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Analizing two-way interaction between the competitiveness and logistics performance of countries

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Abstract

Logistics has crucial importance in national and international trade and, hence, in the development and competitiveness of a country. On the other hand, making investments in different pillars of competitiveness, such as infrastructure, higher education, etc., is expected to enhance logistics performance. In this study, this two-way interaction between the competitiveness and logistics performance of countries is investigated using a hybrid methodology. Initially, the causal directions between the competitiveness of countries and their logistics performance are established by using a Bayesian Net (BN). Subsequently, the cause-effect information gathered from the BN is taken as the input in a Partial Least Square (PLS) path model to highlight the competitiveness pillars that are more critical in contributing to countries' logistics performance. As the last step, an importance-performance map analysis (IPMA) is applied to specify the importance of the pillars that have a significant effect on logistics performance. As a result, a roadmap is provided to policymakers that specify which pillars to focus on, thus delivering a significant and immediate improvement in the logistics performance and highlighting which logistics performance indicators will lead to improvements in the competitiveness of the countries. An empirical study is conducted based on two basic indexes, as follows: (1) the Global Competitiveness Index (GCI) and its pillars are used to track the competitiveness performance, and (2) the Logistics Performance Index (LPI) is used to analyze the logistics performance. According to the results, the most important GCI pillars that affect the logistics performance of a country are determined to be "Business Sophistication", "Financial Market Development", "Infrastructure" and "Good Market Efficiency" and "Higher Education and Training". On the other hand, the improvement in the logistics performance index, in its turn, will especially influence the Market Size pillar of a country.

Keywords: Logistics performance; competitiveness; Bayesian Net; Partial Least Square (PLS).

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1. Introduction

The quality of a logistics network depends on the services, investments, and policies developed by the government, and directly affects the success of a country in global trade. At the macro level, the government provides transportation infrastructure, applies standard regulations, etc., in order to improve logistics activities and this, in its turn, lead in developing the economic growth and competitiveness of their country. Consequently, the logistics performance and the competitiveness of a country are highly interrelated to one another (Arvis et al., 2018, Önsel Ekici et al., 2016).

The global trade level of a country is dependent on the efficiency of its logistics network. The latter, on the other hand, depends on the services, investments, and policies provided by the governments. In fact, governments are important actors in building infrastructure, developing and implementing efficient transport regulations and customs clearance procedures.

Every two year, the World Bank has published the Logistics Performance Index (LPI) since 2007 (Arvis et al., 2018) and has attracted attention to the importance of logistics performance of countries. The LPI evaluates the efficiency of the countries in moving the goods across and within borders based on the quality of their transport infrastructure, custom and border clearance, ease of international shipment, ability to track and trace, logistics services and timeliness. The LPI uses conventional statistical techniques to aggregate the data into a single indicator, which is then used to compare countries, regions, and income groups. It is based on a worldwide survey of operators and feedback from operators and quantitative data are aggregated to get the logistics performance of the related country. For example; LPI 2018 allows for comparisons across 160 countries, 1051 logistics professionals participated in the survey (Artvis et al., 2018).

On the other hand, each year, World Economic Forum (WEF) evaluates the competitiveness level of 137 countries by the Global Competitiveness Index (GCI) (Schwab, 2017). The GCI is based on 114 indicators that are grouped into 12 pillars (Table 1). These pillars are in turn organized into three subindices: basic requirements, efficiency enhancers, and innovation and sophistication factors.

Table 1. Pillar of GCI (Schwab, 2017)

Pillar ID	Sub-index	Pillar	Explanation
Pillar 1	Basic requirements	Institutions	This pillar is related to the efficiency of the public and private shareholders which is important for good and sustainable development of an economy.
Pillar 2	Basic requirements	Infrastructure	Extensive and efficient infrastructure with effective transport modes, extensive telecommunications networks and electricity supplies will result in an effective economy.
Pillar 3	Basic requirements	Macroeconomic environment	When the macroeconomic environment is stable the competitiveness of a country will increase. Although macroeconomic stability alone is not sufficient to increase the productivity of a nation, its weakness will cause important harm to the economy.
Pillar 4	Basic requirements	Heath and primary school	A healthy workforce will play an important role in the competitiveness of a country. Workers who are ill will not be able to work efficiently and will be less productive. On the other hand, basic education will increase the efficiency of each individual worker and will positively influence the economy.
Pillar 5	Efficiency Enhancer	High education and training	Quality higher education and training is especially important for economies which perform beyond simple products and processes. This pillar is concerned with secondary and tertiary enrollment rates, the quality of education as well as the extent of staff training.
Pillar 6	Efficiency Enhancer	Goods market efficiency	Countries with efficient goods markets will be able to produce the right mix of products and services and ensure that they are effectively traded.
Pillar 7	Efficiency Enhancer	Labor market efficiency	The efficiency and flexibility of the labor market will ensure that workers are allocated to their most effective use in the economy
Pillar 8	Efficiency Enhancer	Financial market development	An efficient financial sector, trustworthy and transparent banking sector and appropriate regulations to protect investors and other actors are critical for productivity
Pillar 9	Efficiency Enhancer	Technological Readiness	This pillar measures the agility of the economy in adopting the existing technologies with emphasis on the effective use of information and communication technologies in daily activities and production processes to increase efficiency and competitiveness.
Pillar 10	Efficiency Enhancer	Market size	The market size affects productivity due to the economies of scale. The market size is measured by the domestic and foreign markets and credit is given to export-driven economies and geographic area having many countries but a single market.
Pillar 11	Innovation	Business	Business sophistication is concerned with the quality of a

	and Sophistication Factors	sophistication	country's overall business networks and the quality of individual firms' operations and strategies. These factors are especially important when the countries are at an advanced stage of development, having already reached improvement related to the basic sources of productivity.
Pillar 12	Innovation and Sophistication Factors	Innovation	Innovation is particularly important for economies that are close to the frontiers of knowledge and that adding more value by only integrating and adapting exogenous technologies tends to be reduced

Until 2018, depending on each economy's stage of development, as proxied by its GDP per capita and the share of exports represented by raw materials, the three sub-indices were given different weights in the calculation of the overall Index. However, the GCI 4.0 (Schwab, 2018), eliminates the different weighting and underline that each country should aim to maximize its score on each indicator. Due to the fact that the results of this new scoring approach cannot be compared with the previous ones, it is not taken into account in this research.

