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Exploring the interaction between competitiveness of a country and innovation using Bayesian networks

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ABSTRACT

Innovation cannot be related only to some factors inherent in the environment of a country, nor is it a single entity to be managed without any linkages to the rest of the actors comprising the competitiveness of a country. World Economic Forum (WEF)'s competitiveness model consisting of 12 pillars and 19 sub-pillars is an attempt along these lines. By analysing the interaction between the Innovation pillar and the remaining 11 pillars and their sub-pillars comprising the competitiveness indicators, this paper aims to provide strategic guidelines to policy-makers who search for strategies to improve their country's innovativeness level. For this purpose, WEF's Global Competitiveness Index data for the period (2009-2012) is employed. The innovation performance of 148 countries is analysed using an integrated cluster analysis and a Bayesian Network (BN) framework. The use of BNs enables us to discover the probabilistic dependency structure of competitiveness indicators and its innovation performance, which may be analysed in more detail through evidence observation and sensitivity analyses conducted in the network. Thus, with this research, presenting the multidimensional nature between competitiveness indicators and Innovation, a decision support tool for policy-makers is presented, which can be used to form strategy guidelines for enhancing a country's Innovation level.

KEYWORDS

Innovation; competitiveness; cluster analysis; Bayesian Networks; sensitivity analysis

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1. Introduction

The issues of growth and creation of wealth for countries have been a major challenge and a demanding research area for over two centuries. For growth and creation of wealth in a sustainable manner a country needs sustainable competitiveness. The components of competitiveness are varied and complex such as the rule of law, macroeconomic stability, and transparent and well-functioning institutions. Among these components, innovation is an important one. Innovation can be considered as the successful development and application of new knowledge, with the purpose of launching newness into the economic

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area and transforming knowledge into profit. Schumpeter (1934) differentiated between five different types of innovation: new products, new methods of production, new sources of supply, the exploitation of new markets, and new ways to organize business. Drucker (1985) defined innovation as the process of equipping in new, improved capabilities or increased utility. Fagerberg (2004) claims that innovative countries have higher productivity and income than the less-innovative ones. Innovation, moreover, plays a significant role in creating differences in performance and competitiveness not only among regions and countries but also among firms (Günday et al. 2011).

Innovation is the key to higher productivity and greater prosperity of nations (UK Innovation Report 2003). High quality science and research and development (R&D) alone, however, are not sufficient for the realization of important economic and social objectives. New ideas and inventions, the initial steps leading to innovation, are obviously important but may possess little or no economic and social impact unless commercialized (Aarikka-Stenroos and Sandberg 2012). Griffiths et al. (2009) examine the governmental, economic, and technological factors that have an impact on sustainable economic growth. For this purpose, they analysed 34 nations and the results show that while the environment and influence of government have positive impact on innovation ecology, sufficient resources for R&D, human capital and early seed funding are the key leading instruments for innovation.

Another example for the recognition of the importance of innovation on the wealth of nations is the emphasis on innovation in Europe 2020 (European Commission 2010). In Europe 2020, besides emphasizing a sustainable and inclusive future, the importance of smart growth is underlined, which is concerned about improving the EU performance based on the factors of education, research/innovation and digital society. In the report it is emphasized that strengthening every link in the innovation chain and refocusing on the research/innovation policy is of primary importance to improve EU performance. Additionally, in Europe 2020, one of the seven flagship initiatives is 'Innovation Union', which aims to create an innovation friendly environment among the EU Member States making it easier for great ideas to be turned into products and services identified as new engines to boost growth and jobs.

Fagerberg and Verspagen (2002) show that the importance of innovation for economic growth has increased in recent years. In fact, they measure innovation by the patent growth and show that its importance on economic growth is especially increased in the most recent period. The empirical analysis of Fagerberg, Srholec, and Knell (2007) based on a sample of 90 countries during 1980–2002 underlines the relevance of technology, capacity, and demand and to a lesser extent price competitiveness as the four factors behind the differences in growth and development levels of the countries. Fagerberg and Srholec (2008), in line with the new growth theory, emphasize the role of technology as the driving force of growth and development. In fact, this view is contrary to the former growth theories, which assume that differences in development levels across countries can be explained by only one factor, namely, differences in the amount of accumulated capital per worker. Therefore, for a firm or country to catch up, the technological capability should be constantly improved. Their empirical analysis shows that there is a significant, strong and robust statistical relationship between the level and change of Gross Domestic Product (GDP) per capita and the level and change of the innovation system.

