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Measuring the Logistics Performance Index on the Logistics Market Evidence from the Indonesian logistic industry

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ABSTRACT

Performance Index is a tool for logistics bridging gaps that aims to measure supply chain efficiency, especially distribution. Reliability of delivery in the supply chain is key to logistics performance because consumer characteristics require a high degree of certainty about when and how to carry out processes. This study aims to determine the Logistics Performance Index model for Asian countries and its impact on world trade. This study is quantitative research by collecting forty logistics performance data based on data from the World Bank with logistical metrics related to six operational performances: tracking and tracing, customs, timeless, infrastructure, and international shipments. Descriptive analysis using Principle Component Analysis and TANAGRA software. The results of this study show that the two principal component (ζ) models formed significantly affect the best logistics performance in Asia.

INTRODUCTION

Logistics delivers goods, information, energy, and other resources from source to destination [1]. The flow of goods movement changes from upstream (first mile) to downstream (last mile) due to digitalization. This change process indicates many online trades where shipments no longer go to the store but reach the end user [2]. Delivering the best products to consumers at the optimal time, in the perfect location, at the right price, and with the highest quality - these are common requirements in logistics and transportation. However, in a dynamic context, meeting these needs is becoming increasingly difficult. There is a transition from traditional supply chains to smart supply chains. The highly dynamic logistics market and the complexity of supply chains require new methods and services. Aspects such as flexibility, adaptability, and traceability are becoming increasingly important and can only be achieved through the integration of new technologies, in particular, Blockchain and the Internet of Things (IoT), as well as artificial intelligence (AI). Therefore, this paper aims to conduct a systematic review of the academic literature on Blockchain, IoT, and AI in the context of Smart Logistics [3]. Smart logistics also has an impact on the economy of a country, especially the digital economy. The digital economy has become part of the world community. Various kinds of products have been ordered through the online system, ranging from consumer goods and electronics to design, so digital business people are increasing. A country's export and import performance is a very important factor in business, especially in the economic sector, which will affect the gross domestic product (GDP). At the end of 2019-2020, countries were exposed to COVID-19, which hugely impacted economic growth, especially in the logistics business at ports. According to [4], the global economy is currently predicted to experience a contraction of 3% compared to 2008-2009, far worse than the financial crisis. Ports are crucial in inland shipping networks, value chains, and logistics strategies. [5], [6].

Several kinds of literature discussing Logistics have been produced, including the Logistics Performance Index (LPI) [7], [8], [9] competitive, selection and evaluation port, [10], [11], [12], [13], [14], modeling and performance evaluation [15], [16], [17]. The World Bank researches using KPI aggregate data because ideal data quality and availability are uncompromising. The logistics performance component is a principle for making trade policies, improving efficient transportation systems, and prioritizing investment in transportation infrastructure [18]. In addition, according to [19], the Logistics Business Performance in Turkey has a score of 3.50, meaning that the country includes middle and upper-income after Malaysia and China based on the World Bank's LPI survey results from 2007 to 2014 from 160 countries. Reliability in the supply chain significantly impacts reducing gaps at every level of the supply chain and maintaining consumer trust and satisfaction. Factors that substantially minimize the logistics performance gap are supply chain reliability and service quality, Delivering good quality services, and Supply chain resilience and sustainability [20].

Case models regarding logistical performance were carried out by [21] regarding the effect of logistics on trade. The metrics used are three variables, namely (1) Time (nine indicators), (2). Cost (six indicators) and (3). complexity and risk factors (fourteen indicators). The method used is the gravity method which has been developed by adding explanatory variables. This method assumes trade between the two countries will add to the gross domestic product. The three influential variables are GDP, trade value, and distance between the two countries. The data set was compiled from Word Bank in 2005, containing the cost and time of product delivery from the point of origin (firm) to the destination (port) with a 20 feet FCL container type. In addition, research [7] based on the objects used are 34 member countries of the Organization for Economic Cooperation and Development (OECD) with six criteria on World Bank data. The method used hybrid method consists of (1). Intercritera correlation (CRITIC), (2). Simple additive weighting (SAW) and (3). Peters' fuzzy regression methods. The result is an overall performance prediction score $(-2{:}5092;0)+(0{:}1047;0)C_1+(0{:}1091;0)C_2+(0{:}1542;0)C_3+(1174;0)C_4+(0{:}1903;0)C_5+(0{:}1534;0)C_6$.

