Kinra's (2015, 2019) framework for input decision factors based on the environmental complexity. This analysis focused as proposed by performance management literature on input components. On that basis it has further weighted the input components concluding the infrastructure component to be the most important one. Applying these weights changes the ranking of some countries slightly, for example performers are still ranked at the top. Lastly, through the flexible and adjustable text mining approach other country-specific conditions can be taken into consideration when assessing a country's logistic performance. All in all the approach of this paper is complementing the current LPI methodology by considering the limitations, thus helping policy makers to focus on the right improvements for their country logistics with a current textual big data technique.

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Appendix I

Table of Contents

Table I - All weights

Approach	Customs	Infrastructure	Service Quality	Tracking & Tracing	International Shipments	Timeliness
Subjectiv - Rezaei et al.	0,16	0,24	0,22	0,10	0,13	0,16
Subjectiv - Ulutas & Karaköy	0,16	0,23	0,22	0,13	0,12	0,15
Objectiv - Ulutas & Karaköy	0,18	0,18	0,12	0,14	0,23	0,16
Combined - Ulutas & Karaköy	0,17	0,26	0,16	0,10	0,16	0,15
LPI	0,17	0,17	0,17	0,17	0,17	0,17

Table II - Only input components

Approach	Customs	Infrastructure	Service Quality
Subjectiv - Rezaei et al.	0,26	0,39	0,36
Subjectiv - Ulutas & Karaköy	0,26	0,38	0,36
Objectiv - Ulutas & Karaköy	0,38	0,38	0,25
Combined - Ulutas & Karaköy	0,29	0,44	0,27
Text analysis - Kinra	0,29	0,44	0,27

Table III - LPI score

Country	LPI Score	LPI Rank	Adjusted Score	Adjusted Rank	Score Difference	Rank Difference
Germany	4,11	1	4,19	1	0,07	0
Singapore	4,09	2	4,13	3	0,04	-1
Sweden	4,08	3	4,03	5	-0,04	-2
Netherlands	4,07	4	4,15	2	0,08	2
Luxembourg	3,98	5	3,95	11	-0,03	-6
Switzerland	3,97	6	4,08	4	0,10	2
Japan	3,97	7	4,02	6	0,05	1
United Kingdo	3,95	8	3,88	14	-0,07	-6
Belgium	3,94	9	3,99	8	0,05	1
Norway	3,93	10	4,02	7	0,08	3
Ireland	3,89	11	3,73	18	-0,16	-7
Finland	3,89	12	3,97	9	0,09	3
Hong Kong, Cl	3,88	13	3,91	13	0,03	0
Canada	3,87	14	3,92	12	0,05	2
United States	3,86	15	3,95	10	0,09	5
Denmark	3,85	16	3,82	16	-0,02	0
France	3,84	17	3,86	15	0,01	2
Australia	3,84	18	3,75	17	-0,09	1
Austria	3,76	19	3,63	20	-0,13	-1
Taiwan	3,71	20	3,55	24	-0,16	-4
New Zealand	3,65	21	3,57	22	-0,08	-1
Italy	3,64	22	3,63	21	-0,02	1
Korea, Rep.	3,64	23	3,54	25	-0,10	-2
United Arab E	3,63	24	3,64	19	0,01	5
Spain	3,63	25	3,56	23	-0,07	2
Czech Republi	3,51	26	3,27	31	-0,23	-5
China	3,49	27	3,42	27	-0,07	0
South Africa	3,46	28	3,41	28	-0,05	0
Malaysia	3,44	29	3,34	29	-0,10	0
Poland	3,44	30	3,10	38	-0,34	-8
Israel	3,41	31	3,43	26	0,02	5
Bahrain	3,37	32	3,27	32	-0,11	0
Lebanon	3,34	33	3,30	30	-0,04	3
Portugal	3,34	34	3,25	34	-0,09	0
Thailand	3,29	35	3,12	37	-0,17	-2
Kuwait	3,28	36	3,18	35	-0,10	1
Latvia	3,25	37	2,91	45	-0,33	-8
Slovak Republ	3,24	38	2,98	40	-0,26	-2
Turkey	3,22	39	3,04	39	-0,18	0
Saudi Arabia	3,22	40	3,18	36	-0,04	4
Brazil	3,20	41	2,94	44	-0,26	-3
Iceland	3,20	42	3,25	33	0,05	9
Estonia	3,16	43	2,98	41	-0,18	2
Philippines	3,14	44	2,70	55	-0,44	-11
Lithuania	3,13	45	2,77	52	-0,36	-7
Cyprus	3,13	46	2,90	48	-0,23	-2
India	3,12	47	2,91	46	-0,20	1
Argentina	3,10	48	2,79	51	-0,31	-3

Chile	3,09	49	2,90	47	-0,19	2
Mexico	3,05	50	2,86	49	-0,19	1
Panama	3,02	51	2,72	54	-0,30	-3
Hungary	2,99	52	2,95	43	-0,03	9
Vietnam	2,96	53	2,69	57	-0,28	-4
Greece	2,96	54	2,74	53	-0,22	1
Qatar	2,95	55	2,56	65	-0,39	-10
Costa Rica	2,91	56	2,64	58	-0,27	-2
Slovenia	2,87	57	2,70	56	-0,18	1
Senegal	2,86	58	2,61	60	-0,26	-2
Romania	2,84	59	2,40	87	-0,45	-28
Oman	2,84	60	2,97	42	0,13	18
Tunisia	2,84	61	2,47	75	-0,37	-14
Kazakhstan	2,83	62	2,56	64	-0,27	-2
Bulgaria	2,83	63	2,51	70	-0,33	-7
Malta	2,82	64	2,82	50	-0,01	14
Dominican Re	2,82	65	2,41	85	-0,41	-20
Uganda	2,82	66	2,55	66	-0,26	0
Peru	2,80	67	2,60	63	-0,20	4
Uzbekistan	2,79	68	2,43	83	-0,36	-15
Benin	2,79	69	2,49	71	-0,30	-2
Honduras	2,78	70	2,40	86	-0,37	-16
Ecuador	2,77	71	2,42	84	-0,35	-13
Colombia	2,77	72	2,61	61	-0,17	11
Macedonia, F\	2,77	73	2,60	62	-0,17	11
Croatia	2,77	74	2,48	74	-0,29	0
Indonesia	2,76	75	2,49	72	-0,27	3
Paraguay	2,75	76	2,46	78	-0,30	-2
Uruguay	2,75	77	2,62	59	-0,13	18
Bahamas, The	2,75	78	2,47	76	-0,28	2
Bangladesh	2,74	79	2,43	82	-0,31	-3
Syrian Arab Re	2,74	80	2,46	77	-0,28	3
Jordan	2,74	81	2,53	68	-0,21	13
Mauritius	2,72	82	2,45	80	-0,27	2
Serbia	2,69	83	2,33	97	-0,35	-14
Venezuela, RB	2,68	84	2,35	94	-0,32	-10
Congo, Dem. F	2,68	85	2,54	67	-0,13	18
El Salvador	2,67	86	2,51	69	-0,16	17
Bosnia and He	2,66	87	2,28	103	-0,38	-16
Madagascar	2,66	88	2,49	73	-0,17	15
Azerbaijan	2,64	89	2,27	104	-0,37	-15
Guatemala	2,63	90	2,46	79	-0,18	11
Kyrgyz Republ	2,62	91	2,27	105	-0,35	-14
Egypt, Arab Re	2,61	92	2,36	91	-0,25	1
Georgia	2,61	93	2,34	96	-0,28	-3
Russian Feder	2,61	94	2,35	95	-0,26	-1
Tanzania	2,60	95	2,22	112	-0,38	-17
Togo	2,60	96	2,16	120	-0,44	-24
Guinea	2,60	97	2,33	100	-0,27	-3
Haiti	2,59	98	2,23	110	-0,36	-12

Kenya	2,59	99	2,20	115	-0,39	-16
Nigeria	2,59	100	2,36	90	-0,23	10
Yemen, Rep.	2,58	101	2,38	89	-0,20	12
Ukraine	2,57	102	2,35	93	-0,22	9
Iran, Islamic R	2,57	103	2,40	88	-0,18	15
Moldova	2,57	104	2,10	125	-0,48	-21
Cameroon	2,55	105	2,22	113	-0,33	-8
Niger	2,54	106	2,25	108	-0,29	-2
Nicaragua	2,54	107	2,26	107	-0,28	0
Jamaica	2,53	108	2,12	124	-0,42	-16
Côte d'Ivoire	2,53	109	2,36	92	-0,17	17
Pakistan	2,53	110	2,13	122	-0,40	-12
Armenia	2,52	111	2,33	99	-0,20	12
Bolivia	2,51	112	2,29	102	-0,23	10
Gambia, The	2,49	113	2,29	101	-0,21	12
Turkmenistan	2,49	114	2,24	109	-0,26	5
Chad	2,49	115	2,09	126	-0,40	-11
Congo, Rep.	2,48	116	1,95	145	-0,53	-29
Ghana	2,47	117	2,45	81	-0,03	36
Lao PDR	2,46	118	2,06	129	-0,40	-11
Albania	2,46	119	2,19	119	-0,27	0
Comoros	2,45	120	1,95	142	-0,49	-22
Montenegro	2,43	121	2,33	98	-0,10	23
Gabon	2,41	122	2,19	118	-0,22	4
Ethiopia	2,41	123	1,98	140	-0,44	-17
Papua New Gu	2,41	124	2,02	136	-0,39	-12
Maldives	2,40	125	2,22	111	-0,18	14
Djibouti	2,39	126	2,26	106	-0,13	20
Liberia	2,38	127	2,12	123	-0,26	4
Bhutan	2,38	128	2,03	134	-0,35	-6
Cambodia	2,37	129	2,21	114	-0,16	15
Algeria	2,36	130	2,08	127	-0,28	3
Tajikistan	2,35	131	2,04	132	-0,31	-1
Libya	2,33	132	2,20	116	-0,13	16
Myanmar	2,33	133	1,95	143	-0,38	-10
Botswana	2,32	134	2,14	121	-0,17	13
Solomon Islan	2,31	135	2,20	117	-0,11	18
Mozambique	2,29	136	2,05	131	-0,24	5
Sri Lanka	2,29	137	1,96	141	-0,33	-4
Zambia	2,28	138	1,98	139	-0,31	-1
Mali	2,27	139	2,06	130	-0,21	9
Guyana	2,27	140	2,07	128	-0,20	12
Mongolia	2,25	141	1,98	138	-0,27	3
Angola	2,25	142	1,79	149	-0,45	-7
Afghanistan	2,24	143	2,03	133	-0,21	10
Fiji	2,24	144	2,01	137	-0,23	7
Burkina Faso	2,23	145	2,02	135	-0,20	10
Sudan	2,21	146	1,95	146	-0,26	0
Nepal	2,20	147	1,95	144	-0,25	3
Iraq	2,11	148	1,93	147	-0,18	1
Guinea-Bissau	2,10	149	1,65	153	-0,45	-4
Cuba	2,07	150	1,86	148	-0,20	2
Rwanda	2,04	151	1,69	152	-0,35	-1
Namibia	2,02	152	1,79	150	-0,23	2
Sierra Leone	1,97	153	1,75	151	-0,22	2
Eritrea	1,70	154	1,54	154	-0,16	0
Somalia	1,34	155	1,41	155	0,07	0

Appendix II

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A) Detailed determination of weighted input components for the different authors

The authors have not determined the components. They have used the LPI scores and weighted them. These weights were obtained using various methods that we mentioned in our term paper.