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They demonstrate that the countries that succeed in developing and sustaining strong innovation capabilities and efficient governance will do well economically.

Acemoglu, Aghion, and Zilibotti (2002) underline that when a country is closer to the world technology frontier, the selection of high-skill managers will be more important for innovation activities. This is called innovation-based growth. However, relatively backward economies can grow rapidly by investing in and adopting already existing technologies and this is investment-based growth. Therefore, economies that adopt investment-based strategy may initially grow faster than others but then get struck in a non-convergence trap and are taken over by the initial laggards. Closer to the technology frontier, there is less room for copying and adopting well-established technologies.

The cross-country empirical analysis of Castellacci (2008a) shows that there exist three technology clubs with different level of technological development, dynamics of technological change and economic growth trajectory. The marginalized club has low levels of both innovative ability and absorptive capacity, where absorptive capacity is measured by looking at two interrelated aspects: first, the level of human capital (literacy rate, secondary schooling, higher education); secondly, technological infrastructures, referring to fixed and mobile telephony, electricity, and Information and Communication Technologies (ICT) infrastructures (computers, Internet). The followers club lags behind technological frontier in terms of innovative capabilities but its absorptive capacity is much greater than the marginalized group. The advanced club, on the other hand, has a strong human capital base and a well-developed web of technological and economic infrastructure and also great capability to produce new advanced technologies. The taxonomic model suggested by Castellacci (2008b) underlines that in order to sustain competitiveness, countries should have and maintain advanced knowledge providers, an efficient set of supporting infrastructure and a mass-producing manufacturing base.

Castellacci and Natera (2013) presents a model where the knowledge level of a country increases as a function of innovation intensity, technological infrastructures, and human capital. The research results suggest that the developing countries should not only invest and rapidly adopt ICT-related infrastructure but also build and upgrade more traditional infrastructures. The dimension of technology, where developing countries did not show considerable progress, is the intensity of innovative activities. They also show that, as developing and middle-income countries get closer to the technology frontier, tertiary education becomes the most important element of human capital, while primary and secondary education become less important in explaining the differences in economic performance of those countries. In fact, this finding shows similarity to that of Azariadis and Drazen's (1990) analysis, which claims that high-income country variation in adult literacy has no explanatory power for variation in growth rates. Social and private rates of return to education are generally lower in developed countries than in developing ones. Their analysis also shows that relatively highly qualified labour force seems to be a necessary but not a sufficient condition for rapid growth.

Castellacci and Natera (2013) show that the dynamics of national systems of innovation is based, on one hand, on the coevolution of innovative input, scientific output and technological output, which represent the innovative capability variables, and on the other hand, on infrastructure, international trade and human capital, which represent the absorptive capacity factors. However, the human capital, generally emphasized by technology-gap and imitation-based growth models, has an indirect effect on the dynamics of

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national innovation systems. In fact, the specific role of this variable depends on the variable used to measure it. When the secondary education is used, human capital has a two-way link to innovation dynamics whereas, when the tertiary education indicator is used, human capital does not have a direct effect on the dynamics of innovation activities. They also found that, in advanced economies international trade and human capital are the central factors enabling knowledge imitation, whereas R&D is the key variable driving the dynamics of innovative capability. For the middle-income countries infrastructure and international trade are the most important absorptive capacity factors. They are related to each other and coevolve with some of the innovative capability variables. This is especially true for the OECD group, while in Eurasian (former Soviet) economies, human capital has a more central role. Less-developed economies, on the other hand, do not have an intense network of causal relationships and coevolution patterns are not significant.

The World Economic Forum (WEF) has been conducting and publishing a major competitiveness study on a global scale under the title 'The Global Competitiveness Report' since 1979. The definition of competitiveness underlying this competitiveness study is given as 'The set of institutions, policies, and factors that determine the level of productivity of a country. The level of productivity, in turn, sets the sustainable level of prosperity that can be earned by an economy.' (WEF 2009). The measurement model used by the Global Competitiveness Report has changed over time and in 2004, the Global Competitiveness Index (GCI) is introduced, which combines the indexes of Growth Competitiveness and Business Competitiveness published by WEF (Blanke and Lopez-Claros 2004). After a period of testing, GCI replaced these two indices in 2009. WEF publishes GCI for around 148 countries on the basis of over 100 criteria in its Global Competitiveness Report each year. Based on GCI, WEF measures the competitiveness of countries, providing a source of data for all sides concerned, including public and private sectors, which they can employ to develop policies pertaining to factors leading to higher levels of competitiveness (WEF 2012). The Institute for Management Development (IMD) conducts a similar study but it covers less number of countries and hence, is not considered here further (2012).

