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A 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 to maintain competitiveness is expected to improve the logistics performance of a country. In this study, this two-way interaction between competitiveness and logistics performance is investigated using a hybrid methodology. Initially, causal relations between competitiveness and 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 which competitiveness pillars are more critical in contributing to the logistics performance of countries. As the last step, an importance-performance map analysis (IPMA) is conducted to specify the pillars that have high importance but that show a low performance. As a result, a roadmap is provided for policymakers to specify which pillars to focus on, thus delivers a significant and immediate improvement in the logistics performance and highlights 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 "Market Size".

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 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., 2016, Ekici et al., 2016).

Logistics performance both in international trade and domestic endeavors are completely interrelated with the economic growth and competitiveness of countries. The World Bank's Logistics Performance Index (LPI) (Arvis et al., 2016), published every two years since its initial inaugural release in 2007, has raised awareness of the importance of logistics performance of the countries. The index evaluates the logistics performance of countries according to six basic indicators: the efficiency of customs and border management clearance (customs), the quality of trade and transport infrastructure (infrastructure), the ease of arranging competitively priced shipments (international shipment), the competence and quality of logistics services (logistics services), the ability to track and trace consignments (track and trace), and the frequency with which shipments reach consignees within the scheduled or expected delivery times (timeliness). The components have been chosen based on theoretical and empirical research and on the practical experience of logistics professionals involved in international freight forwarding. The six LPI indicators are mapped into two main categories: areas for policy regulation, indicating main inputs to the supply chain (customs, infrastructure, and logistics services) and supply chain performance outcomes (corresponding to LPI indicators of time and reliability: timeliness, international shipments, and tracking and tracing). The LPI uses standard statistical techniques to aggregate the data into a single indicator, which can then be used to compare countries, regions, and income groups. It can also be used for country-level work.

On the other hand, each year the World Economic Forum (WEF) releases the Global Competitiveness Index (GCI) to track the performance of countries on 12 pillars of competitiveness (Schwab, 2017). The GCI assesses the factors and institutions that are the main determinants for improving the long-term growth and competitiveness of the country. Therefore, it aims to help decision makers understand the complex and multifaceted nature of the development challenge. The 12 pillars are presented in Table 1. These pillars, in turn, are organized into three sub-indexes: basic requirements, efficiency enhancers, and innovation and sophistication factors. The three sub-indexes are given different weights in the calculation of the overall index depending on each economy's stage of development, as proxied by its Gross Domestic Product (GDP) per capita and its share of exports represented by raw materials. Institutions (Pillar 1), Infrastructure (Pillar 2), Macroeconomic environment (Pillar 3), and Health and primary educators (Pillar 4) are the pillars that form the basic requirement sub-index and are the keys for a factor-driven economy. Higher education and training (Pillar 5), Good market efficiency (Pillar 6), Labor market efficiency (Pillar 7), Financial market development (Pillar 8), Technological readiness (Pillar 9) and Market size (Pillar 10) form the Efficiency enhancer sub-index and are the keys for an efficiency-driven economy. Finally, Business Sophistication (Pillar 11) and Innovation (Pillar 12) constitute the Innovation and sophistication factors sub-index and are the keys to an innovation-driven economy.

Table 1. Pillar of GCI (Schwab, 2017)