When the LPI and GCI pillars are analyzed in detail, it can be seen that the logistics performance depends heavily on the improvement of some specific pillars of the GCI, while this improvement in the logistics performance is expected to have a positive impact on the competitiveness of a country. However, this interdependence is not the same level of importance for each pillar of the GCI and due to the government budget restrictions, it concentrates initially on the most important and low performing GCI pillars in order to make an efficient and quick improvement in the logistics performance and vice versa. Therefore, the main objective of this research is to reveal the interrelations between the basic constructs of the GCI and the logistics performance of a country and to specify the importance of these interrelations in order to provide a roadmap for government policymakers in their investment decisions.

D'Aleo and Sergi (2017a) and Uca et al. (2015) used multiple linear regressions to show that logistics, as a mediator, plays, in its turn, an important role in increasing the impact of GCI pillars on the economic growth of European countries. They underlined that the rapid growth of freight transport and improvement in the logistics sector may increase in the competitiveness of Europe. However, they did not analyze the causal relationship between the GCI and LPI pillars. D'Aleo and Sergi (2017b) selected only three GCI clusters, namely, infrastructure, institutions, and human factors, and revealed that among them the human factors especially play a very important role for improving the logistics performance index. Onsel Ekici et al. (2016) found a close relationship between the global competitiveness and the logistics efficiency of a country. Initially, they have screened the GCI pillars by specifying those that may have an impact on the logistics competitiveness and found that availability of the fixed broadband Internet is the most important factor that influence the logistics performance. Mohan (2013), on the other hand, studied the reverse relationship and showed that the logistics sector in India affects the global competitiveness of the country.

As seen from the literature, there are limited studies that analyze these relationships between the GCI pillars and LPI indicators. Önsel Ekici et al. (2019) analyzes one way interaction between competitiveness and logistics performance using GCI pillars and LPI indicators. Althogh their research has similar aim with the current study, the former analyze only one way relation and does not take into account two-way interaction. They assume competitiveness effects logistics and do not consider the mutual causal relationships among the GCI pillars and LPI.

An argument about the two-way interaction between logistics and economic growth is encountered in the literature (Nguyen and Tongzon, 2010). Although the improvement in some of the competitiveness indicators has an important positive impact on the logistics performance of a country, logistics improvement, in its turn, is expected to enhance the economic growth an efficient logistics infrastructure will decrease the travel time and enable the producers to reach long distance markets. Additionally, logistics improvement will result with an increase in local production and and attract foreign direct investment, which will lead to economic growth (Lean et al., 2014). Therefore, it is important to analyze whether this reverse relation is really significant.

In this research, we claim that the logistics performance and the competitiveness of a country are highly interrelated to one another. Therefore, the main objectives of this research are to reveal the interrelations between the basic GCI pillars as well as between the GCI pillars and the logistics performance of the country. By this way the limited resources of a country efficiently allocated by focusing on those pillars that have a high level of importance to improve the logistics competitiveness of their countries but that currently show low performance.

In section 2, the proposed methodology based on Bayesian Net, PLS and IPMA are explained. Section 3 analyses the significant relations among competitiveness pillars and between competitiveness pillars and logistics performance of a country. In section 4 the results and the related policy implications are given and finally, conclusions and suggestions are provided in section 5.

2. Methodology

The aim of the methodology is to find significant interrelations between the GCI pillars and logistics performance indicators of a country. A methodology is required to find causal relations among the variables in a system. There are many causal analysis techniques in the literature (see Tan and Platts, (2003) for the appraisal of these techniques). Among them, Bayesian networks and PLS path modeling are also well known causal analysis techniques (Wu, 2010). Bayesian Networks (BN) represents graphically the knowledge of the experts. It does not use strict statistical assumptions and use a directed acyclic graph to decide on the causal relations (Nadkarni and Shenoy, 2004).

On the other hand, PLS path modeling is structural equation modeling (SEM) that models a relationship between latent variables. It is especially suitable when exploratory problems are complex and theoretical knowledge is scarce. Based on the causal diagram developed by BN data mining, PLS is a powerful and widely used technique to validate the hypothesis and to confirm the significant paths by testing the hypotheses developed in the previous step. The main disadvantage of PLS is the difficulty in identifying causal relationships and the main reason for this is the lack of knowledge about past data and / or lack of theoretical support. To address this shortcoming, it is proposed to use a Bayesian network before modeling with PLS (Wu, 2010).

That is why, in this paper, as suggested by Wu (2010), a BN is used as the input to the PLS path analysis. To clarify the use of the BN in the methodology, suppose that there are 10 variables in a system and there is no background knowledge or theoretical support. Then, there will be approximately 7.04×10^{13} possible combinations for the relations among the variables (See Fig. 1). It is not possible to try all these combinations in the PLS models to determine the best fitting model. Instead, a BN can be employed to determine a preliminary causal model that will be analyzed using PLS path modeling.

Wu (2010) and Wu et al. (2012) used a Tree Augmented Naïve Bayes (TAN) network to produce a cause-effect graph, in which one of the variables is treated as the greatest parent node of all the nodes, and this variable is located at the top in the net. However, in this study, since our basic aim is to analyze the whole and complex system by focusing on all possible bidirectional relations, a BN approach is used instead of a TAN network.

Additionally, an Importance-Performance Map analysis (IPMA) is used to extend the results of the PLS path modeling by taking the performance of each category into account.