Rezaei et al. (2018) used a subjective point of view to identify the weights of LPI components. They were assigned using the Best Worst Method.

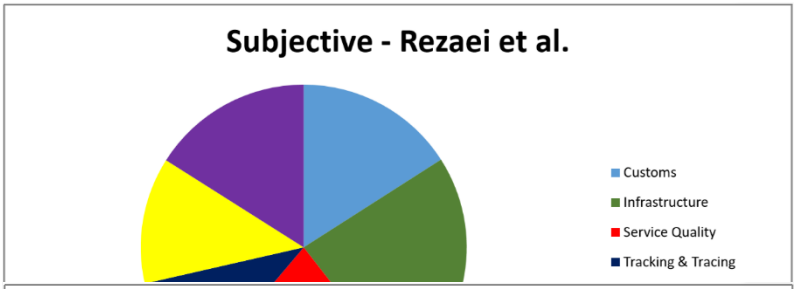
Ulutas & Karaköy (2019) also examined the weighting of LPI components and formed three approaches to assess the ratios: subjective, objective and a combined approach. The subjective approach was determined using the step-wise weight assessment ratio analysis (SWARA), whereas the objective weights were determined using the criteria importance through intercriteria correlation (CRITIC) method. Lastly, the combined view was determined with the help of the proximity indexed value (PIV) method.

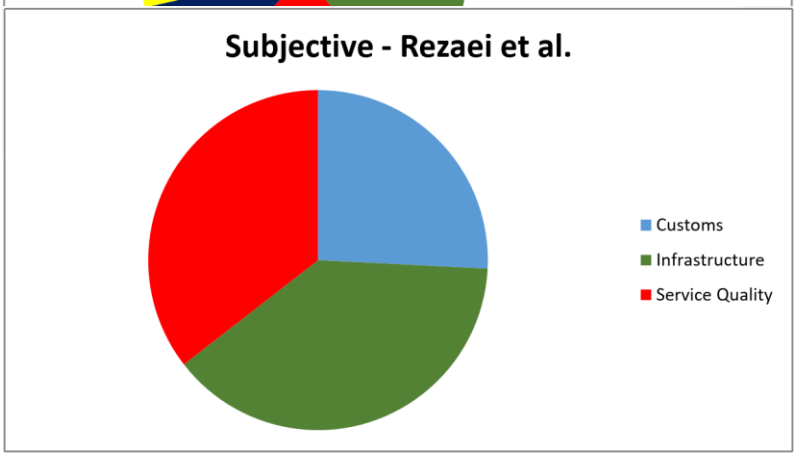
The results of these approaches have been listed in the following table IV:

Approach	Customs	Infrastructure	Service Quality	Tracking & Tracing	International Shipments	Timeliness
Subjective - Rezaei et al.	0,16	0,24	0,22	0,10	0,13	0,16
Subjective - Ulutas & Karaköy	0,16	0,23	0,22	0,13	0,12	0,15
Objective - Ulutas & Karaköy	0,18	0,18	0,12	0,14	0,23	0,16
Combined - Ulutas & Karaköy	0,17	0,26	0,16	0,10	0,16	0,15

Table IV: Weights of components from researchers

In contrast to those authors, this paper used an in-depth determination of the components by assigning decision factors from Kinra (2019) to the components. Because only input variables (decision factors) were used in Kinra's data, only data for the input components was considered. To make a comparison with the different weights of the other authors, the output components must be excluded. For this reason, the weights of the other authors for the input components have to be recalculated. Because previously six components equalled 100% and now only three components equal 100%. See the following pie charts using Rezaei et al. (2018) as an example.





This is calculated by putting the weights of the input components in relation to (dividing by) the sum of the total input weights. Similar to this all weights were calculated with the same equation for all authors.

$$W_C = \frac{V_C}{\sum_{C=1}^{3} V_C}$$

$W_C =$ Weight of the component C

$V_C =$ Old weight of component C

$C =$ Index set for Component, with $C \in \{1,2,3\}$

Table IV shows the weights copied from different researchers and includes therefore the V_C's for the formula above.

Accordingly, this trivial percentage calculation is applied.

For Subjective – Rezaei et al.:

$$W_{Infrastructure} = \frac{V_{Infrastructure}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}24}{0{,}16 + 0{,}24 + 0{,}22} = \frac{0{,}24}{0{,}62} = 0{,}39$$

$$W_{Customs} = \frac{V_{Customs}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}16}{0{,}16 + 0{,}24 + 0{,}22} = \frac{0{,}16}{0{,}62} = 0{,}26$$

$$W_{Service\ Quality} = \frac{V_{Service\ Quality}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}22}{0{,}16 + 0{,}24 + 0{,}22} = \frac{0{,}22}{0{,}62} = 0{,}36$$

For Subjective – Ulutas & Karaköy:

$$W_{Infrastructure} = \frac{V_{Infrastructure}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}23}{0{,}16 + 0{,}23 + 0{,}22} = \frac{0{,}23}{0{,}61} = 0{,}38$$

$$W_{Customs} = \frac{V_{Customs}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}16}{0{,}16 + 0{,}23 + 0{,}22} = \frac{0{,}16}{0{,}61} = 0{,}26$$

$$W_{Service\ Quality} = \frac{V_{Service\ Quality}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}22}{0{,}16 + 0{,}23 + 0{,}22} = \frac{0{,}22}{0{,}61} = 0{,}36$$

For Objective – Ulutas & Karaköy:

$$W_{Infrastructure} = \frac{V_{Infrastructure}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}18}{0{,}18 + 0{,}18 + 0{,}12} = \frac{0{,}18}{0{,}48} = 0{,}38$$

$$W_{Customs} = \frac{V_{Customs}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}18}{0{,}18 + 0{,}18 + 0{,}12} = \frac{0{,}18}{0{,}48} = 0{,}38$$

$$W_{Service\ Quality} = \frac{V_{Service\ Quality}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}22}{0{,}18 + 0{,}18 + 0{,}12} = \frac{0{,}12}{0{,}48} = 0{,}25$$

For Combined – Ulutas & Karaköy:

$$W_{Infrastructure} = \frac{V_{Infrastructure}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}26}{0{,}17 + 0{,}26 + 0{,}16} = \frac{0{,}26}{0{,}59} = 0{,}44$$

$$W_{Customs} = \frac{V_{Customs}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}17}{0{,}17 + 0{,}26 + 0{,}16} = \frac{0{,}17}{0{,}59} = 0{,}29$$

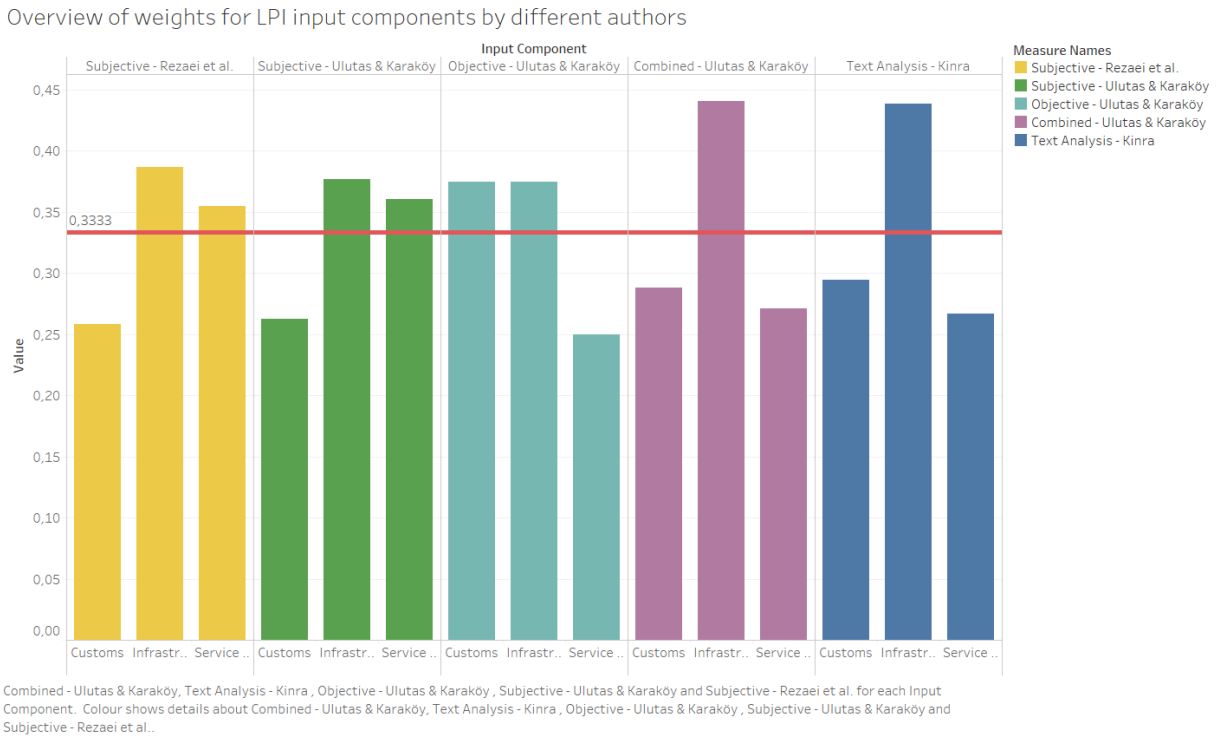
$$W_{Service\ Quality} = \frac{V_{Service\ Quality}}{V_{Customs} + V_{Infra} + V_{Service\ Quality}} = \frac{0{,}16}{0{,}17 + 0{,}26 + 0{,}16} = \frac{0{,}16}{0{,}59} = 0{,}27$$

The weights calculated with the formula and the weights from the text analysis are shown in the following Table V and thus show the W_C's.