Research to evaluate the efficiency of the LPI was carried out (Yu & Hsiao, 2016) with the object of one country belonging to the OECD countries. The method used is The meta-frontier data envelopment analysis with assurance regions (Meta-DEA–AR). The result is a ranking level, a country with high income and the most efficient logistics operation. Vice versa, other countries are focusing on improving their logistics technology. According to the research results [22], measuring a country's logistics performance is correlated and directly affects GDP. In addition, benchmark literature, infrastructure, and customs significantly impact national competitiveness, and tracking and tracing have a relatively sustainable effect in the future [23]. The Logistics Performance Index (LPI) and Global Competitiveness Index (GCI) are variables that have an impact on the Gross Domestic Product (GDP). The relationship between the three conceptual models of variables uses the Baron model effect [24]. Based on mapping and literature studies, research on the logistic performance index contributes significantly to a country's logistics performance. Unfortunately, it's still in 2012, 2015, and 2016. In this paper, we focus on the findings of the principle component model for countries that are the best and lowest in class and Asia, which considers six key performance indicators: customs, infrastructure, logistics quality, competence, tracking and tracing, international shipments, and timeless. In contrast, the gap from previous research is using different KPIs and data sets used for a decade. The development of research based on the World Bank Data set is depicted in Figure 1.

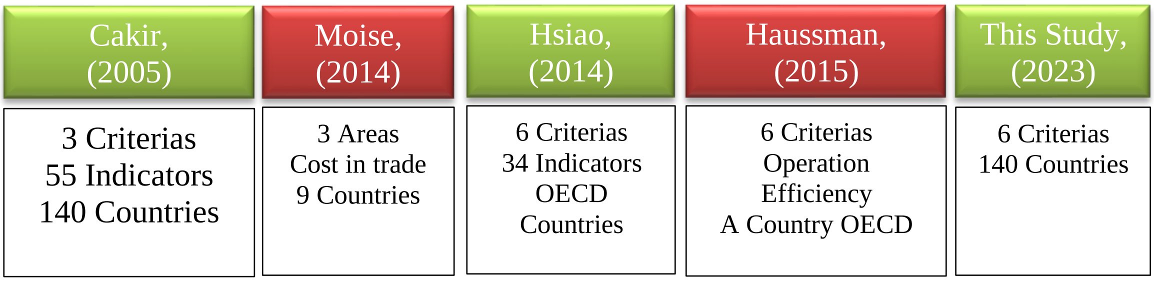


Figure 1. Logistic performance index research development

The rest of this paper is as follows. Four sections briefly introduce and outline. Section one describes the previous literature on the Logistics Performance Index. Section two presents more advantages about ways that will be used to solve the problem and the procedures of principal component analysis. The application of the study and discussion are presented in section three and And next step is to conclude the paper that gives how rearrangement should be done and the main improvement.

MATERIALS AND METHODS

Logistics

Saidi & Hammami, (2011) It defines as the art of managing flows at a low cost. The flow in the supply chain consists of upstream to downstream, including product, information, and physical flows that balance demand and supply based on a better return on investment. The key to quality logistics services is efficiency in the process. Additional costs and time inefficiencies will significantly impact trade (Korinek & Sourdin, 2011). According to (Wilson, 2009), the logistics service components that affect business include trade facilitation, transport infrastructure, time delays, information flows, and logistics services. Turbulence and volatility are two things that characterize today's market, as well as the wider business environment that makes it vulnerable to disruptions and risks to the continuity of its business processes (Behrenbeck et al., 2007).