Pillar ID	Sub-index	Pillar	Explanation
Pillar 1	Basic requirements	Institutions	The institutional environment of a country depends on the efficiency and the behavior of both public and private stakeholders. The legal and administrative framework within which individuals, firms, and governments interact determines the quality of the public institutions and has a strong bearing on the competitiveness and growth. Good private institutions are also important for the sound and sustainable development of an economy.
Pillar 2	Basic requirements	Infrastructure	Extensive and efficient infrastructure is critical for ensuring the effective functioning of the economy. Effective modes of transport, consistent electricity supplies, and a solid and extensive telecommunications network increases overall economic efficiency.
Pillar 3	Basic requirements	Macroeconomic environment	The stability of the macroeconomic environment is important for business and is significant for the overall competitiveness of a country. Although it is certainly true that macroeconomic stability alone cannot increase the productivity of a nation, it is also recognized that macroeconomic disarray harms the economy.
Pillar 4	Basic requirements	Heath and primary school	A healthy workforce is vital to a country's competitiveness and productivity. Workers who are ill cannot function to their potential and will be less productive. The quantity and quality of the basic education received by the population is fundamental in today's economy. Basic education increases the efficiency of each individual worker.
Pillar 5	Efficiency Enhancer	High education and training	Quality higher education and training is crucial for economies that want to move up the value chain beyond simple production processes and products. This pillar measures secondary and tertiary enrollment rates as well as the quality of education as evaluated by business leaders. The extent of staff training is also taken into consideration.
Pillar 6	Efficiency Enhancer	Goods market efficiency	Countries with efficient goods markets are well positioned to produce the right mix of products and services given their particular supply-and-demand conditions, as well as to ensure that these goods can be most effectively traded in the economy. Healthy market competition is important in driving market efficiency. Market efficiency also depends on demand conditions such as customer orientation and buyer sophistication.
Pillar 7	Efficiency Enhancer	Labor market efficiency	The efficiency and flexibility of the labor market are critical for ensuring that workers are allocated to their most effective use in the economy and provided with incentives to give their best effort in their jobs.
Pillar 8	Efficiency Enhancer	Financial market development	An efficient financial sector allocates the resources saved by a nation's population, as well as those entering the economy from abroad, to entrepreneurial or investment projects. Business investment is critical to productivity. The banking sector needs to be trustworthy and transparent, and financial markets need appropriate regulation to protect investors and other actors in the economy at large.
Pillar 9	Efficiency Enhancer	Technological Readiness	This pillar measures the agility with which an economy adopts existing technologies to enhance the productivity of its industries, with a specific emphasis on its capacity to fully leverage information and communication technologies (ICTs) in daily activities and production processes for increased efficiency and enabling innovation for competitiveness.
Pillar 10	Efficiency Enhancer	Market size	The size of the market affects the productivity since large markets allow firms to exploit the economies of scale. Both domestic and foreign markets are included in the measure of the market size to give credit to export-driven economies and geographic areas that are divided into many countries but have a single common market.
Pillar 11	Innovation and Sophistication Factors	Business sophistication	Business sophistication is concerned with two elements that are intricately linked: the quality of a country's overall business networks and the quality of individual firms' operations and strategies. These factors are important for countries at an advanced stage of development when, to a large extent, the more basic sources of productivity improvements have been exhausted.
Pillar 12	Innovation and Sophistication Factors	Innovation	Innovation is particularly important for economies as they approach the frontiers of knowledge, and the possibility of generating more value by merely integrating and adapting exogenous technologies tends to disappear.

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 global competitiveness index, while this improvement in the logistics performance is expected to increase the competitiveness of a country. However, this interdependence is not the same level of importance for each pillar of the GCI. When government budget restrictions are taken into account, it is possible to understand the importance of specifying which specific GCI pillar to concentrate on and to invest 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 policy makers in their investment decisions.

D'Aleo and Sergi (2017a) and Civelek, UCA and Cemberci (2015) used multiple linear regressions to show that logistics, as a mediator, plays 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 among the gcı 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) argued that there is a close relationship between global competitiveness and the logistics efficiency of a country. They initially made a screening related to the GCI pillars that may have an impact on the logistics competitiveness of a country, and then analyzed the validity of these relations using an artificial neural network (ANN) and cumulative belief degrees (CBD) approach. Among the many global competitiveness factors that influence logistics performance, the availability of fixed broadband Internet is the most important target area for improvement related to a sustainable logistics policy.

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 and LPI pillars. Additionally, they provide a fragmented perspective of the factors that affect supply chain performance and do not consider the mutual causal relationships among the GCI and LPI pillars.

There is also a debate in the literature as to whether logistics and economic growth have a two-way interaction (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, logisticforrs improvement, in its turn, is expected to enhance the economic growth because investments and infrastructure will increase the demands for goods and services. Similarly, an improvement in the logistics performance is expected to decrease the travel time, which causes another series of economic consequences, such as enabling producers to gain access to more distant markets. Additionally, such an improvement will stimulate local production and attract foreign direct investment, which is itself an important engine for economic growth (Lean et al., 2014). It would therefore be a worthwhile goal for a further study to analyze and ascertain to what extent this reverse relation is also true.