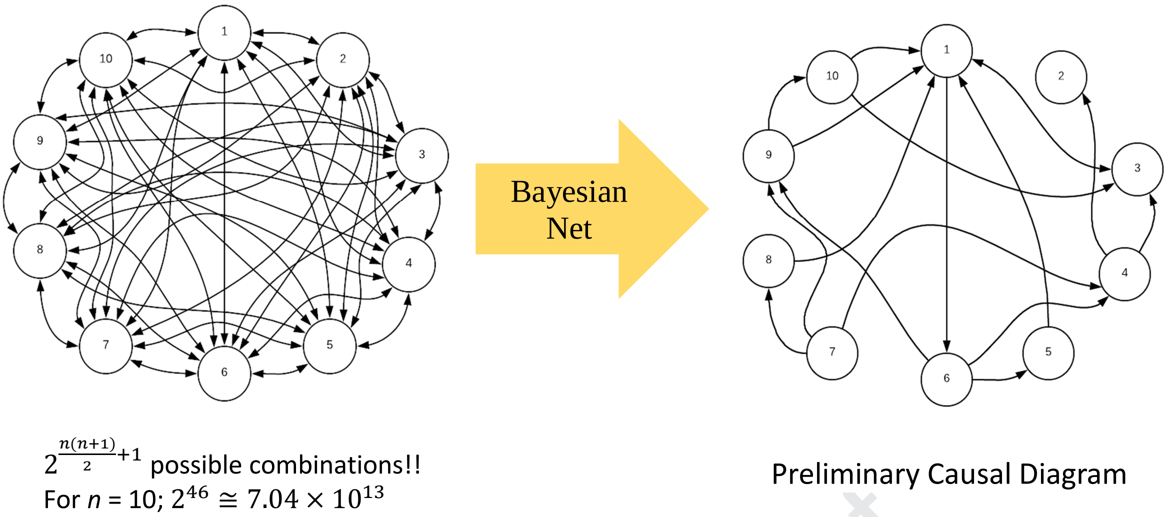

Fig. 1. Use of Bayesian Net in the Methodology

In this study, the 12 pillars of GCI, as well as the LPI indicators, are taken as the variables of the system. In order to analyze the causal direct and indirect effects between variables, a BN is constructed to model all the relations among GCI pillars and LPI indicator. After the BN phase, by using a PLS model, the significant relations between variables are determined. Finally; the effects that have high importance but low performance are revealed by using IPMA.

2.1. Bayesian Net (BN)

Causal maps help us to present the structure of a system that has many variables and relations between these variables (Wu, 2010). The nodes show the variables and the directed arrows represent causal relations between the variables. The Bayesian net (BN), represents the relations between variables by using the probability theory. As a special type of causal map, BN can model uncertainty in a variety of different systems including health, ethics, marketing and logistics (Ekici et al., 2016).

As a type of probabilistic model, BNs are frequently used to understand and simulate complex systems with high uncertainties in many different areas (Daniel et al., 2007). With the help of BNs, updating and revising beliefs based on probabilistic inference become more effective. To construct a BN, the identification of the problem domain has to be initially performed by identifying the variables and assigning the states and initial probabilities to these variables, either by estimation or appropriately based on evidence. As the second step, the relationships between variables have to be determined. Finally, the conditional probability values have to be computed. Once the network is built, the BN is able to compute probabilities based on different "what if" scenarios (Martínez et al., 2017).

The basic advantage of using a BN to analyze cause-effect relations in a complex system is its efficiency in dealing with uncertainty by interpreting the relations between variables based on probability. That is, why they are widely used for data mining in different areas, such as environmental studies, health care, risk analysis, and resource management.

Both BNs and Structural Equation Modeling (SEM) methodology are used to represent causal relations in the literature but they are different in nature (Bruce et al. 2019). An SEM is used to test hypotheses whereas a BN is used to analyze the causal relations between variables. SEMs investigate whether pre-assumed relations are significant whereas BNs analyze the effect of a change in a variable on the other variables of the system.

A more detailed analysis of the literature on BN can be seen in Korb and Nicholson (2011).

2.2. Partial Least Square Path Model (PLS)

PLS in a structural equation modeling (SEM) approach for making multivariate regression analyses (Wu, 2010). It maximizes the explained variation among the given constructs. It makes minimum assumptions related to statistical distribution. PLS can be conducted for problems with small sample size. The most important aspect is the predictive accuracy (Wong, 2013). However; when there is little knowledge about the causal relations or when the theoretical hypothesis is not precisely established, it may be hard to build the causal directions between the constructs. In order to deal with this difficulty, BNs can serve as a useful tool to build an initial causal network. BNs can also show a network of relationships, but they do not need hypothesized interactions between several variables (Lauria and Duchessi, 2007). Therefore, Wu (2010) and Önsel Ekici et al. (2019) propose using the Bayesian network before applying a PLS path modeling for causal analysis. Different from Wu (2010) and Önsel Ekici et al. (2019), in this research, a BN is used rather than Tree Augmented naive Bayes (TAN) in order to analyze the bidirectional relations between competitiveness and logistics performance.

This research uses BN and PLS path modeling consecutively to analyze the causal relations. Initially, a preliminary causal diagram is constructed through BN. Subsequently; a good fitting model is developed using PLS. PLS path modeling is applied by SmartPLS software. As suggested by Önsel Ekici et al. (2019), a stepwise methodology is preferred to find the best model in PLS. Steps of the methodology are as follows:

Step 1: Set the causal diagram established in BN as the initial diagram for PLS modeling

Step 2: Evaluate the model fit of the given diagram using SmartPLS. In this step, The Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) are used to check the whole model fit. The coefficient of the determination (r^2) of the variables that shows the proportion of the variance in the dependent variable that is predictable from the independent variable is used to check the relevance of the individual relations between variables. In this respect, SRMR is expected to be less than 0.08, NFI is greater than 0.9, and (r^2) of the variables is more than 0.75 for a good fitting model.

Step 3: If a good fitting model is found in step 2, finalize the process and declare the last model as the best model.

Step 4: If a good fitting model is not reached in step 2, the insignificant relations in the diagram (i.e., for which (r^2) is less than 0.75) are removed and a new diagram is constructed. The methodology is applied starting from step 2.

Step 5: If no fitting model is reached and there are no insignificant relations in the diagram or the number of relations in the diagram drops to a certain small number after some rounds, then it is concluded that the given system of variables does not constitute a causal relation network.

To give the idea of the methodology, consider the preliminary causal diagram in Fig 1. This diagram is set as the initial diagram for PLS as in Fig. 2. Then model fit is analyzed using SmartPLS, and it is seen that the model fit parameters do not show a good model. Subsequently; the irrelevant relations (for instance, 7 to 9, 7 to 4, 6 to 9, and 6 to 4) are deleted from the initial diagram. The SmartPLS is rerun for the new diagram and the best model with accepted model fit parameters is reached as given in Fig 2.