Principle Component Analysis

Principle Component Analysis (PCA) was first discovered by (Pearson, 1901), by finding explained variance combinations with concepts like regression and reinforced by Hunteman (1989). Meanwhile (Hotelling, 1933) found Principle component axis based on a multivariate statistical approach, found patterns, and minimized data without losing information. (Puspitorini & Efendy, 2020). PCA is a technique for forming linear variables with the original variables, and the number of new variables formed is equal to the number of original variables (Mickey & Sharma, 1997). Besides that PCA is a reliable technique for extracting data with quite a lot of dimensions and the problem is finding the eigenvector and eigenvalue. The notation used in this concept is Linear combination which combines the original variables linearly. This combination is also referred to as latent and Explained Variance. Percentage variation explained includes explained fraction of variation and unexplained fraction. The pattern is illustrated in the following Equation (Bro & Smilde, 2014):

$$= 100\left(1 - \frac{\sum E^2}{\sum X^2}\right) \qquad (1)$$

$$= \frac{\|X\|^2 - \|E\|^2}{\|X\|^2} 100\ \% \qquad (2)$$

$$= X = tP^T + E \qquad (3)$$

Where X = data, P = vector of the PCA coefficient, and E is the residual matrix.
Principle component analysis (PCA) is a technique of forming new variables and the number of new variables is the same as the original variable and the new variable is not correlated.

The objectives of the PCA consist of (Mickey & Sharma, 1997) :
a. Geometric of PCA
The goal is to identify new data from the orthogonal axis where (i) the new axis is called the principal component and the value of the new variable is called the principle component scores, (ii). Each of the new variables is a linear combination with the original variable, (iii). The first number of variables is the maximum variance of the data, (iv) the number of new variables second and so on is not counted, and (v). new variables are not correlated.

b. Analytical Approach
Representation of a mathematical model of principle component analysis. Where ζ1, ζ2, ζp are the principal components, wij is the j-th variable weight for the i-th principal component.

$$\zeta_1 = w_{11}\, x_{11} + w_{12}x_2 + ... + w_{1p}x_p$$
$$\zeta_2 = w_{11}\, x_{11} + w_{12}x_2 + ... + w_{1p}x_p$$
$$\zeta_p = w_{11}\, x_{11} + w_{12}x_2 + ... + w_{1p}x_p \qquad (4)$$

There are four parts how to visualize the PCA model, namely data, score, loading, and residue. This method depends on the type of data users such as continuous data (time series) is more often plotted with bar charts, while normally distributed residual data in plots uses histograms (Bro & Smilde, 2014). And the other hand, the existing literature is a comparison of studies describing the measurement of the Logistic Performance Index in a Country and Port as shown in Table 1.

Table 1. Previous Literature of Logistic Performance Index

Author	Logistic Performance Index		Approach
	Country	Port	
Çakır, (2017) [7]	√	-	Metode Hybrid, (1). Intercritera correlation (CRITIC), (2). Simple additive weighting (SAW) and (3). Peters' fuzzy regression methods.
Wan et al., 2018 [25]	-	√	Analytical hierarchy process
Tseng and Pilcher, (2019) [26]	√	-	FAHP and In-Depth Interviews

Kaliszewsk, et al., 2020 [27]	√	-	Friedman test and a post-hoc analysis dan Least Significant Difference test (LSD).
Aloini, (2020) [5]	-	√	Mining (PM), Social Network Analysis (SNA) and Text Mining
Sergi et al., (2021) [28]	√	-	ANOVA method.
Sheikh et al., (2023) [29]	-	√	Exploratory factor analysis (EFA)
Cui et al., (2023) [30]	√	-	Particle Swarm Optimization (PSO)
Qiu et al., (2024) [31]	-	√	Improved Particle Swarm Optimization (IPSO)
Gurler et al., (2024) [32]	√	-	Genetic algorithm

Methodology

The construction methodology used in this study is based on Principle Component Analysis (PCA). PCA uses aggregate data input and Key Performance Indicators (KPIs) to describe methods for analyzing KPIs to build Logistic Performance Index (LPI) models. The hierarchy of Key Performance Indicators (KPIs) used in determining the Logistic Performance Index (LPI) refers to the World Bank in 2020. The framework and steps to achieve goals are illustrated in Figure 2.