This study is aimed at filling this gap in the literature and showing the interrelations among the GCI and LPI pillars. For this purpose, a hybrid approach is proposed, where the LPI values are taken as dependent variables (output variables) and the WEF Competitiveness pillars are treated as independent variables (input variables) of a Bayesian Net model. In this way, the causal relations among the WEF pillars and the LPI values of the countries are analyzed. For the second step, the results of this model are taken as an input to the Partial Least Square Path Model (PLS), which is a structural equation model that maximizes the explained variation among the various variables. The basic reason for using the Bayesian Network prior the PLS is to reduce the excessive number of possibilities in terms of the causal relations between the variables. We claim that the overall LPI scores are influenced not only by the direct effects from the WEF pillar scores but also by the indirect effects from the causal interactions between the WEF pillar scores. In this way, policy makers will be able to efficiently use their limited resources by focusing on the most important competitiveness pillars to improve the logistics competitiveness of their countries. Therefore, while making decisions on allocating limited resources to accelerate a country's logistics performance, policy makers would like to highlight which GCI pillar(s) are more critical than others in contributing to the LPI overall score. It is therefore necessary to explore the causal relations between the GCI pillars and between the pillars and the LPI overall scores.

Section 2 explains the methodology based on three techniques, namely, the Bayesian Net, PLS and the Importance-Performance Map Analysis (IPMA). Section 3 provides the empirical analysis, which reveals the significant competitiveness pillar affecting the logistics performance. Section 4 discusses the results and finally, conclusions and suggestions are given 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, such as fishbone diagrams, why/why diagrams, influence diagrams, cognitive maps, etc. (see Tan and Platts, 2003 for the appraisal of these techniques.) Bayesian networks and PLS path modeling are also very popular causal analysis techniques (Wu, 2010). Bayesian Networks (BN) provide a graphical representation of the expert's knowledge, and do not require strict statistical assumptions, instead using a directed acyclic graph to help to decide the causal directions between the constructs (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 drawback of PLS is that it is sometimes difficult to establish the causal directions between constructs if there is a lack of background knowledge or previous theoretical support. Wu (2010) proposed using a Bayesian network prior to implementing PLS path modeling for causal analysis. 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 (0210) and Wu et al. (20212), 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, we use a BN instead of a TAN network.

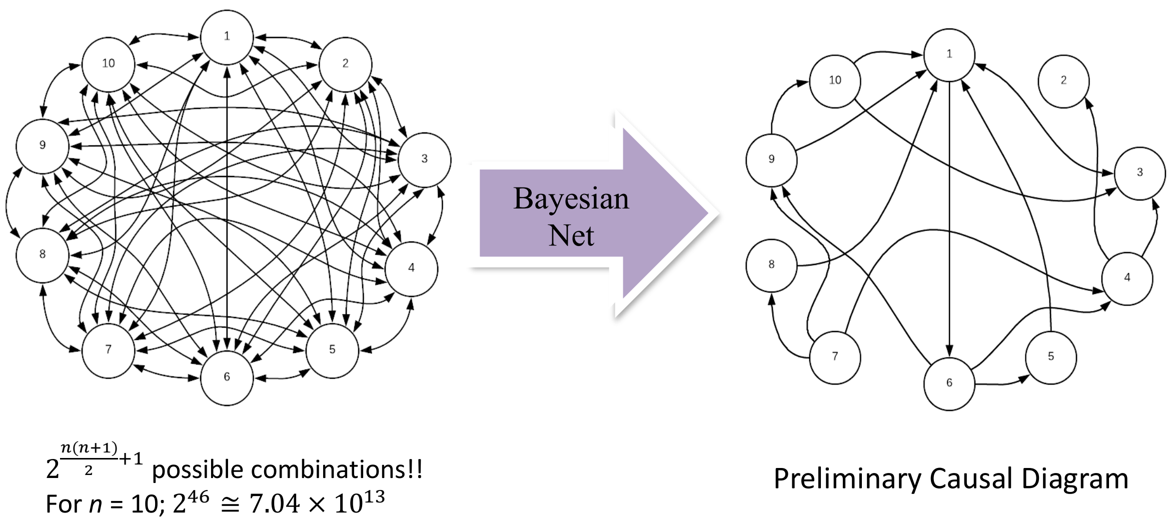

Fig. 1. Use of Bayesian Net in the Methodology

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.