Approach	Customs	Infrastructure	Service Quality
Subjective - Rezaei et al.	0,26	0,39	0,36
Subjective - Ulutas & Karaköy	0,26	0,38	0,36
Objective - Ulutas & Karaköy	0,38	0,38	0,25
Combined - Ulutas & Karaköy	0,29	0,44	0,27
Text analysis - Kinra	0,29	0,44	0,27

Table V: Recalculated weights of input components

Following the results are summarizing displayed within a chart:



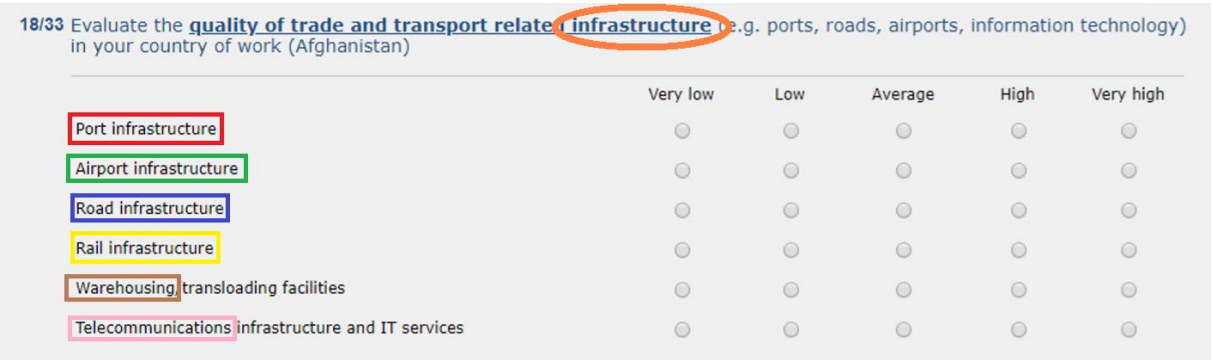
B) Determining the weights based on the text analysis

The following section contains a closer look at the weights for the components using the decision factors and then calculating the weights. First, the decisions factors are assigned to the input components. Next, the calculation of the component weights is presented.

The paper describes that the keywords are assigned to the LPI input components. Because only input variables are considered in text analysis, only the input components are used for comparison (see term paper). In addition, it was said that assigning the keywords of decision factors using the LPI questionnaire. As an example, the keyword airports is allocated to the infrastructure component. Following all of the decision factors are assigned to a component:

1. **Infrastructure** contains the following twelve decision factors:

Waterways, Airways, Roadways, Railways, Public, Warehousing, Telecom:



As these keywords are already considered subcategories in the LPI questionnaire, they were assigned to the infrastructure component.

Geographical Location:

The geographical location is not part of the customs or service quality components. It forms the conditions for the trade and transport related infrastructure. Therefore it is assigned to the infrastructure component.

Post:

In line with telecommunications, Kinra has described post as hard infrastructure and was accordingly assigned to the infrastructure component.

Financial Institutions & Services, Business Legislation:

Financial Institutions & Services and Business Legislation are business institutions, which allow determining the trading and transportation conditions and are consequently part of the infrastructure.

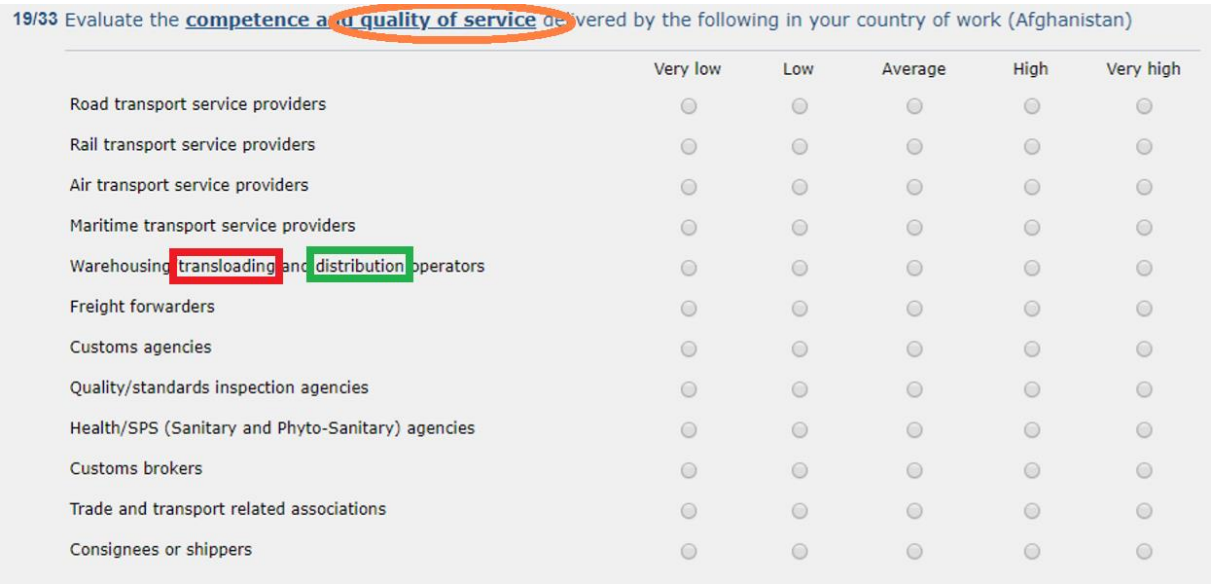
Economic Structure, Political Climate:

The economic structure and political climate are setting the environmental conditions and thus form the political infrastructure.

In general, the LPI questionnaire does not specify clearly to which the decision factors financial institutions & services, business legislation, economic structure and political climate could be assigned. There is no substantial proof in literature that these four decision factors have to be included in the input component infrastructure. See appendix 3 to have an excluded view and changes of the results regarding the weights and adjusted rankings.

2. **Service quality** (Logistics Quality and Competence in 2018) contains the following six decision factors:

Intermodal, Hub and Spoke:



It is only with the competence of transloading that hard infrastructure, such as airports and ports, becomes intermodal transport. The same applies to hub and spoke, which without distribution competence and without a system would simply be warehouses.

EDI Usage in Business Society, Computer Usage Penetration, Electronic Banking Commerce:

The keywords mentioned here represent the competence regarding the use of the respective areas and for this reason have been assigned to the service quality component.

Logistics SCM HR:

Human resources are responsible for the deployment and use of the existing conditions. They are responsible for the services in question 19/33 (see above) and are therefore assigned to the service quality component.

3. **Customs** contains the following two decision factors:

Economic Policy:

It is economic policy that decides on the regulations of the customs, such as in the issues outlined above. For this reason, the keyword economic policy has been assigned to the customs component.

Customs:

The keyword customs fits perfectly with the customs component.

Calculation of the weights for Kinra's text mining:

The weights that result from the text mining were calculated using standard formulas for mean value and percentage.

1. **Average number of keyword counts per component:**

$$\bar{n}_C = \frac{1}{m_C} \sum_{k=1}^{m_C} n_k$$

$\bar{n}_C =$ Average keyword count per keyword in component C

$m_C =$ Number of keywords assigned to the component C, with $m_C \in \{1,2, \dots ,20\}$

$k =$ Index set for keyword, with $k \in \{1,2, \dots , m_C\}$

$n_k =$ word frequency of keyword k

$C =$ Index set for Component, with $C \in \{1,2,3\}$

This can be summarized as the average number of keyword counts per component.

2. **Weights for each component:**

$$W_C = \frac{\bar{n}_C}{\sum_{C=1}^{3} \bar{n}_C}$$

$$W_C = \text{Weight of the component } C$$

The part under the fraction line is the total sum of average number of keyword counts per component. The average number of keyword counts per component divided by (or related to) the total sum of average values equals the weight of the component.

In the following, the weighting is calculated for the service quality (C=1) component as an example:

1. **Average number of keyword counts per component:**

There are six keywords assigned to the component service quality, therefore is $m_1 = 6$.

$$\bar{n}_1 = \frac{1}{m_1} \sum_{k=1}^{m_1} n_k = \frac{1}{6} (n_{Inter} + n_{H\&S} + n_{EDIU} + n_{ComU} + n_{EBank} + n_{HR})$$

$$\bar{n}_1 = \frac{1}{6} (2912 + 327 + 1022 + 1115 + 619 + 20) = 1002{,}50$$

This means that an average of 1002,5 words were counted for each keyword assigned to the service quality component.

If the same procedure is followed for the other two components, with C=2 for infrastructure and C=3 for customs, these results in:

$$\bar{n}_2 = \frac{1}{12} \begin{pmatrix} 7675 + 704 + 1411 + 1863 + 1425 + 2007 + 435 + 344 \\ +93 + 2002 + 919 + 893 \end{pmatrix} \approx 1647{,}58$$

$$\bar{n}_3 = \frac{1}{2} (947 + 1265) = 1106{,}00$$

2. **Weights for each component**

The average number of words counted per keyword is now divided by the sum of all three average values to determine the proportion that a component makes up of the total number of components. This is again done for the service quality component as an example.

$$W_1 = \frac{\bar{n}_1}{\sum_{C=1}^{3} \bar{n}_C} = \frac{1002{,}50}{(1002{,}5 + 1647{,}58 + 1106)} \approx 0{,}2669$$

This means that the component service quality is weighted with a share of 26,69% measured on the three components and is thus weighted with 0,2669.

Using the same procedure to calculate the weightings for the other two components, this results in

$$W_2 = \frac{\bar{n}_2}{\sum_{C=1}^{3} \bar{n}_C} = \frac{1647{,}58}{(1002{,}5 + 1647{,}58 + 1106)} \approx 0{,}4386$$

$$W_3 = \frac{\bar{n}_3}{\sum_{C=1}^{3} \bar{n}_C} = \frac{1106{,}00}{(1002{,}5 + 1647{,}58 + 1106)} \approx 0{,}2945$$

C) Calculations for Table 3

To calculate the adjusted scores in Table III, the previously determined weights for the scores of the respective input components from the LPI 2010 were applied. In order to illustrate this, the first two countries are recalculated from the 2010 LPI, which are shown in the following table.