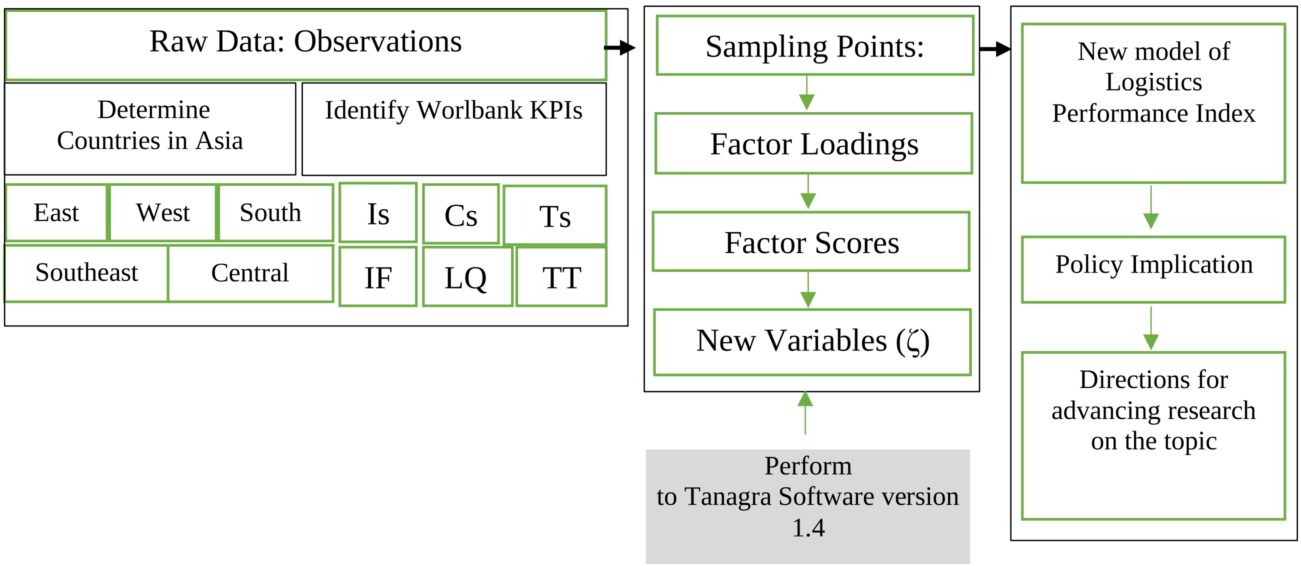


Figure 2. Framework for Logistic Performance Index by Principle Component Analysis

There are five steps to achieving a goal.

Step 1. KPIs are determined from the results of World Bank research on the assessment of logistics performance in the world for a decade. And researchers used 40 Countries' data that went into Asia.

Step 2. Data set input processed with Tanagra Software version 1.4

Step 3. Determining the LPI model based on the Principle Component formed
Step 4. State Grouping the best and lowest in class.
Step 5. Model validation between World Bank research and paperwork

RESULTS AND DISCUSSIONS

Results

A. Perform Principle Component Analysis

Principle Component Analysis (PCA) can be completed using computer data mining programs, namely Tanagra, and Matlab and the most popular are the Statistical Analysis System (SAS) and Statistical Package for the Social Science (SPSS), XL stat, and Tanagra Software. PCA can be formed either on mean-corrected or standardized data. This data processing uses TANAGRA 1.4 Software. As shown in Table 12 the Dataset of average Key Performance Indicator (KPI) Logistic Performance Countries in Asia consists of 40 Countries in Asia (East, Southeast, Central, South, and West) and 6 variables (Cs, IF, IS, LQC, TT, Ts). Data is taken from the World Bank survey every 2 years and the data is processed by researchers for 5 periods (2018-2010) using a scorecard. The variables used by Worlbank in measuring LPI are based on empirical and theoretical research and benchmarking with professionals in global third-party logistics (3PL).

Definition of variables used by Worlbank in international scorecards:

a) Customs, the efficiency of the permitting process by officers such as speed and service
b) Infrastructure, quality infrastructure related to transportation and trade such as information technology, highways, ports, and railways
c) International shipments, Low cost in the distribution process
d) Logistics Quality and Competence, Competence and quality in service to customers such as customs brokers and operators)
e) Tracking and Tracing, the ability to track and trace shipments Timeless, timeliness of delivery based on exact schedule and destination