In our application, the GCI pillars and LPI are set as the variables in the system. The relations among the GCI pillars are also considered to determine the indirect effects. For this, the possible relations among the GCI pillars and LPI indicators are initially constructed using a BN Model. Subsequently, the significant relations and importance of the effects are revealed using PLS and IPMA. The main stages of the methodology are explained in the following sections.

2.1. Bayesian Net (BN)

A causal map is a kind of knowledge structure representation that represents the configuration of a given system consisting of many different variables (Wu, 2010). In causal maps the variables are represented by concepts (nodes), whereas the relations are represented by directed arrows. The Bayesian net (BN), a special type of causal map, is a graphical representation of probabilistic relationships between multiple variables. The BN is especially useful in modeling uncertainty in a domain and has been applied in particular to problems that require a diagnosis based on a variety of types of input data in a system of variables (Ekici and Onsel Ekici, 2016).

As a type of probabilistic model, BNs are frequently used for understanding and simulating 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, which is easier and benefits from 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.

In the literature, BNs are compared to structural equation modeling (SEM), since they both can depict causal networks and influences and can analyze the degree of causality (Bruce et al. 2019). However, in fact the two methods differ from one another in that the SEM is a statistical tool to test hypotheses or to test whether an assumed causal relation in the graph is significant, whereas BNs are probabilistic models used to investigate the consequences of conditions or events on outcomes and to identify the causal relations within variables.

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)

Structural equation modeling (SEM) is a methodology for conducting both multivariate exploratory and confirmatory regression analyses (Hair et al., 2016). PLS and covariance-based SEM are two main approaches in SEM to model the relationships between latent variables (Wu, 2010). Covariance-based SEM, which uses software packages such as AMOS, LISREL, etc., is based on maximizing the explained covariation among the constructs. It is preferred when the sample size is large, the data are normally distributed, and the model is correctly specified with appropriate variables and theoretically proposed linkages (Wong, 2013). In many real-life data sets it is difficult to satisfy these assumptions.

PLS, on the other hand, is based on maximizing the explained variation among various constructs and requires minimum assumptions about the statistical distribution of the data sets. PLS work well with a small sample size (Wu et al. 2012), but prior theory development may not be specific. The most important aspect is the predictive accuracy (Wong, 2013). However, the major drawback of the PLS is that it is sometimes difficult to establish the causal directions between constructs due to lack of background knowledge or previous theoretical support. Similar to SEM models, BNs can also show the nature of relationships, but they do not need hypothesized interactions between several variables (Lauria and Duchessi, 2007). That is, why Wu (2010) proposed using the Bayesian network prior to implementing a PLS path modeling for causal analysis. Different from Wu (2010), we used a BN rather than Tree Augmented naive Bayes (TAN), since we want to analyze the bidirectional relations between competitiveness and logistics performance. Therefore, in this paper we have linked the BN with the PLS path modeling for causal analysis. The causal directions of a preliminary causal diagram constructed by BN have to be reversed before estimating the PLS path modeling (Jitmaneeroj, 2016). SmartPLS software is used to estimate the PLS path modeling and to test whether the hypothesized causal relationships generated by the BN data mining are statistically significant.

In this study, a sequential methodology is used to find the best model in PLS. As presented in Fig. 2, the preliminary causal diagram found in the BN is used as the initial diagram analyzed by the PLS modeling. The model fit of the whole model and the coefficient of determination (r^2) values of the variables are checked to approve the model. The Standardized Root Mean Square Residual (SRMR) should be less than 0.08, and the Normed Fit Index (NFI) should be greater than 0.9 for the model fit as the (r^2) of the variables is expected to be more than 0.75 in a good fitting model. If these requirements are not satisfied, the insignificant relations in the diagram are deleted and the PLS model is rerun. For instance, in Fig. 2 relations 7 to 9, 7 to 4, 6 to 9, and 6 to 4 are deleted from the initial diagram. The procedure is applied until a fitting model is found. If no fitting model is found at all, it is concluded that there is no significant set of relations in the given system of variables.