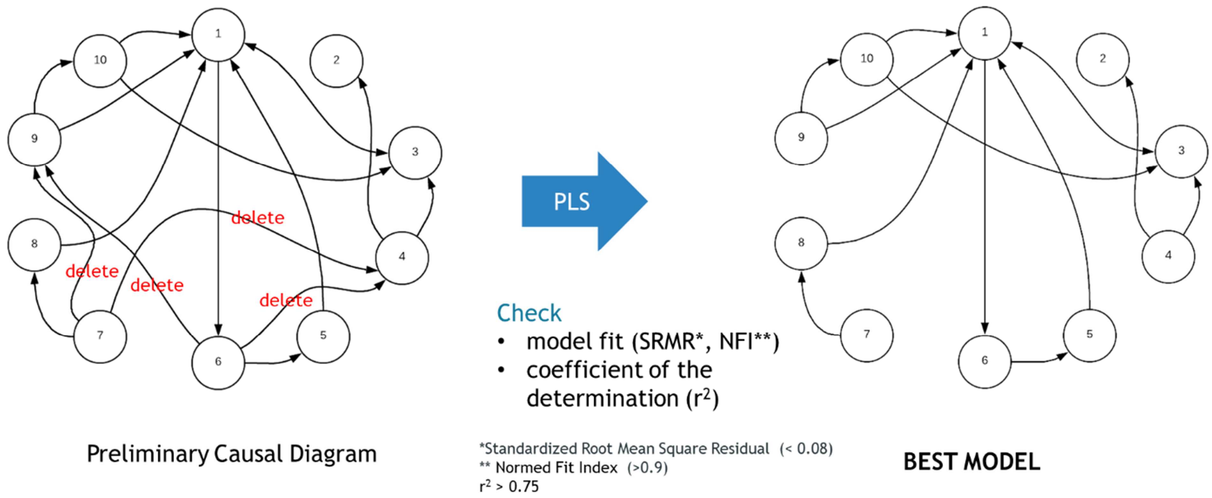

Fig. 2. Use of PLS in the Methodology

2.3. Importance-Performance Map Analysis (IPMA)

As a result of the PLS, a good-fitting model including significant relations in the system of variables is found. Although this relation set provides very useful information to make interpretations for a specific variable, it does not give insight about the magnitude or importance of the relations. The IPMA provides the importance of variables on their effect on a specific variable. To make this analysis, the SmartPLS software scalarizes variables' values (Jitmaneeroj, 2016). The aim is to rank the variables based on their effect and their performance. The variables having relatively high effect with relatively low performance are preferred. Thus, performance importance ratio is found by dividing total effect to performance. This ratio is used to rank the variables according to their effect on a selected variable.

3. Empirical Analysis

In order to find the two-way interaction between the competitiveness and logistics performance of countries, the LPI and WEF's GCI data for the years 2010-2012-2014-2016 (https://tcdata360.worldbank.org/) are used.

It may be important to underline that although some of the LPI and GCI pillars seem to be identical, they define different perspectives and hence use different measures. For instance, although there is infrastructure indicator in both, Infrastructure in the LPI defines "The quality of trade- and transport-related infrastructure" while the Pillar 2 - Infrastructure in GCI is the "Extensive and efficient infrastructure including modes of transport, electricity supplies and telecommunications network of a country"

3.1. Bayesian Net (BN)

The construction of a BN model consists of two stages: (1) the determination of relations between variables, called "structure learning phase" and (2) the quantification of variables using a conditional probability for each node, called "the parameter learning phase". In this study, only the first phase is used in order to be able to give the causal model proposal for the PLS model and "Greedy Thick Thinning" algorithm in GeNIe software (https://www.bayesfusion.com/) is used for structure learning. This algorithm begins with no relations between variables and then, in the first phase an arc is added every time the marginal likelihood is increased. The same procedure is repeated in the second phase of the algorithm for arc deletion. An arc is deleted until an increase is realized in marginal likelihood. In this study, the number of variables in the model is 13. That is why the maximum number of parents that a node can have is set to 12.

When the BN procedure is applied to the system of 13 variables (Twelve pillars and one LPI), the BN structure in Fig. 3 is found. According to the resulting diagram, the LPI is affected by Pillar 11 (Business sophistication) and Pillar 2 (Infrastructure), while it affects Pillar 10 (Market Size). Among the variables in the system, Pillar 3 (Macroeconomic environment), Pillar 7 (Labor market efficiency), and Pillar 10 (Market size) have no effect on the other variables but are affected by the others. On the other hand, Pillar 8 (Financial market development) is affected by no other variables. Having five relations with other variables, Pillar 2 (Infrastructure), Pillar 6 (Goods market efficiency), Pillar 11 (Business sophistication) and Pillar 12 (Innovation) are the most central variables.

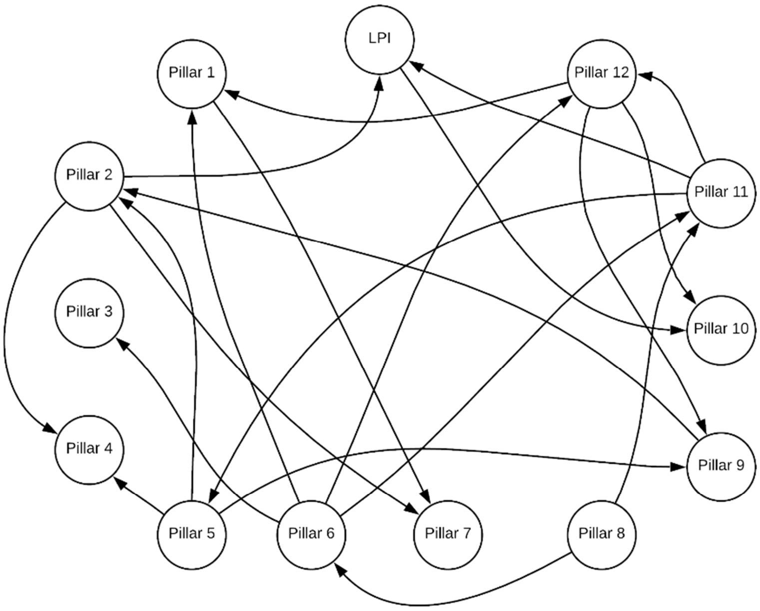

Fig. 3. BN structure

3.2. Partial Least Square Path Model (PLS)

The initial network structure for the PLS path modeling is the outcome of the BN presented in Fig. 3. The model fit of the initial network is evaluated using the consistent PLS algorithm in SmartPLS Software. Without any modification, the model structured by BN found with a good fit (SRMR = 0.044 and NFI = 0.920). Please see Fig. 4. for the results. For our target variable, logistics performance, r^2 is 0.750 and the factor loadings of indicators of this variable are greater than 0.89. Therefore, we used the results of this model to interpret the relations for logistics performance.