Country	Year	LPI Rank	LPI Score	Customs	Infrastructure	International shipments	Logistics competence	Tracking & tracing	Timeliness
Germany	2010	1	4.11	4.00	4.34	3.66	4.14	4.18	4.48
Singapore	2010	2	4.09	4.02	4.22	3.86	4.12	4.15	4.23

Adjusted scores are calculated with the weighted function.

$$S_L^* = \left(S_{Service\ Quality} W_1 + S_{Infrastructure} W_2 + S_{Customs} W_3\right)$$

$S_L^* =$ Adjusted score for country L

$S_{Service\ Quality} =$ LPI's logistics competence score from 2010 of country L

$S_{Infrastructure} =$ LPI's infrastructure score from 2010 of country L

$S_{Customs} =$ LPI's customs score from 2010 of country L

$W_C =$ Weight of the Component C

For the calculation of the adjusted score for Germany, the equation is as follows.

$$S_{Germany}^* = (4{,}14 * 0{,}2669 + 4{,}34 * 0{,}4386 + 4{,}00 * 0{,}2945) \approx 4{,}19$$

And thus the adjusted score for Singapore is derived from the equation

$$S^*_{Singapore} = (4{,}12 * 0{,}2669 + 4{,}22 * 0{,}4386 + 4{,}02 * 0{,}2945) \approx 4{,}13$$

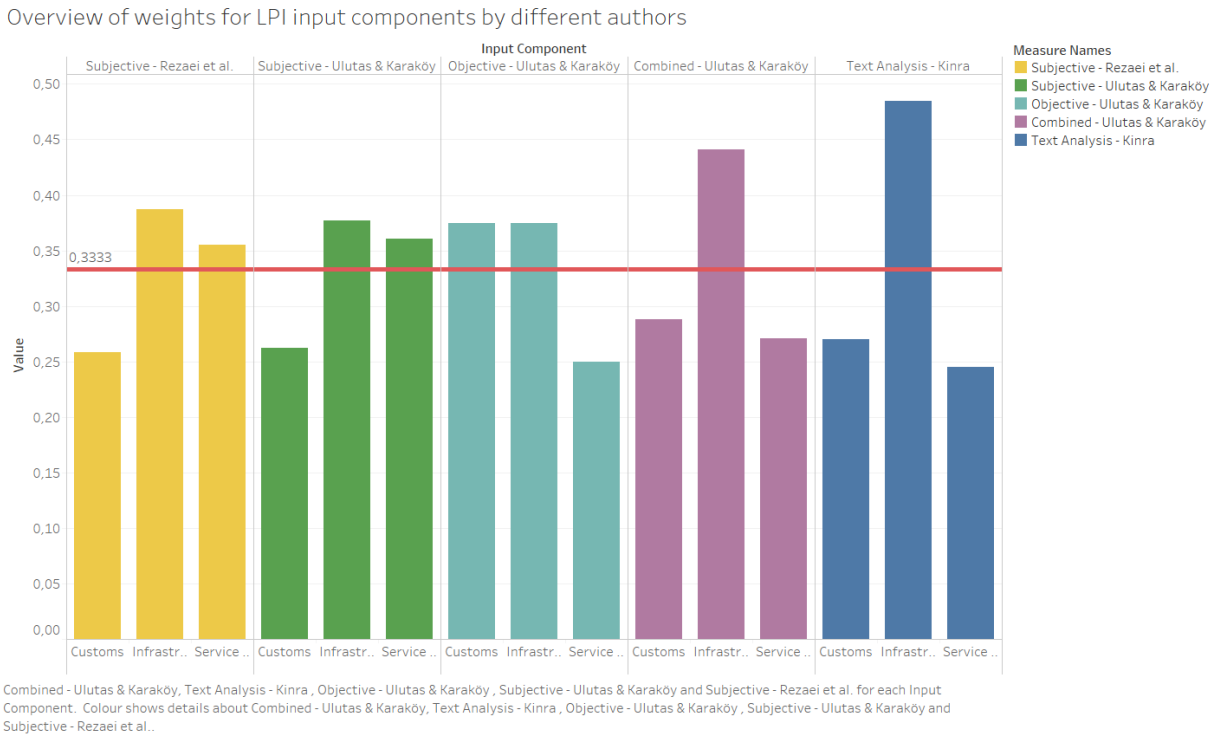
If the adjusted scores are calculated for all countries, the scores from Table III are obtained.

Appendix III

In general, the LPI questionnaire does not specify clearly to which the decision factors financial institutions & services, business legislation, economic structure and political climate could be assigned. There is no substantial proof in literature that these four decision factors have to be included in the input component infrastructure. Therefore, this sections shows the changes of the results when the previously mentioned decision factors are excluded.

Excluding the decision factors has an influence on the calculations for the weightings of the input components. In consequence, the weights in Table II and therefore the rankings made in Table III within the Appendix I are recalculated to see the impact and changes. The new adjusted ranking is calculated according to the methodology within Appendix II part B.

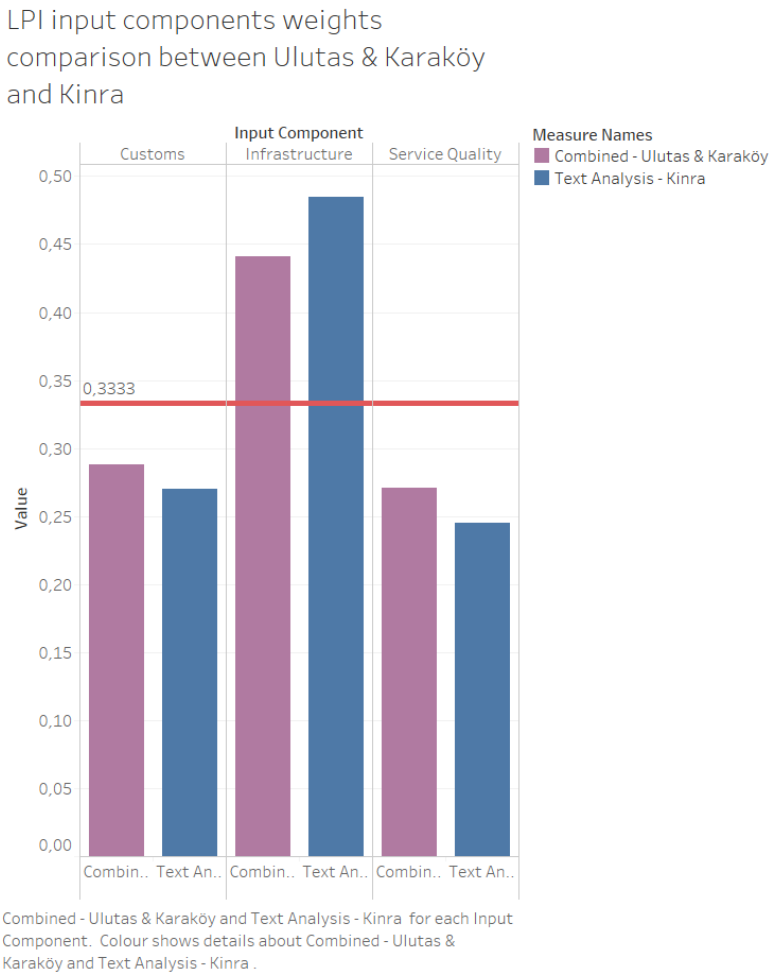
After recalculating the results of the weights for the input components change. The weight of infrastructure increases from 44% to 48%. The other two input components decrease by 2 percentage points in each case. Hence, the weight of customs is now 27% and for the service quality it results in 25%. The new adjusted weights are displayed in the following figure compared to the weights from other researchers.



In the graph the values of the weights are shown on the vertical axis and the input components assigned to each author on the horizontal axis. The red horizontal line in the illustration simulates the same weights used by LPI.

The results of the new adjusted weights are still in line with the weights from the combined view stating that infrastructure is the most important input component followed by customs and service quality, although the weights differ (more compared to the first weights with the text

analysis). Text mining can still be used for weighting as the importance levels are changing and thus provides a better focus for decision makers. This is supported by the fact that the texts from CSCMP consider a country's development that will benefit in the near future and can therefore provide a better picture for future decisions than, for example managers (freight forwarders) who evaluate the whole from their past experience. However, the weights calculated in the paper are closer to the combined view of Ulutas & Karaköy. As shown in the following illustration, the newly adjusted weights differ more.



In the following illustration, the respective weights of the different authors for the individual components are compared. The red line represents the equal weighting and the black horizontal lines the average value over the respective input components.

This adjusted illustration also shows that the weights of the input components differ from those of the LPI (red line). In addition, infrastructure continues to be the component with the strongest influence and the other two components are weighted on average weaker than the LPI currently does.

Because the weights for the input components change with the removal of the four decision factors, the calculated rankings and scores from Table III also change. The new adjusted weights are used to recalculate Table III as described in Appendix II part C. This results in Table VI.