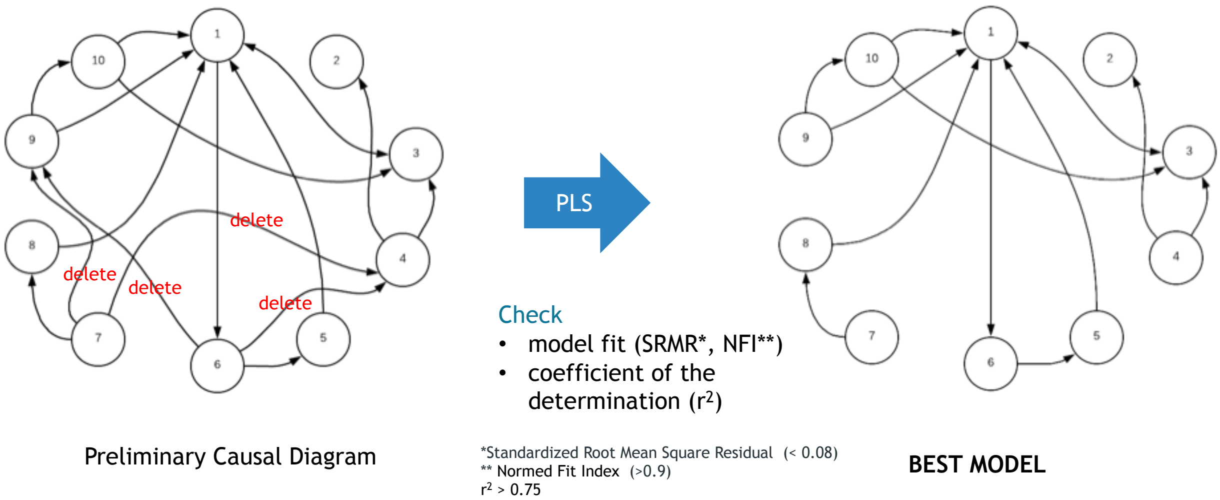

Fig. 2. Use of PLS in the Methodology

2.3. Importance-Performance Map Analysis (IPMA)

The IPMA extends the results of the PLS path modeling by taking the performance of each category into account. To construct this model, the SmartPLS software rescales the individual category scores to obtain index values by subtracting the minimum possible value from a data point and dividing these data point by the difference between the maximum and minimum data points (Jitmaneeroj, 2016). The basic aim is to improve the categories that have a relatively high importance but a relatively low performance. The IPMA treats the overall score as the target construct and contrasts the total effect, i.e., the importance on the x-axis and the average values of the rescaled data source scores, i.e., performance, on the y-axis. The data source with the lowest performance-importance ratio will justify the first priority for policy reforms.

3. Empirical Analysis

The empirical analysis of the methodology to determine the most important competitiveness pillars that have an impact on the LPI values are given in the following sub-sections. 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)

For structure learning through the BN, the 'GeNIe' software (https://www.bayesfusion.com/) and its "Greedy Thick Thinning" structure learning algorithm are used. This algorithm begins with an empty graph and repeatedly adds the arc that maximally increases the marginal likelihood until no arc addition will result in a positive increase. Then it removes the arcs until no arc deletion will result in a positive increase in the marginal likelihood. Although the size of the conditional probability tables of a node grows exponentially according to the number of the node's parents, the maximum number of parents that a node can have is set to 12 (The maximum number for our net since we have at most 13 variables).

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.