Furman, Porter, and Stern (2002) underline that the national innovative capacity depends on the strength of a nation's common infrastructure, the environment for innovation and the linkages between these two. They provide a regression-based analysis and find that R&D manpower and spending, the extent of intellectual property protection, openness to international trade, the share of research performed by the collaboration of universities and the private sector, the degree of technological specialization and the country's knowledge stock are the basic reasons behind the variation across countries. Though this list may seem as exhausting, in fact it only refers to a small subset of the factors used to determine the GCI of a country.

Porter and Stern (2001) state that the external environment in which a company operates is at least as important as the internal factors, which determine the capabilities within the companies for creating and commercializing innovation. Therefore, the nation in which the company is heavily operating influences the company's innovation capability. Their research is based on the innovation level of the OECD as well as that of emerging countries in order to explain the innovative output differences based on national circumstances. The authors claim that the national innovative capacity, the overall human and financial resources, the industrial cluster-specific environment and the quality of linkages

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of a country are the main drivers of innovation output of the companies operating within this country. In fact, once again, all these factors constitute a small part of the total list of indicators used in GCI.

Filippetti and Peyrache (2011) underline that innovation is multidimensional in nature. They group the variables explaining the differences in the rate of technological change across countries into three ingredients, namely; differences in capital investment, differences in the level of education and differences in the expenditures on R&D and related innovation activities.

As demonstrated by the work cited above, there exists indeed a wide extent of literature with the purpose of identification of the main characteristics of a country for moving its way to the higher ranks of innovation. However, as is also underlined by Castellacci and Natera (2013), the existing literature provides only limited insight into the drivers of innovation in a country and the mechanisms that may explain their evolution through time. The literature on innovation and growth has typically focused on the cross-country comparative analysis. Although there exists substantial amount of research devoted to the analysis of the impact of innovation on economic growth, the investigation of the drivers of national innovation activities has so far received limited attention. On that instance, the existing research is either based on a specific country's analyses or missing the broad perspective for the environment within which innovation evolves by considering only a small subset of the innovation enhancing factors. For that purpose, a broader perspective is needed to explore the main drivers for a country's success in innovation.

Our main hypothesis in this paper is that innovation cannot be related only to some factors inherent in the environment of a country, nor is it a single entity to be managed without any linkages to the rest of the actors comprising the competitiveness of a country. Hence, a comprehensive study on innovation should cover the interaction between competitiveness indicators and innovation.

With this claim, we apply the use of the Bayesian Networks (BNs) for the analysis of the simultaneous interaction of the competitiveness indicators of a country and its innovation performance. The choice of the BNs as the tool of the analysis is due to their capability to provide the probabilistic dependencies of all the variables in the network. This graphical probabilistic network not only enables us to see the dependency structure between competitiveness indicators and innovation; it also allows us to perform what if analysis for that purpose to see the effect of a change in any of the variables to the others in the network. The inference we aim to provide with this research is in the form of marginal and posterior probabilities of variables in the BN, the variables' dependency structure in the network and the change of probabilities based on observed evidences. Here, the variables correspond to the competitiveness indicators of countries and their innovation level and evidence observation corresponds to scenario analysis performed in order to provide a guide to policy enhancers.

To the best of our knowledge, there is no research considering all the GCI-related factors when analysing the interaction between competitiveness and innovation. The underlying dynamics of this interaction depends to a large extent on the characteristics of the cluster a country belongs to, based on its level of development, and thus, may differ from one cluster to another. In that instance, with this research we aim to contribute the literature for filling this gap, providing a staged analysis to show how a country can

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make its way to higher levels of innovation. The decision support tool, provided with this research, can be used as a decision support tool for policy-makers to form strategy guidelines for enhancing a country's Innovation level. On that instance, the research questions, explored in this paper are as follows: 'What are the competitiveness indicators that affect Innovation and how do they differ between different country groups?' 'To which indicators should a country focus in order to scale up to higher levels of Innovation and how an improvement in those factors are going to affect the level of Innovation of the country?' 'How does a change in Innovation level depending on the cluster the country belongs affect the other competitiveness indicators?'