Notice that in Fig. 4 the r^2 values for the latent variables that are affected by another latent variable(s) are denoted by blue circles. For instance, for logistics performance, it is 0.750, for Pillar 1 it is 0.815, for Pillar 12 it is 0.868, etc. It is expected that the r^2 of a latent variable is greater than 0.75 in a good fitting model. It is observed in Fig. 4 that for some variables, such as Pillar 3, Pillar 5, Pillar 6, Pillar 7, and Pillar 10, r^2 is less than 0.75. It can be inferred that the variations in these variables are not well explained by the effecting variables in the system. Since our objective is to analyze the relations for a logistic performance and that the indicators for the entire model (such as SRMR and NFI) show a good fit, it is not necessary to make modifications to fix the r^2 values.

In order to find the indirect, direct as well as total effects, a bootstrapping procedure was run in SmartPLS. The results are presented in Table 2. The path coefficients can also be seen on the arcs in Fig. 4. In Table 2 the path coefficients marked with stars (*) are significant. According to the results, almost all relations are found to be significant. Only four relations out of the 22 hypothesized relationships are insignificant and, hence, are not directly related to the logistics performance. Pillar 11 and Pillar 2 have direct significant effects on the logistics performance with magnitudes of 0.496 and 0.399, respectively (see Fig. 4 and Table 2).

Similarly, almost all of the total effects (see Table 2), which simultaneously include direct and indirect effects, are found to be significant. This result also supports the good fit of the proposed model.