Table 2. Detailed average KPI values from 40 Countries in Asia

CC	Cs	IF	IS	LQC	TT	Ts	CC	Cs	IF	IS	LQC	TT	Ts
SGP	4.04	4.18	3.82	4.07	4.05	4.32	KOR	3.41	3.73	3.50	3.65	3.75	3.99
THA	3.09	3.18	3.32	3.19	3.34	3.74	CHN	3.25	3.67	3.50	3.53	3.58	3.86
VNM	2.77	2.81	3.14	2.99	3.15	3.55	TWN	3.40	3.66	3.59	3.69	3.76	4.01
MYS	3.16	3.42	3.47	3.38	3.41	3.75	MNG	2.43	2.53	2.75	2.53	2.59	3.08
IDN	2.64	2.71	2.96	2.92	3.10	3.55	IND	2.87	2.98	3.18	3.17	3.24	3.59
PHL	2.69	2.65	3.20	2.90	3.10	3.31	MDV	2.45	2.50	2.56	2.50	2.53	2.90
BRN	1.08	1.04	1.10	1.06	1.13	1.27	LKA	1.94	1.82	2.11	2.04	2.09	2.36
MMR	2.15	2.10	2.28	2.23	2.36	2.89	BGD	1.93	1.91	2.30	2.15	2.23	2.57
JPN	3.83	4.16	3.59	4.00	4.04	4.23	NPL	2.16	2.08	2.31	2.26	2.41	2.81
HKG	3.86	4.03	3.85	3.93	3.97	4.16	PAK	2.50	2.47	2.88	2.65	2.63	3.03

Notes :

Index : 1. 2. 3. 4
CC : Code Countries
Cs : Customs
IF : Infrastructure
Ts : Timeless
LQC : Logistics Quality and Competence
TT : Tracking and Tracing
IS : International shipments

Discussions

B. Interpreting Principle Component Analysis Output With Tanagra

This section consists of:

Descriptive Statistics

Figure 3 shows that the KPI that most affects the Logistic Performance Index is Timeless with an average index of 3.27, while the other variables are worth 2.79. This proves that Timeless is a key factor in closing the gap in the distribution supply chain. Illustrated in Figure 3. Those six variables are Ts, TT, IS, TQC, IF, and Cs.

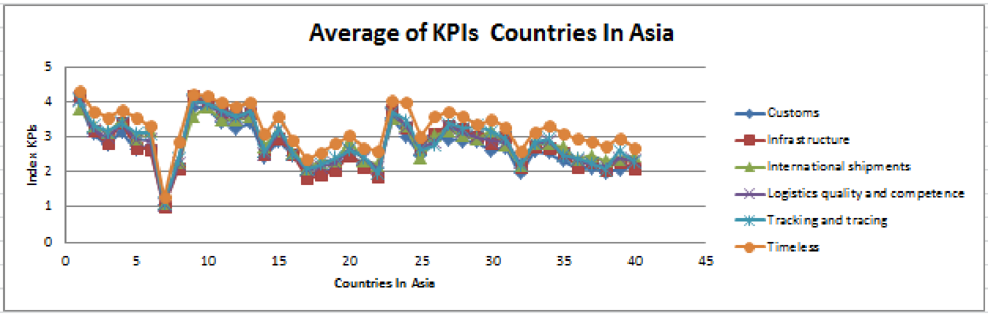


Figure 3. KPIs related Logistic Performance Index

Descriptive statistics contains basic statistical outputs such as the mean, standard deviation, and covariance matrix of the original variable. Mean, standard deviation as well as variance and total variance of the six variables Ts (3.27; 0.61 and 0.381; 15.7%), TT (2.89; 0.65 and 0.51; 21.01%), IS (2.85; 0.57 and 0.329;13.52%), LQC (2.82; 0.63 and 0.402;16.55%), IF (2.77; 0.71 and 0.428;17.64%) and Cs (2.64; 0.62 and 0.378; 15.57%). The total variance is 2,429 and the percentage of the total variance is 100%. Based on the variance above, the number of Principle Components (ζ) that can be extracted is six. Based on the analysis carried out by the computational results, the coefficient of each variable that explains the factor score is obtained. Mean, standard deviation and correlation matrices are used to transform before they are implemented in the new example. Factor score coefficients are also called Eigenvectors. Eigenvectors give weight to form equations for new variables.