The outline of the remainder of this paper is as follows: In Section 2, the WEF competitiveness model is presented. The proposed methodology to be employed here is explained in Section 3. Section 4, displays the country groupings obtained through clustering, which is followed by the development of the BN in Section 5. In Section 6, results of the sensitivity and the scenario analyses are summarized; and its indicative analysis for improving the innovation level of countries in different clusters are provided Interpretation of results are given in Section 7, and in Section 8, we summarize and conclude.

2. WEF competitiveness model and the GCI

As explained above, GCI is a comprehensive tool, bringing together in a framework a large number of factors to assess the competitiveness of countries. In the rest of this paper, competitiveness and competitiveness indicators are used synonymously. Accordingly, GCI is employed in this paper for analysing the interaction between the levels of competitiveness indicators and the corresponding innovation level of countries.

GCI measures the microeconomic and macroeconomic foundations of national competitiveness defined as a weighted average of three sub-indices. These sub-indices are designated as Basic Requirements, Efficiency Enhancers, and Innovation and Sophistication Factors. Each sub-index consists of a number of so-called competitiveness pillars, which add up to 12 pillars in total. The sub-indices and their corresponding pillars are introduced in Figure 1. According to WEF, the dominant sub-index of a country becomes the key for the classification of its national economy. This association among the sub-indices and classes of national economies is displayed in Figure 1.

When composing GCI, the weights of the sub-indices are determined according to the stage of development of countries (Sala-i-Martin et al. 2008). There are three stages of development, separated by two transition stages in between, resulting in five clusters of countries. These stages of development are based on GDP per capita values (Table 1) for the majority of countries, but for economies with a high dependency on mineral resources such as oil, the GDP per capita is not indicated as the sole criterion.

3. The proposed methodology

The fiercely competitive global environment prevailing worldwide forces the policy-makers search for new means and approaches to improve the innovation level of their country and assess its impact on the competitiveness. To that end, in this paper, a new methodology is proposed, which aims to create an interactive and visual decision support system as a guide for policy-makers and all sides concerned.

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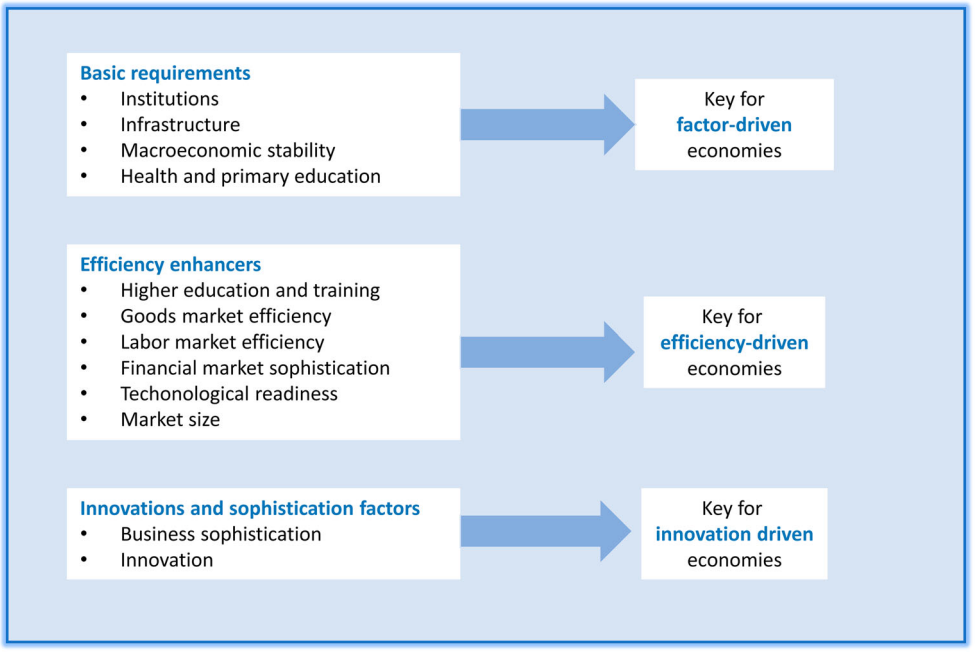


Figure 1. The WEF competitiveness model (WEF 2012).