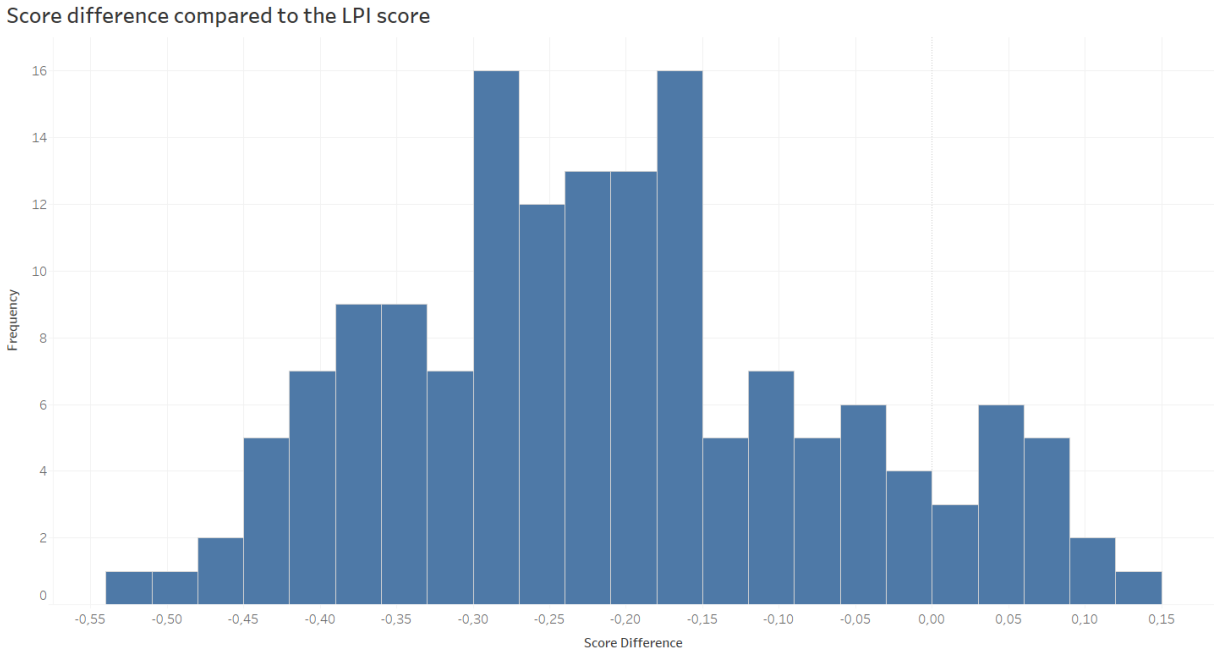
Country	LPI Score	LPI Rank	New Adjusted Score	New Adjusted Rank	Score Difference	Rank Difference
Germany	4,11	1	4,20	1	0,08	0
Singapore	4,09	2	4,14	3	0,05	-1
Sweden	4,08	3	4,03	6	-0,04	-3
Netherlands	4,07	4	4,15	2	0,09	2
Luxembourg	3,98	5	3,96	11	-0,02	-6
Switzerland	3,97	6	4,09	4	0,11	2
Japan	3,97	7	4,03	7	0,07	0
United Kingdo	3,95	8	3,89	14	-0,07	-6
Belgium	3,94	9	3,99	8	0,05	1
Norway	3,93	10	4,03	5	0,10	5
Ireland	3,89	11	3,73	18	-0,16	-7
Finland	3,89	12	3,98	9	0,10	3
Hong Kong, Cl	3,88	13	3,91	13	0,04	0
Canada	3,87	14	3,93	12	0,06	2
United States	3,86	15	3,97	10	0,11	5
Denmark	3,85	16	3,84	16	-0,01	0
France	3,84	17	3,87	15	0,02	2
Australia	3,84	18	3,75	17	-0,09	1
Austria	3,76	19	3,63	21	-0,13	-2
Taiwan	3,71	20	3,56	24	-0,15	-4
New Zealand	3,65	21	3,57	22	-0,08	-1
Italy	3,64	22	3,63	20	-0,01	2
Korea, Rep.	3,64	23	3,54	25	-0,09	-2
United Arab E	3,63	24	3,65	19	0,02	5
Spain	3,63	25	3,56	23	-0,07	2
Czech Republi	3,51	26	3,27	32	-0,24	-6
China	3,49	27	3,43	27	-0,06	0
South Africa	3,46	28	3,41	28	-0,05	0
Malaysia	3,44	29	3,36	29	-0,08	0
Poland	3,44	30	3,09	38	-0,35	-8
Israel	3,41	31	3,44	26	0,03	5
Bahrain	3,37	32	3,27	31	-0,10	1
Lebanon	3,34	33	3,28	30	-0,06	3
Portugal	3,34	34	3,24	34	-0,09	0
Thailand	3,29	35	3,12	37	-0,17	-2
Kuwait	3,28	36	3,19	35	-0,09	1
Latvia	3,25	37	2,91	46	-0,34	-9
Slovak Republ	3,24	38	2,98	40	-0,26	-2
Turkey	3,22	39	3,05	39	-0,18	0
Saudi Arabia	3,22	40	3,19	36	-0,03	4
Brazil	3,20	41	2,95	44	-0,25	-3
Iceland	3,20	42	3,26	33	0,06	9
Estonia	3,16	43	2,96	43	-0,20	0
Philippines	3,14	44	2,69	56	-0,45	-12
Lithuania	3,13	45	2,77	52	-0,37	-7
Cyprus	3,13	46	2,90	47	-0,23	-1
India	3,12	47	2,91	45	-0,20	2

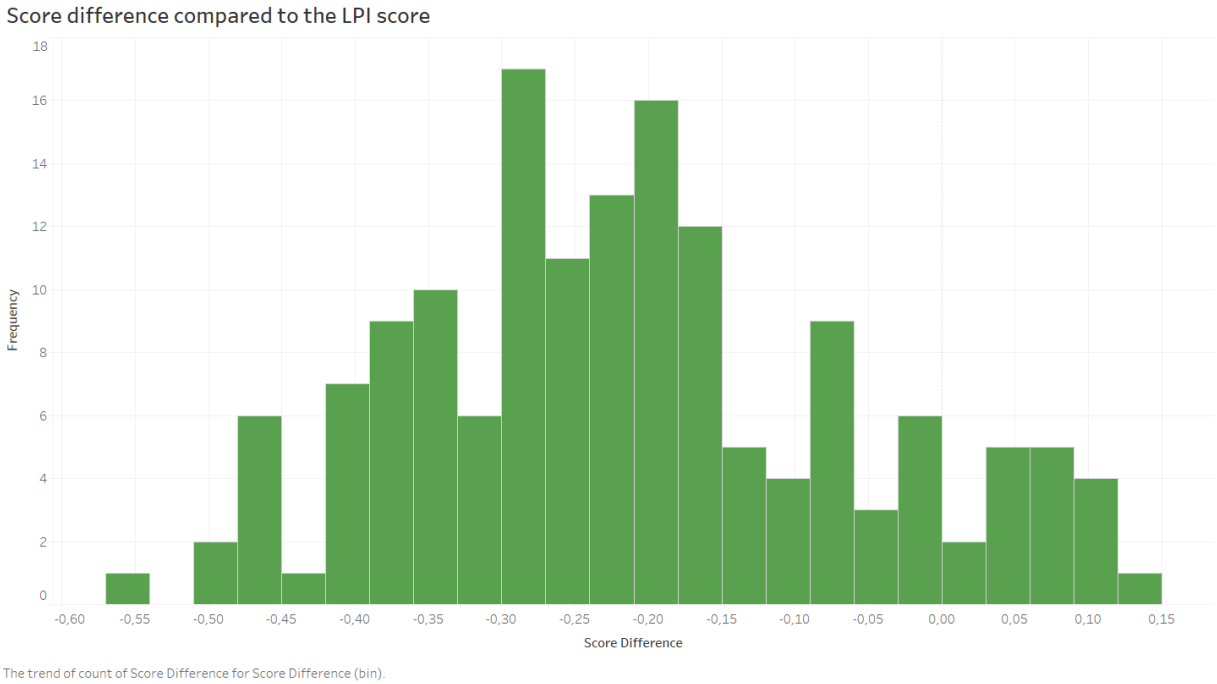
Argentina	3,10	48	2,79	51	-0,31	-3
Chile	3,09	49	2,90	48	-0,20	1
Mexico	3,05	50	2,86	49	-0,18	1
Panama	3,02	51	2,72	54	-0,31	-3
Hungary	2,99	52	2,96	42	-0,02	10
Vietnam	2,96	53	2,68	57	-0,29	-4
Greece	2,96	54	2,75	53	-0,20	1
Qatar	2,95	55	2,57	64	-0,38	-9
Costa Rica	2,91	56	2,63	58	-0,28	-2
Slovenia	2,87	57	2,69	55	-0,18	2
Senegal	2,86	58	2,61	60	-0,25	-2
Romania	2,84	59	2,38	88	-0,46	-29
Oman	2,84	60	2,98	41	0,14	19
Tunisia	2,84	61	2,48	74	-0,36	-13
Kazakhstan	2,83	62	2,57	65	-0,26	-3
Bulgaria	2,83	63	2,49	73	-0,34	-10
Malta	2,82	64	2,82	50	-0,00	14
Dominican Re	2,82	65	2,41	85	-0,41	-20
Uganda	2,82	66	2,54	67	-0,28	-1
Peru	2,80	67	2,61	61	-0,20	6
Uzbekistan	2,79	68	2,44	82	-0,36	-14
Benin	2,79	69	2,49	72	-0,30	-3
Honduras	2,78	70	2,40	86	-0,38	-16
Ecuador	2,77	71	2,42	84	-0,36	-13
Colombia	2,77	72	2,61	62	-0,17	10
Macedonia, F\	2,77	73	2,60	63	-0,17	10
Croatia	2,77	74	2,47	75	-0,30	-1
Indonesia	2,76	75	2,49	71	-0,27	4
Paraguay	2,75	76	2,46	78	-0,30	-2
Uruguay	2,75	77	2,62	59	-0,14	18
Bahamas, The	2,75	78	2,46	76	-0,28	2
Bangladesh	2,74	79	2,43	83	-0,31	-4
Syrian Arab Re	2,74	80	2,46	77	-0,28	3
Jordan	2,74	81	2,54	66	-0,20	15
Mauritius	2,72	82	2,44	81	-0,28	1
Serbia	2,69	83	2,33	97	-0,35	-14
Venezuela, RB	2,68	84	2,36	92	-0,32	-8
Congo, Dem. F	2,68	85	2,52	68	-0,15	17
El Salvador	2,67	86	2,51	69	-0,17	17
Bosnia and He	2,66	87	2,27	103	-0,39	-16
Madagascar	2,66	88	2,50	70	-0,16	18
Azerbaijan	2,64	89	2,27	105	-0,37	-16
Guatemala	2,63	90	2,45	80	-0,18	10
Kyrgyz Republ	2,62	91	2,25	108	-0,37	-17
Egypt, Arab Re	2,61	92	2,35	94	-0,27	-2
Georgia	2,61	93	2,32	99	-0,29	-6
Russian Feder	2,61	94	2,35	95	-0,26	-1
Tanzania	2,60	95	2,20	114	-0,40	-19
Togo	2,60	96	2,13	121	-0,46	-25
Guinea	2,60	97	2,31	100	-0,29	-3