The new variables formed there are five (ζ1- ζ5) is a linear combination of the original standardized data. In terminology, ζ is called the Principle Component (PC). The sum of the squares of each Principle component weight is 1. And the sum of the new variables formed respectively (equation 5).

The new variables formed are :

$\zeta_1 = 0.407Cs + 0.408IF + 0.406IS + 0.411\ LQC + 0.409TT + 0.407Ts$

$\zeta_2 = 0.460\ Cs + 0.486\ IF - 0.577IS + 0.155LQC - 0.098TT - 430Ts$

$\zeta_3 = 0.455Cs - 0.036\ IF + 0.478\ IS - 0.218LQC - 0.7166\ TT - 0.0293Ts$

$\zeta_4 = 0.113Cs - 0.274\ IF + 0.428IS + 0.181LQC + 0.321\ TT - 0.770Ts$

$\zeta_5 = (-0.59Cs) + 0.696IF + 0.295IS - 0.032LQC - 128TT - 0.232Ts$ ……………………. (5)

From the equation above, there is only one PC (ζ1) which explains that the six KPIs affect the LPI and no KPIs dominate. Eigenvalue describes the importance of each dimension. The eigenvalue reflects the correlation between active factors and variables. The Eigenvalue result at the output is equal to the calculated variant of each new variable. The total variance in the new variable is the same as the original variable, which is 2,429. In Axis 1, a variance worth 5.79.% is obtained from the proportion value (eigenvalue/total variance) and so on. We see that the two first factors 98.73 % are represented in Table 3 below.

Table 3. Eigenvalues on the new variable

Principle Component	ζ_1	ζ_2	ζ_3	ζ_4	ζ_5	ζ_6
Mean	2.64	2,77	2,85	2,82	2,89	3,27
Standard deviation	0.62	0,71	0,57	0,63	0,65	0,61
Eigen Value	5.86	0.06	0.03	0.03	0.01	0.00
Proportion (%)	5.79	1.09	0.56	0.42	0.21	0.09
Cumulative (%)	97.64	98.73	99.29	99.71	99.91	100

Loadings

Loading is a simple correlation between the original and new variables where the original variables are very influential in forming new variables. The largest value of loadings (communality estimates) greatly affects the formation of the principal component score (eigenvectors). In addition, the loading value can also be determined based on equation 1.6. Loading value is illustrated in Table 4.

Table 4. Component loadings for KPIs and each principal component

October 2024	**October 2024**	**October 2024**	**October 2024**	**October 2024**	**October 2024**
LQS	0.996	0.034	-0.04	0.03	-0.00
TT	0.988	-0.025	-0.131	0.05	-0.01
IF	0.988	0.124	0.066	-0.04	0.077
Cs	0.987	0.118	0.083	0.02	-0.07
TS	0.986	-0.109	0.088	0.02	-0.07
IS	0.982	-0.148	-0.122	0.07	0.03
Var Expl	5.858	0.065	0.033	0.03	0.01

Equation for loading factor :

$$l_{ij=} \frac{w_{ij}}{\hat{s_j}} \sqrt{\lambda_i} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (6)$$

Notes :

l_{ij} : Loading the jth variable for the principle component to -i

w_{ij} : The weight of the jth variable for the principle component to-i

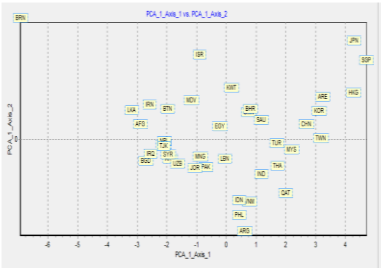
s_j : Standar deviasi variabel ke-j

λ_i : Eigenvalue from principle component to -i

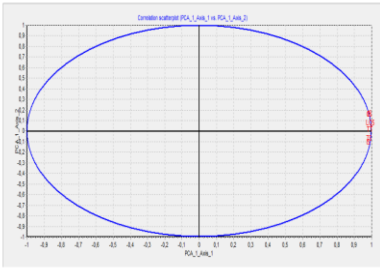
Scatter plots

A scatter plot is a popular factorial method that is a representation of a graph that visualizes data. This study uses 5 dimensions, We can modify the first dimension (horizon) and the second dimension (vertical), and so on on the other dimensions.