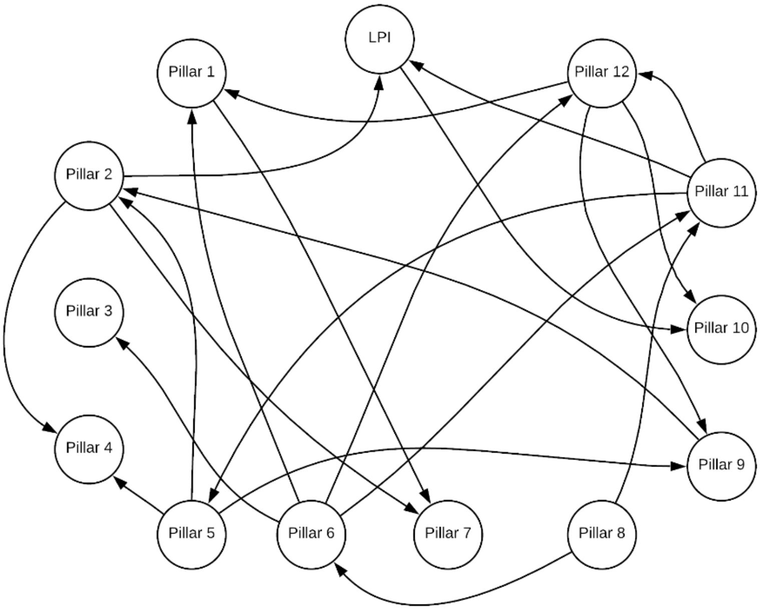

Fig. 3. BN structure

3.2. *Partial Least Square Path Model (PLS)*

Based on the network structure derived in the previous step (Fig. 3), a PLS model was developed on the SmartPLS Software. A consistent PLS algorithm was used to test the significance of the network as a whole. Without any modification, the model structured in the previous step found with a good fit (SRMR = 0.044 and NFI = 0.920). As seen in Fig. 4., the coefficient of the determination (r^2) of the logistics performance variable is 0.750. The factor loadings of the logistics performance indicators are greater than 0.89. Therefore, we used the results of this model to interpret the relations for the logistics performance.

Notice that in Fig. 4 the r^2 values for the latent variables that are affected from another latent variable(s) are denoted by blue circle. 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.

To test the significance of the hypothesized causal relationships, a bootstrapping procedure was run. The resulting path coefficients, indirect effects and total effects with t statistics are given in Table 2. The path coefficients can also be seen in Fig. 4 on the arcs. 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, which 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).

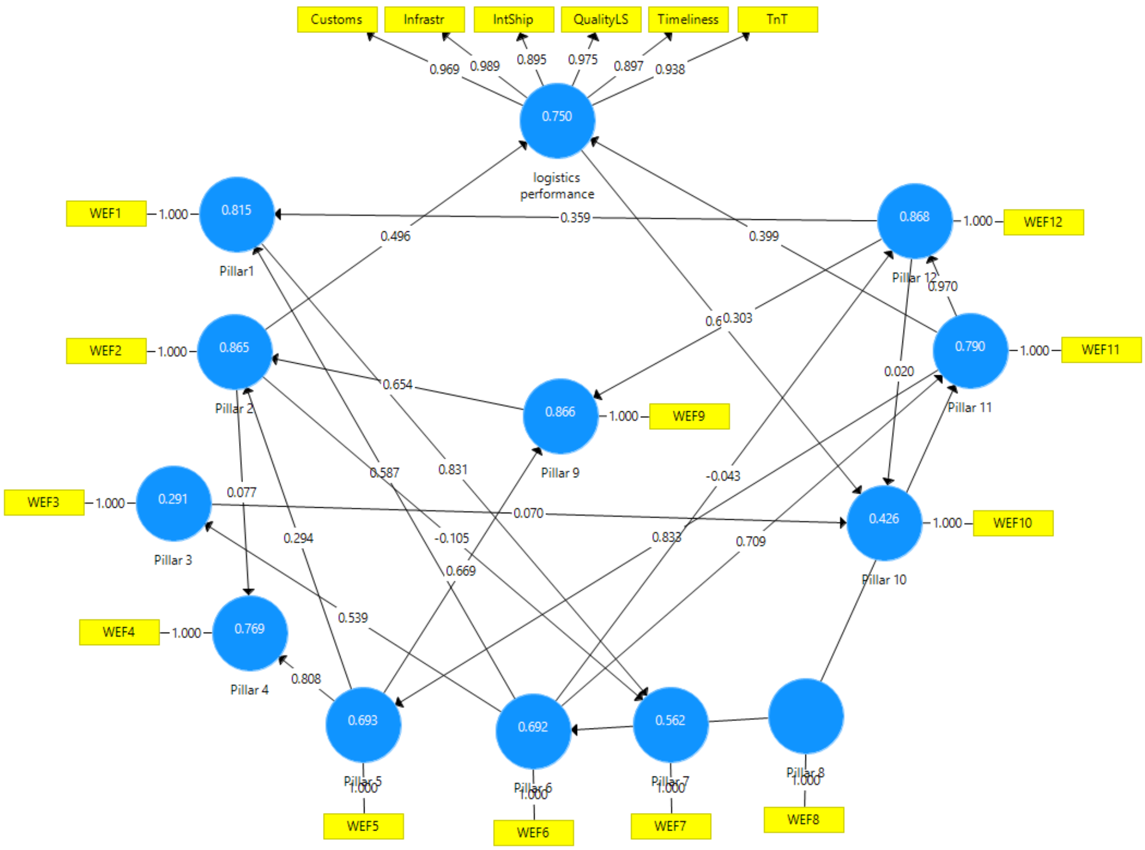

Fig. 4. PLS model developed in SmartPLS

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

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.