Haiti	2,59	98	2,23	110	-0,36	-12
Kenya	2,59	99	2,20	117	-0,39	-18
Nigeria	2,59	100	2,37	90	-0,22	10
Yemen, Rep.	2,58	101	2,38	89	-0,20	12
Ukraine	2,57	102	2,36	91	-0,21	11
Iran, Islamic R	2,57	103	2,39	87	-0,18	16
Moldova	2,57	104	2,09	125	-0,48	-21
Cameroon	2,55	105	2,21	112	-0,34	-7
Niger	2,54	106	2,26	106	-0,28	0
Nicaragua	2,54	107	2,26	107	-0,28	0
Jamaica	2,53	108	2,11	124	-0,42	-16
Côte d'Ivoire	2,53	109	2,36	93	-0,17	16
Pakistan	2,53	110	2,12	122	-0,41	-12
Armenia	2,52	111	2,33	98	-0,20	13
Bolivia	2,51	112	2,28	101	-0,23	11
Gambia, The	2,49	113	2,28	102	-0,22	11
Turkmenistan	2,49	114	2,24	109	-0,25	5
Chad	2,49	115	2,08	126	-0,41	-11
Congo, Rep.	2,48	116	1,92	146	-0,55	-30
Ghana	2,47	117	2,45	79	-0,02	38
Lao PDR	2,46	118	2,05	129	-0,41	-11
Albania	2,46	119	2,19	118	-0,27	1
Comoros	2,45	120	1,94	143	-0,51	-23
Montenegro	2,43	121	2,34	96	-0,09	25
Gabon	2,41	122	2,18	119	-0,23	3
Ethiopia	2,41	123	1,96	140	-0,45	-17
Papua New Gu	2,41	124	2,01	136	-0,40	-12
Maldives	2,40	125	2,22	111	-0,19	14
Djibouti	2,39	126	2,27	104	-0,12	22
Liberia	2,38	127	2,11	123	-0,27	4
Bhutan	2,38	128	2,01	134	-0,37	-6
Cambodia	2,37	129	2,21	113	-0,16	16
Algeria	2,36	130	2,08	127	-0,28	3
Tajikistan	2,35	131	2,04	132	-0,31	-1
Libya	2,33	132	2,20	116	-0,14	16
Myanmar	2,33	133	1,95	142	-0,38	-9
Botswana	2,32	134	2,14	120	-0,18	14
Solomon Islan	2,31	135	2,20	115	-0,11	20
Mozambique	2,29	136	2,05	130	-0,24	6
Sri Lanka	2,29	137	1,95	141	-0,34	-4
Zambia	2,28	138	1,97	139	-0,32	-1
Mali	2,27	139	2,05	131	-0,22	8
Guyana	2,27	140	2,06	128	-0,20	12
Mongolia	2,25	141	1,98	138	-0,27	3
Angola	2,25	142	1,79	149	-0,46	-7
Afghanistan	2,24	143	2,02	133	-0,22	10
Fiji	2,24	144	2,00	137	-0,23	7
Burkina Faso	2,23	145	2,01	135	-0,21	10
Sudan	2,21	146	1,93	145	-0,27	1
Nepal	2,20	147	1,94	144	-0,26	3
Iraq	2,11	148	1,91	147	-0,19	1
Guinea-Bissau	2,10	149	1,65	153	-0,46	-4
Cuba	2,07	150	1,87	148	-0,20	2
Rwanda	2,04	151	1,68	152	-0,36	-1
Namibia	2,02	152	1,78	150	-0,24	2
Sierra Leone	1,97	153	1,74	151	-0,23	2
Eritrea	1,70	154	1,52	154	-0,18	0
Somalia	1,34	155	1,41	155	0,08	0

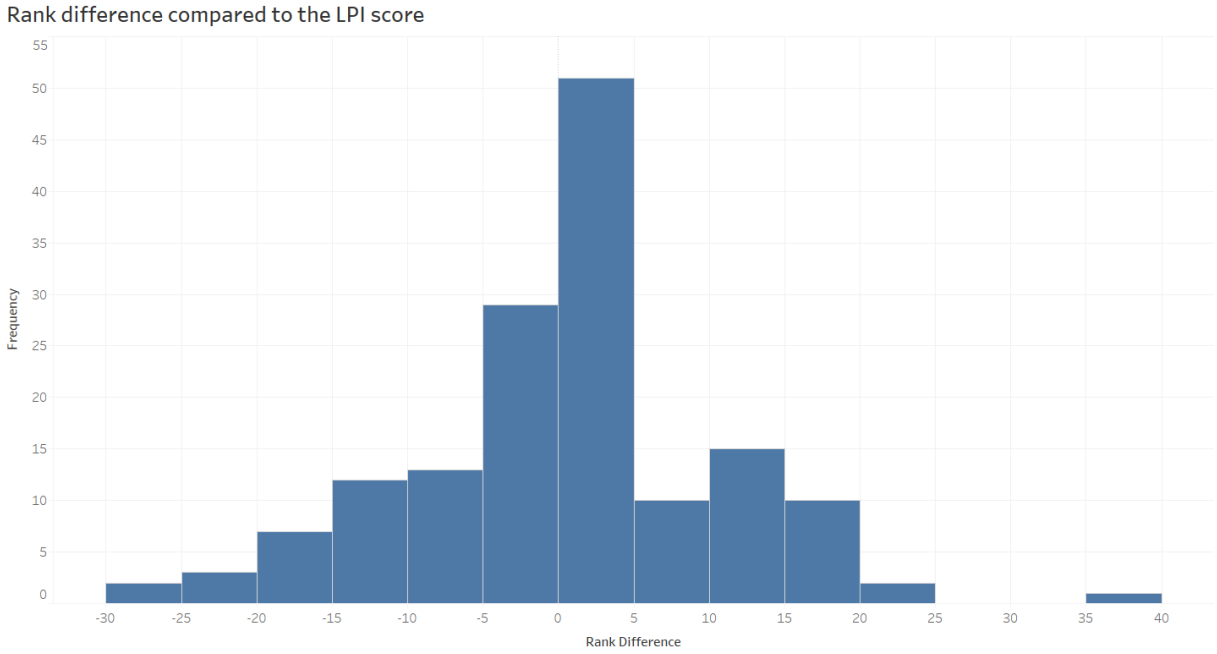
Table VI: LPI score and ranking comparison to new adjusted weights

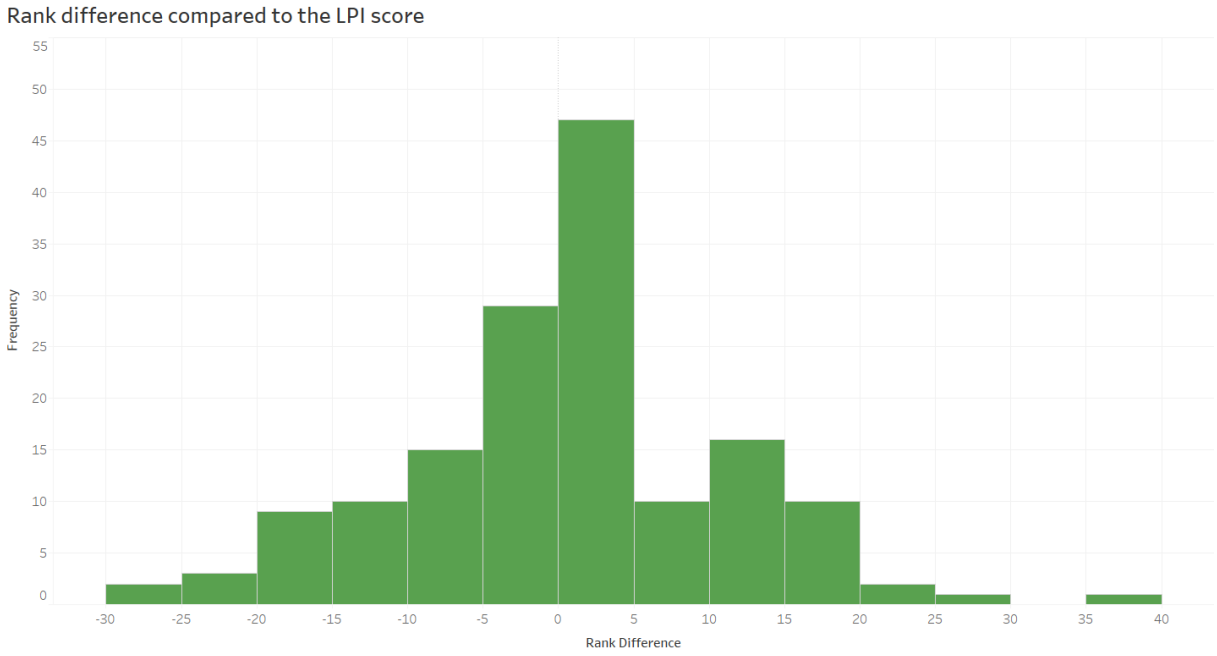
This Table VI additionally shows the differences between the actual LPI score as well as ranking and the score calculated with the new adjusted weights. For a clearer presentation/overview, the deviations to the LPI and their occurrence are shown in the blue histograms. The green histograms resulting from the (original) Table III are used for comparison.



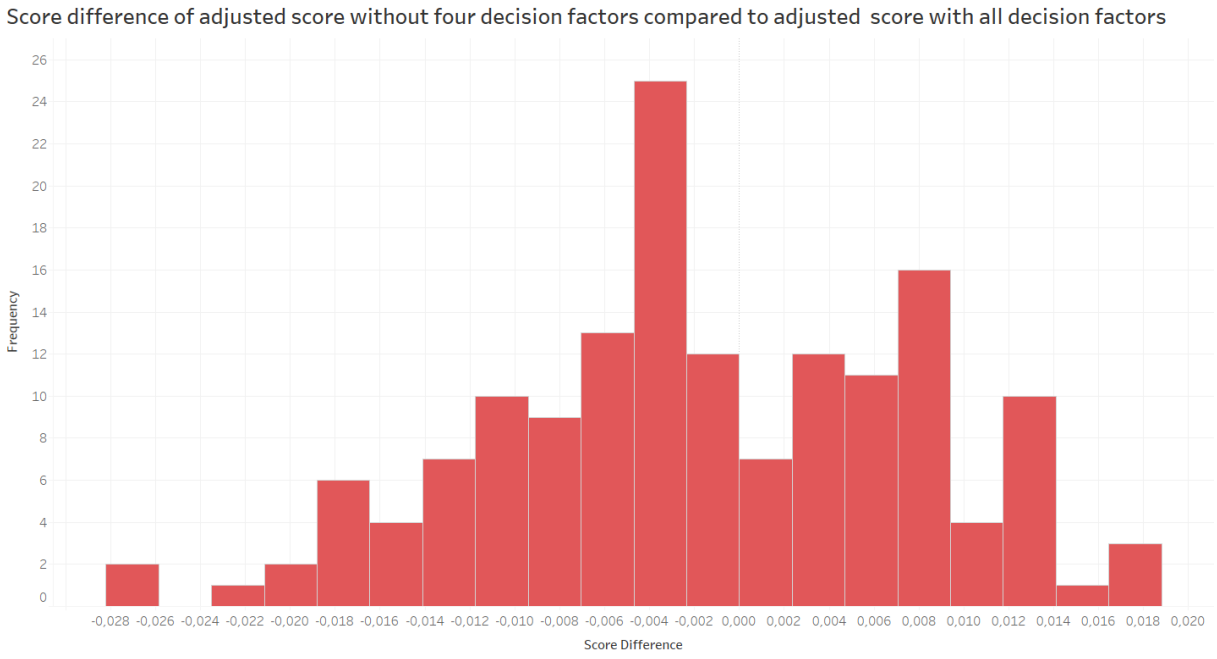


In these two histograms, classes were formed which can be seen on the horizontal axis. The bars show the number of deviations assigned to a class. In both cases more observations are below zero. This means that both, the adjusted weights and the new adjusted weights, decrease the score rather than increase it. However, the deviations are not particularly crucial, which can be seen in the following histograms. These show the changes in the ranking. Again, the blue histogram shows the original results from Table III and the green histogram shows ranking deviations when using the new adjusted weights.