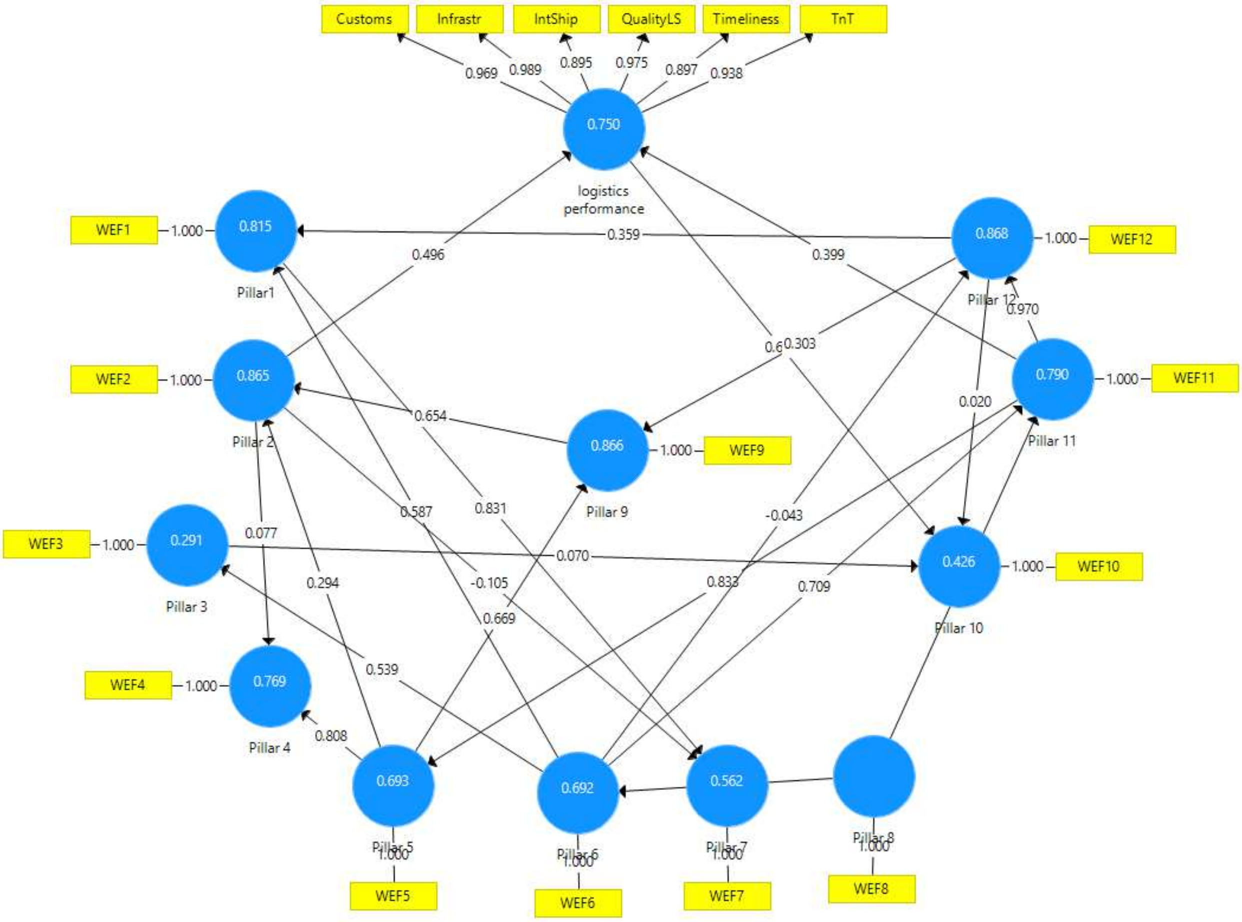

Fig. 4. PLS model developed in SmartPLS

Table 2. Results of the PLS path models

Causal Relationship	*Path Coefficient*	*t statistics*	*Indirect effect*	*t statistics*	*Total Effect*	*t statistics*
Pillar 11 -> Pillar 10			0.502*	13.238	0.502*	13.238
Pillar 11 -> Pillar 12	0.965*	23.631			0.965*	23.631
Pillar 11 -> Pillar 2			0.8*	43.332	0.8*	43.332
Pillar 11 -> Pillar 4			0.734*	44.6	0.734*	44.6
Pillar 11 -> Pillar 5	0.832*	60.24			0.832*	60.24
Pillar 11 -> Pillar 7			0.203*	5.29	0.203*	5.29
Pillar 11 -> Pillar 9			0.849*	43.004	0.849*	43.004
Pillar 11 -> Pillar1			0.345*	9.219	0.345*	9.219
Pillar 11 -> logistics performance	0.402*	5.407	0.395*	7.354	0.797*	31.745
Pillar 12 -> Pillar 10	0.013	0.239	0.059*	5.628	0.072	0.989
Pillar 12 -> Pillar 2			0.197*	7.981	0.197*	7.981
Pillar 12 -> Pillar 4			0.016	1.902	0.016	1.902
Pillar 12 -> Pillar 7			0.276*	8.809	0.276*	8.809
Pillar 12 -> Pillar 9	0.301*	10.888			0.301*	10.888
Pillar 12 -> Pillar1	0.357*	10.368			0.357*	10.368
Pillar 12 -> logistics performance			0.097*	5.854	0.097*	5.854
Pillar 2 -> Pillar 10			0.299*	7.725	0.299*	7.725
Pillar 2 -> Pillar 4	0.081	1.881			0.081	1.881
Pillar 2 -> Pillar 7	-0.104*	2.615			-0.104*	2.615
Pillar 2 -> logistics performance	0.494*	8.024			0.494*	8.024
Pillar 3 -> Pillar 10	0.067	1.434			0.067	1.434
Pillar 5 -> Pillar 10			0.219*	7.361	0.219*	7.361
Pillar 5 -> Pillar 2	0.295*	7.032	0.437*	16.133	0.732*	28.87
Pillar 5 -> Pillar 4	0.804*	20.219	0.059	1.851	0.864*	68.629
Pillar 5 -> Pillar 7			-0.076*	2.602	-0.076*	2.602
Pillar 5 -> Pillar 9	0.67*	25.93			0.67*	25.93
Pillar 5 -> logistics performance			0.362*	7.523	0.362*	7.523
Pillar 6 -> Pillar 10			0.389*	14.186	0.389*	14.186
Pillar 6 -> Pillar 11	0.71*	22.778			0.71*	22.778
Pillar 6 -> Pillar 12	-0.038	0.967	0.685*	15.9	0.648*	18.908
Pillar 6 -> Pillar 2			0.56*	20.129	0.56*	20.129
Pillar 6 -> Pillar 3	0.537*	11.063			0.537*	11.063
Pillar 6 -> Pillar 4			0.521*	19.382	0.521*	19.382
Pillar 6 -> Pillar 5			0.591*	20.335	0.591*	20.335
Pillar 6 -> Pillar 7			0.622*	26.978	0.622*	26.978
Pillar 6 -> Pillar 9			0.591*	20.598	0.591*	20.598
Pillar 6 -> Pillar1	0.588*	18.682	0.231*	9.221	0.819*	53.002
Pillar 6 -> logistics performance			0.562*	17.975	0.562*	17.975
Pillar 8 -> Pillar 10			0.426*	16.186	0.426*	16.186
Pillar 8 -> Pillar 11	0.205*	6.191	0.59*	20.357	0.795*	39.6
Pillar 8 -> Pillar 12			0.736*	40.395	0.736*	40.395
Pillar 8 -> Pillar 2			0.63*	26.986	0.63*	26.986
Pillar 8 -> Pillar 3			0.447*	9.432	0.447*	9.432
Pillar 8 -> Pillar 4			0.584*	23.849	0.584*	23.849
Pillar 8 -> Pillar 5			0.662*	27.18	0.662*	27.18
Pillar 8 -> Pillar 6	0.831*	45.062			0.831*	45.062
Pillar 8 -> Pillar 7			0.558*	19.465	0.558*	19.465
Pillar 8 -> Pillar 9			0.666*	29.933	0.666*	29.933
Pillar 8 -> Pillar1			0.752*	37.874	0.752*	37.874
Pillar 8 -> logistics performance			0.631*	33.797	0.631*	33.797

Pillar 9 -> Pillar 10			0.195*	6.892	0.195*	6.892
Pillar 9 -> Pillar 2	0.653*	16.366			0.653*	16.366
Pillar 9 -> Pillar 4			0.052	1.905	0.052	1.905
Pillar 9 -> Pillar 7			-0.068*	2.568	-0.068*	2.568
Pillar 9 -> logistics performance			0.322*	7.191	0.322*	7.191
Pillar1 -> Pillar 7	0.83*	21.896			0.83*	21.896
logistics performance -> Pillar 10	0.61*	7.155			0.61*	7.155

As seen from Table 2, Pillar 11 (Business sophistication), Pillar 12 (Innovation), Pillar 2 (Infrastructure), Pillar 5 (High education and training), Pillar 6 (Goods Market Efficiency), Pillar 8 (Financial Market Development) and Pillar 9 (Technological Readiness) significantly influence the logistics performance. Logistics, in its turn, influence Pillar 10 (Market Size) significantly.

In the following section, the IPMA analysis is conducted in order to specify the pillars having high importance but low performance. This analysis can help the policymakers on the prioritization of the investment plans to specific pillars to decide which pillar to focus on immediately in order to obtain significant improvements in the logistics performance of the country. Additionally, it will be possible to reveal which pillars of the competitiveness will be improved, in its turn, through improvement on logistics performance of the country.

3.3. Importance-Performance Map Analysis (IPMA)

The IPMA procedure of the SmartPLS was applied by setting the target construct as the logistics performance. The results are presented in Table 3 and Fig. 5.

Table 3. IPMA results for the logistics performance as the target variable

	Total Effect	Performances	Performance importance	Importance rank
Pillar 11 - Business sophistication	0.797	68.452	85.89	1
Pillar 8 - Financial market development	0.631	68.888	109.17	2
Pillar 2 – Infrastructure	0.494	59.389	120.22	3
Pillar 6 - Goods market efficiency	0.562	74.568	132.68	4
Pillar 5 - Higher education and training	0.362	67.158	185.52	5
Pillar 9 - Technological readiness	0.322	62.628	194.50	6
Pillar 12 – Innovation	0.097	59.81	616.60	7

The pillars are ranked according to performance importance values. If the government authorities aim to have a quick improvement in the logistics performance of their country, the first five pillars that they should primarily focus on are Business sophistication, Financial market development, Infrastructure, Goods market efficiency, High Education and Training. These are followed by Technological Readiness and Innovation pillars of competitiveness.