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 Importance-Performance Map analysis is conducted to highlight the pillars that have a high importance but a low performance. In this way, policy makers will have a useful guideline to decide which pillar to focus on immediately in order to obtain an immediate and significant improvements in the logistics performance of the country.

3.3. IPMA Importance-Performance Map Analysis (IPMA)

In order determine the importance of the pillars that have a significant effect on the logistics performance, 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. 3.

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 performance importance values of the causal relations are ranked in ascending order to determine the importance of the pillars' effect on the logistics performance. According to the results, governments should focus on Pillar 11 (Business sophistication), Pillar 8 (Financial market development), Pillar 2 (Infrastructure), Pillar 6 (Goods market efficiency), Pillar 5 (High education and training), Pillar 9 (Technological Readiness), and Pillar 12 (Innovation), respectively, in order to achieve an improvement in the logistics performance of their country.

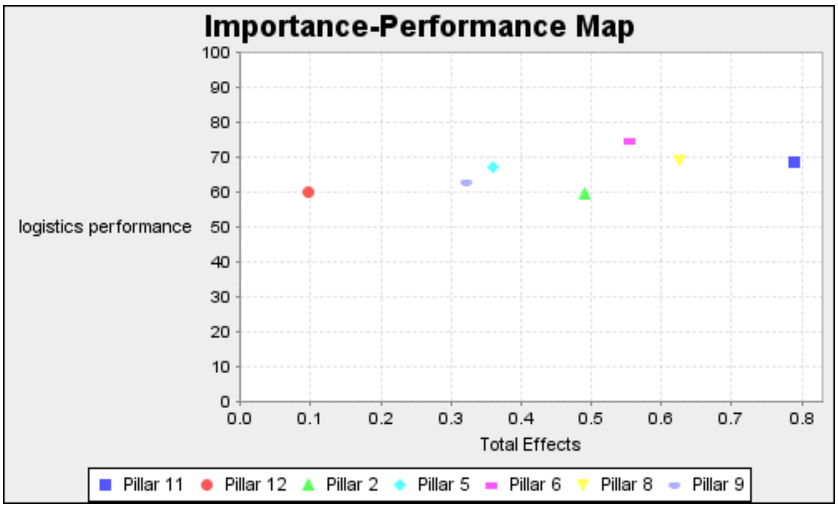

Fig. 3. Results of the IPMA

4. Discussions

In this paper we have proposed a hybrid method that includes Bayesian Networks and PLS in order to investigate the bidirectional relations between the competitiveness and logistics performance of a country. In the first stage of the method, 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 or not they are significant from a statistical perspective. 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.

The results of the integrated model are discussed in this section. According to the results, the most important pillar that affects the logistics performance of a country is Business Sophistication. Business sophistication is a key factor for an innovation-driven economy and is concerned with the quality of a country's overall business networks, as well as the quality of operations and the strategy of individual firms. This pillar investigates the quantity and quality of the local suppliers, the geographic concentrations of firm, i.e., the state of cluster development, suppliers, producers of related products and services, and the specialized institutions in a particular field, the competitive advantage of the country's companies in international markets, the extent of the presence of the country's companies in the value chain, their ability to control the international distribution of their products, and the level of sophistication of the production processes in the country. Business sophistication is very important for economies in stage 3 of development.

In fact, as was also underlined by Stevens and Johnson (2016), the supply chain management is undergoing a transition to collaborative supply chain clusters. When compared to past experience, in the current world the enablers of change and performance improvement are different and, as a result, the relevance of narrow, linear-based supply chain models has been challenged as firms have increasingly looked towards networked and collaborative supply chain strategies to deliver superior performance. Supply chain performance is directly influenced by the alignment, linkage and coordination of people, processes, information, knowledge, and strategies across the supply chain between all points of contact and influence to facilitate the efficient and effective flows of material, money, information, and knowledge in response to customer needs (Stevens and Johnson, 2016).