From these visualizations it can be seen that almost half of all rankings change by a maximum of five places. In addition, there are only a few outliers that change by more than 20 places. This means that in general countries remain in their classified group, for example Germany stays a top ranked country although the input components are weighted differently. From this it can be concluded that there are no extreme changes in the ranking of the LPI, regardless of which of the two weightings determined by text analysis are used. The two red histograms results from the Table VII and confirm that these deviations between the different weightings of the text analysis are very minimal.



The trend of count of Score Difference for Score Difference (bin).

The trend of count of Rank Difference for Rank Difference (bin).

It can be observed that the deviations of the score change in a very small range compared to the actual scores. This becomes even clearer when looking at the changes in the ranks. Here it is visible that the ranking changes by a maximum of four places and it can also be seen from Table VII that 90 rankings do not change at all if the four decision factors are excluded.

Country	Adjusted Score	Adjusted Rank	Adjusted Score (excluded)	Adjusted Rank (excluded)	Score Difference	Rank Difference
Germany	4,19	1	4,20	1	0,01	0
Singapore	4,13	3	4,14	3	0,01	0
Sweden	4,03	5	4,03	6	0,00	1
Netherlands	4,15	2	4,15	2	0,01	0
Luxembourg	3,95	11	3,96	11	0,01	0
Switzerland	4,08	4	4,09	4	0,01	0
Japan	4,02	6	4,03	7	0,01	1
United Kingdo	3,88	14	3,89	14	0,01	0
Belgium	3,99	8	3,99	8	0,00	0
Norway	4,02	7	4,03	5	0,02	-2
Ireland	3,73	18	3,73	18	0,00	0
Finland	3,97	9	3,98	9	0,01	0
Hong Kong, Cl	3,91	13	3,91	13	0,01	0
Canada	3,92	12	3,93	12	0,01	0
United States	3,95	10	3,97	10	0,02	0
Denmark	3,82	16	3,84	16	0,01	0
France	3,86	15	3,87	15	0,01	0
Australia	3,75	17	3,75	17	0,00	0
Austria	3,63	20	3,63	21	0,00	1
Taiwan	3,55	24	3,56	24	0,01	0
New Zealand	3,57	22	3,57	22	0,00	0
Italy	3,63	21	3,63	20	0,01	-1
Korea, Rep.	3,54	25	3,54	25	0,01	0
United Arab E	3,64	19	3,65	19	0,01	0
Spain	3,56	23	3,56	23	0,00	0
Czech Republi	3,27	31	3,27	32	0,00	1
China	3,42	27	3,43	27	0,01	0
South Africa	3,41	28	3,41	28	0,00	0
Malaysia	3,34	29	3,36	29	0,01	0
Poland	3,10	38	3,09	38	-0,01	0
Israel	3,43	26	3,44	26	0,01	0
Bahrain	3,27	32	3,27	31	0,01	-1
Lebanon	3,30	30	3,28	30	-0,02	0
Portugal	3,25	34	3,24	34	-0,01	0
Thailand	3,12	37	3,12	37	0,00	0
Kuwait	3,18	35	3,19	35	0,01	0
Latvia	2,91	45	2,91	46	0,00	1
Slovak Republ	2,98	40	2,98	40	0,00	0
Turkey	3,04	39	3,05	39	0,00	0
Saudi Arabia	3,18	36	3,19	36	0,01	0
Brazil	2,94	44	2,95	44	0,01	0
Iceland	3,25	33	3,26	33	0,01	0
Estonia	2,98	41	2,96	43	-0,02	2
Philippines	2,70	55	2,69	56	-0,01	1
Lithuania	2,77	52	2,77	52	0,00	0
Cyprus	2,90	48	2,90	47	0,00	-1
India	2,91	46	2,91	45	0,00	-1

Argentina	2,79	51	2,79	51	0,00	0
Chile	2,90	47	2,90	48	0,00	1
Mexico	2,86	49	2,86	49	0,01	0
Panama	2,72	54	2,72	54	-0,01	0
Hungary	2,95	43	2,96	42	0,01	-1
Vietnam	2,69	57	2,68	57	-0,01	0
Greece	2,74	53	2,75	53	0,02	0
Qatar	2,56	65	2,57	64	0,02	-1
Costa Rica	2,64	58	2,63	58	-0,01	0
Slovenia	2,70	56	2,69	55	0,00	-1
Senegal	2,61	60	2,61	60	0,00	0
Romania	2,40	87	2,38	88	-0,01	1
Oman	2,97	42	2,98	41	0,01	-1
Tunisia	2,47	75	2,48	74	0,01	-1
Kazakhstan	2,56	64	2,57	65	0,01	1
Bulgaria	2,51	70	2,49	73	-0,02	3
Malta	2,82	50	2,82	50	0,01	0
Dominican Re	2,41	85	2,41	85	-0,01	0
Uganda	2,55	66	2,54	67	-0,02	1
Peru	2,60	63	2,61	61	0,00	-2
Uzbekistan	2,43	83	2,44	82	0,01	-1
Benin	2,49	71	2,49	72	0,00	1
Honduras	2,40	86	2,40	86	-0,01	0
Ecuador	2,42	84	2,42	84	0,00	0
Colombia	2,61	61	2,61	62	0,00	1
Macedonia, FY	2,60	62	2,60	63	0,00	1
Croatia	2,48	74	2,47	75	-0,01	1
Indonesia	2,49	72	2,49	71	0,00	-1
Paraguay	2,46	78	2,46	78	0,00	0
Uruguay	2,62	59	2,62	59	0,00	0
Bahamas, The	2,47	76	2,46	76	-0,01	0
Bangladesh	2,43	82	2,43	83	0,00	1
Syrian Arab Re	2,46	77	2,46	77	0,00	0
Jordan	2,53	68	2,54	66	0,01	-2
Mauritius	2,45	80	2,44	81	-0,01	1
Serbia	2,33	97	2,33	97	0,00	0
Venezuela, RB	2,35	94	2,36	92	0,01	-2
Congo, Dem. F	2,54	67	2,52	68	-0,02	1
El Salvador	2,51	69	2,51	69	-0,01	0
Bosnia and He	2,28	103	2,27	103	0,00	0
Madagascar	2,49	73	2,50	70	0,01	-3
Azerbaijan	2,27	104	2,27	105	0,00	1
Guatemala	2,46	79	2,45	80	-0,01	1
Kyrgyz Republ	2,27	105	2,25	108	-0,01	3
Egypt, Arab Re	2,36	91	2,35	94	-0,01	3
Georgia	2,34	96	2,32	99	-0,01	3
Russian Feder	2,35	95	2,35	95	0,00	0
Tanzania	2,22	112	2,20	114	-0,02	2
Togo	2,16	120	2,13	121	-0,03	1
Guinea	2,33	100	2,31	100	-0,02	0

Haiti	2,23	110	2,23	110	0,00	0
Kenya	2,20	115	2,20	117	-0,01	2
Nigeria	2,36	90	2,37	90	0,01	0
Yemen, Rep.	2,38	89	2,38	89	0,00	0
Ukraine	2,35	93	2,36	91	0,01	-2
Iran, Islamic R	2,40	88	2,39	87	0,00	-1
Moldova	2,10	125	2,09	125	0,00	0
Cameroon	2,22	113	2,21	112	-0,01	-1
Niger	2,25	108	2,26	106	0,00	-2
Nicaragua	2,26	107	2,26	107	0,00	0
Jamaica	2,12	124	2,11	124	0,00	0
Côte d'Ivoire	2,36	92	2,36	93	0,00	1
Pakistan	2,13	122	2,12	122	0,00	0
Armenia	2,33	99	2,33	98	0,00	-1
Bolivia	2,29	102	2,28	101	0,00	-1
Gambia, The	2,29	101	2,28	102	-0,01	1
Turkmenistan	2,24	109	2,24	109	0,00	0
Chad	2,09	126	2,08	126	-0,01	0
Congo, Rep.	1,95	145	1,92	146	-0,03	1
Ghana	2,45	81	2,45	79	0,01	-2
Lao PDR	2,06	129	2,05	129	-0,01	0
Albania	2,19	119	2,19	118	0,00	-1
Comoros	1,95	142	1,94	143	-0,02	1
Montenegro	2,33	98	2,34	96	0,01	-2
Gabon	2,19	118	2,18	119	-0,01	1
Ethiopia	1,98	140	1,96	140	-0,02	0
Papua New Gu	2,02	136	2,01	136	-0,01	0
Maldives	2,22	111	2,22	111	-0,01	0
Djibouti	2,26	106	2,27	104	0,01	-2
Liberia	2,12	123	2,11	123	-0,01	0
Bhutan	2,03	134	2,01	134	-0,02	0
Cambodia	2,21	114	2,21	113	-0,01	-1
Algeria	2,08	127	2,08	127	0,00	0
Tajikistan	2,04	132	2,04	132	0,00	0
Libya	2,20	116	2,20	116	0,00	0
Myanmar	1,95	143	1,95	142	0,00	-1
Botswana	2,14	121	2,14	120	0,00	-1
Solomon Islan	2,20	117	2,20	115	0,00	-2
Mozambique	2,05	131	2,05	130	0,00	-1
Sri Lanka	1,96	141	1,95	141	-0,01	0
Zambia	1,98	139	1,97	139	-0,01	0
Mali	2,06	130	2,05	131	0,00	1
Guyana	2,07	128	2,06	128	-0,01	0
Mongolia	1,98	138	1,98	138	0,00	0
Angola	1,79	149	1,79	149	-0,01	0
Afghanistan	2,03	133	2,02	133	-0,01	0
Fiji	2,01	137	2,00	137	0,00	0
Burkina Faso	2,02	135	2,01	135	-0,01	0
Sudan	1,95	146	1,93	145	-0,01	-1
Nepal	1,95	144	1,94	144	-0,01	0
Iraq	1,93	147	1,91	147	-0,02	0
Guinea-Bissau	1,65	153	1,65	153	-0,01	0
Cuba	1,86	148	1,87	148	0,00	0
Rwanda	1,69	152	1,68	152	0,00	0
Namibia	1,79	150	1,78	150	-0,01	0
Sierra Leone	1,75	151	1,74	151	-0,01	0
Eritrea	1,54	154	1,52	154	-0,02	0
Somalia	1,41	155	1,41	155	0,01	0