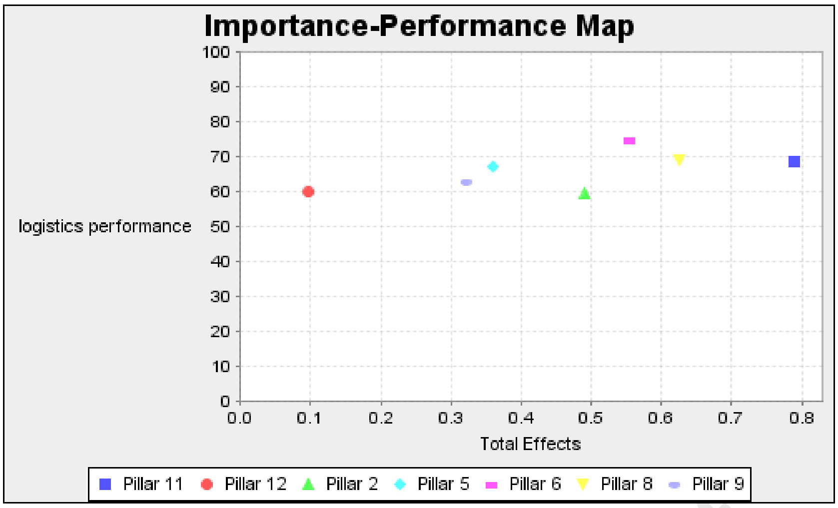

Fig. 5. Results of the IPMA

4. Discussions and Implications

In this paper, we have proposed a hybrid method that includes Bayesian Networks and PLS in order to investigate the bidirectional relations between logistics performance and the competitiveness of a country. In the first stage; a BN is constructed from the data in order to define all possible two-way relations between the variables in the analyzed domain. In the second stage, these relations are used as a basis for the PLS to test whether they are statistically significant. The integration of these two methods is useful in the sense that PLS is a statistical method to test hypotheses about assumed causal relations, whereas BNs can construct probabilistic models by simply investigating the dependence relations between variables. Therefore, by integrating the BN and PLS methodologies, the need for knowledge about the relations between variables in PLS is gathered from the result of the BN.

According to the results of the proposed methodology, among the first five pillars having the highest importance but showing low performance, the first competitiveness pillar that the governments should focus on is Business Sophistication. Business sophistication is related to the quality of the operational and strategic activities of the individual firms.

In fact, this finding is in parallel with the research results conducted by Stevens and Johnson (2016), who show the trend toward collaborative supply chain clusters. Firms are increasingly motivated to build supply chain networks and collaborative supply chain strategies in order to improve their logistics performance and to increase the efficiency of their flows of information and money in face of customer demand (Stevens and Johnson, 2016).

The positive relationship between partnership quality and supply chain performance is also underlined in the survey conducted by Srinivasan et al. (2011) on 127 US firms. This relation is especially shown to increase in highly uncertain environments.

In order to improve the business sophistication of their countries, governments should take measures to increase their local supplier quantity and quality. They should also give incentives for cluster development and for building control mechanisms for international distribution.

Financial market development is the second pillar that should be given priority to enhance the logistics performance of a country. This pillar evaluates the ability and efficiency of the financial sector in providing affordable financial services and ease of access to loans.

The relation between logistics and financial performance has also been investigated in the literature. For example, Schramm-Klein and Morschett (2006) and Shang and Marlow (2005) highlighted a positive connection between these two aspects of performance in large enterprises.

Governments should take measures to increase the efficiency of financial services in meeting business needs by providing affordable financial services and ease of access to loans. They should also increase trustworthiness, confidence, and soundness of banks as well as regulation of the securities exchanges.

Infrastructure is the third important GCI pillar that influence the logistics performance. In fact; the improvements made in terminals, ports and airports will ease the access to long distance markets and, thus, increase the international and local trade.This will result in a significant reduction in costs and, hence, will have a positive effect on the logistics performance of the country. High-quality and effectiveness of transportation modes will make the movement of goods, services, and workers easier (Schwab, 2017). This is in parallel with the finding of this research.

According to the LPI report 2016 (Arvis et al., 2018**)**, although infrastructure seems to be improving, it is still a constraint in developing countries. However, satisfaction with rail infrastructure remains low. Respondents in all LPI quintiles are nearly always more satisfied with service providers than with infrastructure quality. Governments should make an investment in logistics infrastructure and motivate the development of logistics parks (Mc Kinnon et al., 2017).

The fourth important pillar is Good Market Efficiency. This pillar investigates the extent to which a country provides an even playing field for companies to participate in its markets. It is measured in terms of the extent of market power, openness to foreign firms and the degree of market distortions.

The governments should reduce the various distortions of goods market efficiency, including the number of procedures and the time required to start a business, the effect of taxation as well as the trade barriers.

The fifth important pillar is Higher Education and Training. This pillar analyzes the education enrollment rates, the quality of the education system as well as the extent of staff training and access to the Internet in schools in a country.

Despite the increase in automation, logistics is still a human-centric business that necessitates mant blue-collar works especially at the operational level. When these blue-collar workers have lower quality, this will negatively influence logistics performance and, consequently, the production and international trade. In developed countries, it is difficult to find qualified blue-collar workforce. This is basically due to the low salary and relatively low status of the operational logistics workers.

More competitive global economies have a higher demand for highly qualified logistics related labot which is also scarce in both developing and developed countries. In fact, although many developing countries are struggling with high unemployment, their skilled labor is limited and does not follow the recent technological developments. In the developing countries the situation is even worse in terms of limited training budgets, appropriate course content and qualified educators. Vocational schools for logistics jobs are also insufficient lacking (Arvis et al., 2018).

In fact, Myers et al. (2004) also indicate the importance of investing in human capital to improve the logistics performance. Their research highlights that the well educated logistics managers will have more technical competence and problem-solving capability and, thus, will be more efficient.

The demand for government intervention will show differences with respect to developing and developed countries. For example; in advanced economies, additional funding will be especially used for world-class logistics education, while in developing countries, the government support will be especially focused on training and knowledge transfer.

Another important finding of this study is that Logistics Performance, in its turn, influences the Market Size pillar of competitiveness significantly. This pillar is related to the local and foreign market size, the gross domestic product and exports as a percentage of the GDP. GDP gives information about the general situation of the economy and if the GCI values and the economic growth of the countries are compared for the last ten years, it can be seen that there is a strong correlation between GCI performance and growth of the economy (Schwab, 2018). When the logistics performance is improved this will permit greater access to distant markets, stimulate local production and increase foreign direct investment which is itseld an important tool of the economic growth (Schwab, 2018). In fact, the performance of EU countries such as Germany shows the validity of this claim.

5. Conclusion and Further Suggestions

This study analyzes the two-way cause-effect relationships between the GCI and LPI values of a country. By this way; a road map is provided to the government authorities in their decision related to the actions that they should primarily focus on in order to improve the logistics performance of their countries. The study shows that GCI pillars have different importance levels in this respect. The proposed methodology developed for this purpose is an integrated model based on Bayes Nets, PLS, and IPMA techniques. The analysis showed that policymakers should primarily invest in improving the Business Sophistication, Financial Market Development and Infrastructure, Good Market Efficiency and Higher Education and Training in order to improve the logistics performance of their countries. The improvement in logistics performance, in its turn, will positively influence the Market Size pillar of competitiveness.