As was also underlined by Srinivasan et al. (2011), there is a positive relationship between partnership quality and supply chain performance, which is strengthened in the presence of high demand and supply-side risks but weakened in the presence of high environmental uncertainty. The empirical evidence is based on the survey data of 127 US firms.

Financial market development is the second most important pillar that affects the logistics performance of a country. This pillar evaluates the availability and the extent to which the financial sector provides the affordability of financial services, financing through a local equity market, ease of access to loans, venture capital availability, i.e., how easy it is for start-up entrepreneurs with innovative but risky projects to obtain equity funding, soundness of banks, the extent to which the regulators ensure the stability of the financial market, and the degree of legal protection of borrowers' and lenders' rights. In fact, the link between the logistics performance and financial performance has been analyzed in the literature (Schramm-Klein and Morschett, 2006; Shang and Marlow, 2005) and a positive connection between these two performance aspects is generally assumed, especially for large enterprises.

The third GCI pillar that affects the logistics performance of a country is infrastructure. According to the Global Competitiveness Report, an extensive and efficient infrastructure is critical to achieve the effective functioning of the economy. Effective modes of transport, including high-quality roads, railroads, ports, and air transport, enable entrepreneurs to send their goods and services to market in a secure and timely manner and facilitate the movement of workers to the most suitable jobs (Schwab, 2017). This is in parallel of this finding. In fact, the improvements made in terminals and in regional and long-distance connections, the enlargement and modernization of ports and airports, wider access roads to logistics nodes as well as the logistics platforms and distribution centers that are located with consideration to the supply, demand and optimum places for intermodality will facilitate the goods trade enormously, leading to a significant reduction in costs and increasing the logistics performance of the country.

According to LPI report 2016 (Arvis et al., 2016), infrastructure seems to be improving, although 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.

On the other hand, one of the most important result of this study is that, Logistics Performance, in its turn, influences the Market Size pillar of competitiveness significantly. This pillar investigates the domestic and foreign market size, the Gross domestic product valued at the purchasing power parity and exports as a percentage of the GDP. GDP is used to indicate the health of a country's economy. The evolution of the global economy has been motivated by its contribution to economic growth over the past decades. GDP is a quantitative measure that gives information about the general situation of the economy. The GCI aims to measure the factors that determine productivity, because it has been found to be the main determinant of long term growth. Comparing the results of the GCI in 2007 with the economic growth over the following 10 years suggests that a strong GCI performance in fact predicts the future growth. According to the GCI 2017-2018 report (Schwab, 2017) there are encouraging signs of recovery since the 2008 financial crises, with GDP growth accelerating to 3.5 percent in 2017.

On the other hand, large markets will allow firms to benefit from economies of scale and in the era of globalization international markets will become a substitute for domestic markets. Exports can be thought as a substitute for the domestic demand in determining the size of the market for the firms in a country (Schwab, 2017). Therefore, this finding underlines the fact that countries that are export-driven and that have high economic growth as well as geographic areas that have a single common market, such as the European Union, will also have a high logistics performance. In fact, when we investigate the logistics performance of EU countries, such as Germany, we can see that this claim is true.

5. Conclusion and Further Suggestions

This study aimed to model the two-way cause-effect relationships between the GCI and LPI values of a country and, thus, developed a road map for governments in their development of strategies in order to undertake constructive actions to improve the logistics performance of their countries. For this purpose, an integrated model based on Bayes Nets, PLS and IPMA techniques was used. The analysis showed that policy makers should primarily focus on improving the Business Sophistication, Financial Market Development and Infrastructure in order to improve the logistics performance of their countries.

This study has two main contributions. Firstly, it presents a new methodology for analyzing cause-effect relations in a system by integrating Bayes Nets, PLS and IPMA. Second, the methodology is applied to analyze competitiveness indicators and logistics performance. As mentioned above, the methodology enabled to prioritize the competitiveness indicators for immediate improvement in logistics. In this regard, it may be possible to use the methodology to analyse cause-effect relations in different complex systems.

As a further suggestion we are planning to test the hypothesis that the competitiveness pillars a country should focus on in order to improve its logistics performance will depend on its logistics performance stage. For this reason, in a further study, we will cluster the countries according to their LPI values; then, for each cluster group, we will analyze the causal relations among the WEF pillars and the LPI values of the countries.

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