Table VII: Comparison of score and ranking from adjusted and new adjusted weights

In conclusion, if the four decision factors financial institution services, economic structure, business legislation and

political climate are excluded, the weightings of the input components change. The scores and ranks from the LPI change only slightly. This is mainly due to the fact that the individual scores for the LPI components (see Table VIII) of a country are close to each other and therefore only an extreme change in the weightings has a profound effect on the ranking. Nevertheless, the weights show the increased importance of the input component infrastructure. This is in line with the previous results from this paper. Furthermore, the text mining approach can still be considered a robust alternative method for determining the weights, as the weights have a similar structure to the weights already identified and recommended by other researchers.

Country	LPI Score	LPI Infrastructure Score	LPI Customs Score	LPI Service Quality Score
Germany	4,11	4,34	4,00	4,14
Singapore	4,09	4,22	4,02	4,12
Sweden	4,08	4,03	3,88	4,22
Netherlands	4,07	4,25	3,98	4,15
Luxembourg	3,98	4,06	4,04	3,67
Switzerland	3,97	4,17	3,73	4,32
Japan	3,97	4,19	3,79	4,00
United Kingdon	3,95	3,95	3,74	3,92
Belgium	3,94	4,01	3,83	4,13
Norway	3,93	4,22	3,86	3,85
Ireland	3,89	3,76	3,60	3,82
Finland	3,89	4,08	3,86	3,92
Hong Kong, Chi	3,88	4,00	3,83	3,83
Canada	3,87	4,03	3,71	3,99
United States	3,86	4,15	3,68	3,92
Denmark	3,85	3,99	3,58	3,83
France	3,84	4,00	3,63	3,87
Australia	3,84	3,78	3,68	3,77
Austria	3,76	3,68	3,49	3,70
Taiwan	3,71	3,62	3,35	3,65
New Zealand	3,65	3,54	3,64	3,54
Italy	3,64	3,72	3,38	3,74
Korea, Rep.	3,64	3,62	3,33	3,64
United Arab Em	3,63	3,81	3,49	3,53
Spain	3,63	3,58	3,47	3,62
Czech Republic	3,51	3,25	3,31	3,27
China	3,49	3,54	3,16	3,49
South Africa	3,46	3,42	3,22	3,59
Malaysia	3,44	3,50	3,11	3,34
Poland	3,44	2,98	3,12	3,26
Israel	3,41	3,60	3,12	3,50
Bahrain	3,37	3,36	3,05	3,36
Lebanon	3,34	3,05	3,27	3,73
Portugal	3,34	3,17	3,31	3,31
Thailand	3,29	3,16	3,02	3,16
Kuwait	3,28	3,33	3,03	3,11
Latvia	3,25	2,88	2,94	2,96
Slovak Republic	3,24	3,00	2,79	3,15
Turkey	3,22	3,08	2,82	3,23
Saudi Arabia	3,22	3,27	2,91	3,33
Brazil	3,20	3,10	2,37	3,30
Iceland	3,20	3,33	3,22	3,14
Estonia	3,16	2,75	3,14	3,17
Philippines	3,14	2,57	2,67	2,95
Lithuania	3,13	2,72	2,79	2,85
Cyprus	3,13	2,94	2,92	2,82
India	3,12	2,91	2,70	3,16

Argentina	3,10	2,75	2,63	3,03
Chile	3,09	2,86	2,93	2,94
Mexico	3,05	2,95	2,55	3,04
Panama	3,02	2,63	2,76	2,83
Hungary	2,99	3,08	2,83	2,87
Vietnam	2,96	2,56	2,68	2,89
Greece	2,96	2,94	2,48	2,69
Qatar	2,95	2,75	2,25	2,57
Costa Rica	2,91	2,56	2,61	2,80
Slovenia	2,87	2,65	2,59	2,90
Senegal	2,86	2,64	2,45	2,73
Romania	2,84	2,25	2,36	2,68
Oman	2,84	3,06	3,38	2,37
Tunisia	2,84	2,56	2,43	2,36
Kazakhstan	2,83	2,66	2,38	2,60
Bulgaria	2,83	2,30	2,50	2,85
Malta	2,82	2,89	2,65	2,89
Dominican Rep	2,82	2,34	2,51	2,42
Uganda	2,82	2,35	2,84	2,59
Peru	2,80	2,66	2,50	2,61
Uzbekistan	2,79	2,54	2,20	2,50
Benin	2,79	2,48	2,38	2,64
Honduras	2,78	2,31	2,39	2,57
Ecuador	2,77	2,38	2,32	2,60
Colombia	2,77	2,59	2,50	2,75
Macedonia, FYI	2,77	2,55	2,55	2,76
Croatia	2,77	2,36	2,62	2,53
Indonesia	2,76	2,54	2,43	2,47
Paraguay	2,75	2,44	2,37	2,59
Uruguay	2,75	2,58	2,71	2,59
Bahamas, The	2,75	2,40	2,38	2,69
Bangladesh	2,74	2,49	2,33	2,44
Syrian Arab Rep	2,74	2,45	2,37	2,59
Jordan	2,74	2,69	2,31	2,49
Mauritius	2,72	2,29	2,71	2,43
Serbia	2,69	2,30	2,19	2,55
Venezuela, RB	2,68	2,44	2,06	2,53
Congo, Dem. R	2,68	2,27	2,60	2,93
El Salvador	2,67	2,44	2,48	2,66
Bosnia and Her	2,66	2,22	2,33	2,30
Madagascar	2,66	2,63	2,35	2,40
Azerbaijan	2,64	2,23	2,14	2,48
Guatemala	2,63	2,37	2,33	2,74
Kyrgyz Republic	2,62	2,09	2,44	2,37
Egypt, Arab Rep	2,61	2,22	2,11	2,87
Georgia	2,61	2,17	2,37	2,57
Russian Federa	2,61	2,38	2,15	2,51
Tanzania	2,60	2,00	2,42	2,38
Togo	2,60	1,82	2,40	2,45
Guinea	2,60	2,10	2,34	2,68

Haiti	2,59	2,17	2,12	2,46
Kenya	2,59	2,14	2,23	2,28
Nigeria	2,59	2,43	2,17	2,45
Yemen, Rep.	2,58	2,35	2,46	2,35
Ukraine	2,57	2,44	2,02	2,59
Iran, Islamic Re	2,57	2,36	2,22	2,65
Moldova	2,57	2,05	2,11	2,17
Cameroon	2,55	2,10	2,11	2,53
Niger	2,54	2,28	2,06	2,42
Nicaragua	2,54	2,23	2,24	2,31
Jamaica	2,53	2,07	2,00	2,32
Côte d'Ivoire	2,53	2,37	2,16	2,57
Pakistan	2,53	2,08	2,05	2,28
Armenia	2,52	2,32	2,10	2,59
Bolivia	2,51	2,24	2,26	2,38
Gambia, The	2,49	2,17	2,38	2,37
Turkmenistan	2,49	2,24	2,14	2,34
Chad	2,49	2,00	2,27	2,04
Congo, Rep.	2,48	1,62	2,02	2,42
Ghana	2,47	2,52	2,35	2,42
Lao PDR	2,46	1,95	2,17	2,14
Albania	2,46	2,14	2,07	2,39
Comoros	2,45	1,76	1,96	2,26
Montenegro	2,43	2,45	2,17	2,32
Gabon	2,41	2,09	2,23	2,31
Ethiopia	2,41	1,77	2,13	2,14
Papua New Gui	2,41	1,91	2,02	2,20
Maldives	2,40	2,16	2,25	2,29
Djibouti	2,39	2,33	2,25	2,17
Liberia	2,38	2,00	2,28	2,16
Bhutan	2,38	1,83	2,14	2,24
Cambodia	2,37	2,12	2,28	2,29
Algeria	2,36	2,06	1,97	2,24
Tajikistan	2,35	2,00	1,90	2,25
Libya	2,33	2,18	2,15	2,28
Myanmar	2,33	1,92	1,94	2,01
Botswana	2,32	2,09	2,09	2,29
Solomon Island	2,31	2,23	2,08	2,27
Mozambique	2,29	2,04	1,95	2,20
Sri Lanka	2,29	1,88	1,96	2,09
Zambia	2,28	1,83	2,17	2,01
Mali	2,27	2,00	2,08	2,13
Guyana	2,27	1,99	2,02	2,25
Mongolia	2,25	1,94	1,81	2,24
Angola	2,25	1,69	1,75	2,02
Afghanistan	2,24	1,87	2,22	2,09
Fiji	2,24	1,98	1,95	2,11
Burkina Faso	2,23	1,89	2,22	2,02
Sudan	2,21	1,78	2,02	2,15
Nepal	2,20	1,80	2,07	2,07
Iraq	2,11	1,73	2,07	2,10
Guinea-Bissau	2,10	1,56	1,89	1,56
Cuba	2,07	1,90	1,79	1,88
Rwanda	2,04	1,63	1,63	1,85
Namibia	2,02	1,71	1,68	2,04
Sierra Leone	1,97	1,61	2,17	1,53
Eritrea	1,70	1,35	1,50	1,88
Somalia	1,34	1,50	1,33	1,33

Table VIII: LPI input component score of 2010

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