The contribution of this study is three-fold. Firstly, it presents a new methodology for analyzing the two-way cause-effect relations in a system by integrating Bayes Nets, PLS, and IPMA. Second, the methodology is applied to analyze the interrelations between competitiveness indicators and logistics performance. As mentioned above, the methodology enabled to prioritize the competitiveness indicators for immediate improvement in logistics. Additionally, the study shows that this cause and effect relationship between the pillars and logistics performance is in a two-way direction and influence each other. (D'Aleo and Sergi, 2017a, 2017b; Marti et al., 2014; Önsel Ekici et al., 2016).

As a further suggestion, it is possible to analyze competitiveness and logistics relations based on the logistics performance stage of a country. Therefore, in a future study, the countries can be clustered according to their LPI values and the proposed methodology can be used separately for each cluster. The results for each cluster may provide more precise action plans for the countries. The proposed methodology can also be similarly used to analyze two-way cause-effect relations in other different complex systems.

References

Arvis, J-F., Saslavsky, D., Ojala, L., Shepherd, B., Raj, A. Naula, T. (2018). Connecting to compete 2018 trade logistics in the global economy: The logistics performance index and its indicators. The International Bank for Reconstruction and Development/The World Bank, Washington DC.

Bruce G. Marcot B.G., Penman T.D. (2019), "Advances in Bayesian network modelling: Integration of modelling technologies", Environmental Modelling and Software 111, 386–393

D'Aleo, V., Sergi, B.S. (2017a), "Does Logistics influence economic growth? The European experience", Management Decision, 55, 8, 1613-1628

D'Aleo, V., Sergi, B.S. (2017b), "Human factor: The competitive advantage driver of the EU's logistics sector", International Journal of Production Research, 55, 3, 642-655

Daniel B.K., Zapata-Rivere J.D., McCalla G.I. (2007) "A Bayesian Belief Network Approach for Modeling Complex Domains" in Mittal A., Kassim A. (Eds.) "Bayesian Network Technologies: Applications and Graphical Models" IGI Publishing

Ekici, A., Önsel Ekici, S. (2016) "A Bayesian Network Analysis of Ethical Behavior." Journal of Macromarketing, 36.1, 96-115.

Jitmaneeroj, B. (2016) "A New Approach to Prioritizing SME Regulation Reforms", Journal of Small Business and Enterprise Development 23.3, 854-872.

Korb, K.B., Nicholson, A.E. (2011) Bayesian Artificial Intelligence. London: CRC Press.

Lauria, E.J.M., Duchessi, P.J. (2007) “A methodology for developing Bayesian networks: An application to information technology (IT) implementation”, European Journal of Operational Research 179.1, 234–252.

Lean, H.H., Huang, W., Hong, J. (2014). “Logistics and economic development: experience from China”, Transport Policy 32, 96–104

Marti, L., Puertas, R., García, L. (2014) “The importance of the Logistics Performance Index in international trade”. Applied Economics 46 (24), 2982–2992.

Martínez-Martínez L.H., Delgado-Hernández D.J.,de-León-Escobedo D., Flores-Gomora J., Arteaga-Arcos J.C. (2017) “Woody debris trapping phenomena evaluation in bridge piers: A Bayesian Perspective”, Reliability Engineering and System Safety 161 38–52

McKinnon, A., Flöthmann, C., Hoberg, K., Bush, C. (2017) Logistics Competencies, Skills and Training: A Global Overview. World Bank Group.

Mohan, J.B. (2013) “The Impact ofLogistics Management on Global Competitiveness”, International Journal of Business and Management Invention”, 2, 39-42

Myers, M. B., Griffith, D. A., Daugherty, P. J., Lusch, R. F. (2004). “Maximizing the human capital equation in logistics: education, experience, and skills. Journal of Business Logistics”, 25(1), 211-232.

Nadkarni, S. and Shenoy, P.P. (2004) “A causal mapping approach to constructing Bayesian networks”, Decision Support Systems, 38, 259-281

Nguyen, H.-O., Tongzon, J. (2010) “Causal nexus between the transport and logistics sector and trade: the case of Australia”, Transportation Policy 17 (3), 135–146

Önsel Ekici, Ş.,Kabak, Ö., Ülengin, F. (2016) “Linking to compete: Logistics and global competitiveness interaction”, Transport Policy, 48, 117-128

Önsel Ekici, Ş., Kabak, Ö., Ülengin, F. (2019) “Improving logistics performance by reforming the pillars of Global Competitiveness Index”, Transport Policy 81, 197-207.

Schramm-Klein, H., Morschett, D. (2006) “The relationship between marketing performance, logistics performance and company performance for retail companies”, International Review of Retail, Distribution and Consumer Research 16.2, 277-96.

Schwab, K. (Ed.) (2017) The Global Competitiveness Report 2017-2018. World Economic Forum, https://www.weforum.org/reports/the-global-competitiveness-report-2017-2018

Schwab, K. (Ed.) (2018) The Global Competitiveness Report 2018. World Economic Forum, https://www.weforum.org/reports/the-global-competitiveness-report-2018-2019

Shang, K., Marlow, P.B. (2005) “Logistics capability and performance in Taiwan’s major manufacturing firms”, Transportation Research Part E 41.3, 217-34.

Srinivasan, M., Mukherjee, D., Gaur, A.S. (2011) “Buyer–supplier partnership quality and supply chain performance: Moderating role of risks, and environmental uncertainty”, European Management Journal, 29, 260– 271.

Stevens, G.C., Johnson, M. (2016) “Integrating the supply chain… 25 years on”, International Journal of Physical Distribution & Logistics Management 46.1, 19-42.

Tan, K.H. and Platts, K. (2003) “Linking objectives to actions: A decision support approach based on cause-effect linkages”, Decision Sciences. 34(3), 569-593

Uca, N., Civelek, M.E., Çemberci, M. (2015), “The effect of the components of Logistics Performance Index on Gross Domestic product: Conceptual Model Proposal”, Eurasian Business and Economics Journal, 1, 86-93

Wu, W-W, Lan, L.W., Lee, Y-T. (2012). “Exploring the critical pillars and causal relations within the NRI: An innovative approach”, European Journal of Operational Research 218, 230-238.

Wu, W-W. (2010) “Linking Bayesian networks and PLS path modeling for causal analysis”, Expert Systems with Applications 37, 134-139.

Wong, K. K. K. (2013). “Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS”, Marketing Bulletin, 24(1), 1-32.