The proposed methodology uses different pillars and sub-pillars of GCI to explore the interaction between competitiveness indicators of a country and its innovation level. In that instance, Innovation appears as one of the twelve main pillars of GCI as published in the Global Competitiveness Reports of WEF (WEF 2012).

Initially, a cluster analysis is conducted in order to group 148 countries according to their similarities and dissimilarities based on the pillars and sub-pillars employing a hierarchical agglomerative technique (Hair et al. 2010). Subsequently, a BN is developed through structural learning using the tool WinMine (Heckerman et al. 2000). In this research, the BNs will be used to discover the dependency structure between the pillars and sub-pillars of GCI and to evaluate their effect on innovation performance of countries. Finally, to determine the indicators that have the highest impact on the innovation level in each cluster and to analyse how increasing the innovation level affects the competitiveness level of countries, several sensitivity analyses are conducted, followed by the analysis of plausible strategies to be adopted in each cluster.

As given in Table 2, the 12th pillar of the GCI model refers to the innovation level of countries. A close examination of the sub-pillars of Innovation reveals that these are

Table 1. The stages of development as employed by WEF (WEF 2012).

	Stages of development				
	Factor driven stage 1	Transition from stage 1–2	Efficiency driven stage 2	Transition from stage 2–3	Innovation driven stage 3
GDP per capita thresholds (USD)	<2000	2000–2999	3000–8999	9000–17,000	>17,000

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indeed necessary means and policies for the development of an environment conducive to innovation. These are listed as Capacity for Innovation; Quality of Scientific Research Institutions; Company Spending on R&D; University-Industry Research Collaboration; Government Procurement of Advanced Technology Products; Availability of Scientists and Engineers; Utility Patents; and Intellectual Property Protection. Although it is questionable whether patents are the cause or result of innovation, all the sub-pillars indeed have an impact on the level of innovation in a country.

The indicators under Business Sophistication can be listed as Local Supplier Quantity, Local Supplier Quality, State of Cluster Development, Nature of Competitive Advantage, Value Chain Breadth, Control of International Distribution, Production Process Sophistication, Extent of Marketing, and Willingness to Delegate Authority. We observe that all these indicators more or less contribute to the various phases of innovation process and its success in the market. Willingness to Delegate Authority, for example, has been cited as one of the important innovation drivers for manufacturing firms (Ulusoy et al. 2015).

4. Determination of the country groupings through cluster analysis

As mentioned before, WEF obtains its five country groupings based on GDP. Since in this research a diversified innovation level for each country grouping is aimed at, the groupings of the 148 countries considered is determined through a cluster analysis employing the set of pillars and sub-pillars of the Global Competitiveness Reports (WEF 2009, 2010, 2011, 2012). Although the pillars remain the same, there appear slight differences in the sub-pillars of the GCI model throughout the years. The set of pillars and sub-pillars used are listed in Table 2, where the first digit corresponds to the pillar number and the second digit to sub-pillar designation as referred to in the Global Competitiveness Reports.[1]

Table 2. The set of pillars and sub-pillars used in the study.

1A Public institutions
1B Private institutions
2A Transport infrastructure
2B Electricity and telephony infrastructure
3 Macroeconomic environment[a]
4A Health
4B Primary education
5A Quantity of education
5B Quality of education
5C On-the-job training
6A Competition
6B Quality of demand conditions
7A Labour market flexibility
7B Efficient use of talent
8A Financial market efficiency
8B Trustworthiness and confidence
9 Technological readiness
10A Domestic market size
10B Foreign market size
11 Business sophistication
12 Innovation

Note: [a]The third pillar macroeconomic environment does not have any sub-pillars.

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In order to justify our choice of constructing the clusters anew, we first obtain a learned BN using the available WEF grouping. However, that analysis reveals that the WEF grouping of countries does not form an indicator for the Innovation variable; hence, it is not possible to use this grouping for our purpose here.

The list of countries analysed by WEF differs slightly in the last four years. The total number of different countries present in this study is 148, which corresponds to 558 observations in our dataset.