Based on Figure 4, the PC1 correlation of axes 1 and 2 in four quadrants, in the first quadrant has a positive LPI which means it has good performance (ten countries), namely SGN, JPN, HKG, ARE, KOR, CHN, SAU, BHR, KWT, and TWN (Fig. 4a). While the country with The best and low in Class in LPI is Southeast Asia at 4.28 (SGP) and minus 6.91 (BRN). Correlation also illustrates the sustainability of the computed variables. The six variables (KPIs) have a high correlation, (Fig.4b and c). Best and lowest countries by region. The six variables (KPIs) have a high correlation, (Fig.4b and c). The best and lowest countries by region of Asia (east south, east, south, west, and middle). Two PCs were extracted as many as 2 are shown on the elbows. Based on the 4d image, SGN has the best performance index with the highest variable Being number two compared to others. This explains that [1] The country has played the role of a logistics hub in Asia because it is designed for warehousing centers, and stopovers for ships from Europe to Asian Countries.



(a)



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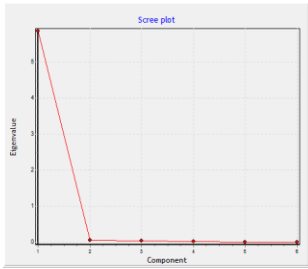

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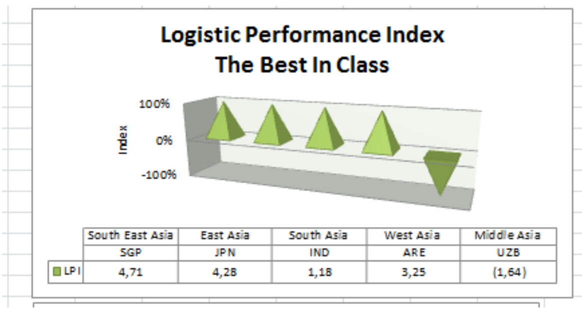
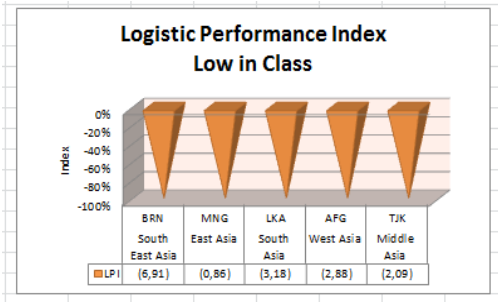


(d)



(e)

Figure 4 (a). Scatter plots between axes 1 and 2, (b) correlation of KPIs on axes 1 and 2, (c). scree plot and eigenvalue plot of parallel analysis (d) LPI the best in class (e) LPI low in class (countries in Asia).

Based on the results of the above research, the author compares with research [33], Datasets used for LPI score 160 countries. LPI score uses variables customs, time, infrastructure, international shipping, and tracking. By using the K-means clustering algorithm and multivariate adaptive regression spline (MARS). The results obtained are the formation of (i) five clusters with 4 models, namely models 1; 2; 3, and 4 (cluster1-2 extracted; cluster3; cluster 4; cluster 5) and 2 (cluster 3). In contrast, the LPI score of each cluster is 3.17 (customs); 1.88–3.00 (tracking); 2.91–3.59 (customs); 3.62–4.12 (time), and (ii). The number of countries is 129; 80; 22 and the validation of each cluster using the generalized cross-validation (GCV) criterion value is 100.

CONCLUSION

This study found that the PC model formed was ζ1 = 0.407Cs +0.408IF+0.406IS +0.411 LQC+0.409TT+0.407Ts where the most influential KPIs were LQC, TT, IF, and CS, while the less influential IS. While equally influential are Cs and TS although the comparative value between KPIs is slightly significant Countries with The best and lowest Class in Asia is Southeast Asia (SGP 4.71; BRN minus 6.91) while based on other Aisa clusters is (1). East (JPN 0.68 ; MNG minus 0.86), (2). South (IND 1.18; LKA, minus 3.18), (3). West (ARE 3.25; minus 2.88) and (4). Central (UZB 1.64 ; TJKminus2.10). Further research can consider the total cost model of logistics based on performance so that the State can improve the economy, especially investment in logistics.

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