Also the process of clustering differs from the one of the WEF model. Unlike the WEF model, no weights are assigned to pillars and their sub-pillars and each pillar or sub-pillar contributes to the overall result equally. As a result of the hierarchical clustering process conducted using the statistical package SPSS (2013), the best clustering result is obtained using Ward's minimum variance, taking Euclidian distance as the distance measure, Silhoutte Coefficient is 0.76 and maximum among the other alternative distance measures and cluster methods-with the number of clusters equal to 5. The clusters obtained along with the names they will be referred to, are listed in Table 3.

In this research, we do not intend to distinguish among countries within the same group with respect to their competitiveness level but would like to be able to reach some conclusions concerning the differences in competitiveness levels between clusters. According to cluster analysis, the Laggers cluster is composed of countries at the lowest level of competitiveness while those in the Leaders cluster are composed of highly competitive countries. The Developing Ones cluster includes the countries, which still have a low competitiveness level but which can be accepted to be in a transition stage between the Laggers and the Runners Up. Finally, the countries assigned to the Runners Up cluster are average performing countries, and those in the Followers cluster are in a transition stage between the Runners Up and the Leaders. Note that the Leaders include, among others, a number of EU countries, which are designated as the *innovation leaders* by Innovation Union Scoreboard (2011). For example, Switzerland, Denmark, Finland, Germany, and Sweden, which are above the EU27 average in terms of innovation performance, are among the Leaders in terms of competitiveness. Similarly, Austria, Belgium, France, Luxemburg, the Netherlands, Slovenia, and the UK, which have an innovation performance level close to that of EU27 average, are also among the Leaders. They were referred to as *innovation followers* in the Innovation Union Scoreboard study. The Czech Republic, Malta, Poland, Portugal, Slovak Republic, and Spain, which have an innovation performance below that of the EU27 average and are accepted as *moderate innovators* according to the Innovation Union Scoreboard, are in the Followers cluster. Greece, Hungary, and Italy, which are *moderate innovators* as well, are included in the Runners Up cluster here.

Using ANOVA we analyse whether significant differences exist concerning WEF competitiveness indicators among the clusters of countries. The results revealed that the means of the clusters of all the pillars and sub-pillars are not equal to each other. However, that does not guarantee that each pillar has different level in the clusters, therefore the Scheffe test (Scheffé 1953) is conducted as a post-hoc test in order to make a pairwise comparison of cluster means for all the pillars and sub-pillars considered. As a result, it was possible to indicate similarity and difference among the clusters with respect to different indicators.

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Table 3. Clusters of countries.

Cluster 1 Laggers	Cluster 2 Developing Ones	Cluster 3 Runners Up	Cluster 4 Followers	Cluster 5 Leaders
Angola	Albania	Algeria	Barbados	Australia
Bangladesh	Armenia	Argentina	Brunei Darussalam	Austria
Benin	Belize	Azerbaijan	Chile	Bahrain
Botswana	Bosnia and Herzegovina	Bolivia	Costa Rica	Belgium
Burkina Faso	Cambodia	Brazil	Cyprus	Canada
Burundi	Cape Verde	Bulgaria	Czech Republic	Denmark
Cameroon	Dominican Republic	China	Estonia	Finland
Chad	El Salvador	Colombia	Iceland	France
Côted'Ivoire	Georgia	Croatia	Jordan	Germany
Ethiopia	Guatemala	Ecuador	Kuwait	Hong Kong SAR
Gabon	Guyana	Egypt	Latvia	Ireland
Gambia, The	Honduras	Greece	Lithuania	Israel
Ghana	Jamaica	Hungary	Malta	Japan
Guinea	Kenya	India	Mauritius	Korea, Rep.
Haiti	Kyrgyz Republic	Indonesia	Montenegro	Luxembourg
Lesotho	Lebanon	Iran, Islamic Rep.	Panama	Malaysia
Liberia	Macedonia, FYR	Italy	Poland	Netherlands
Madagascar	Moldova	Kazakhstan	Portugal	New Zealand
Malawi	Mongolia	Libya	Puerto Rico	Norway
Mali	Morocco	Mexico	Seychelles	Oman
Mauritania	Nicaragua	Peru	Slovak Republic	Qatar
Mozambique	Paraguay	Philippines	Slovenia	Saudi Arabia
Namibia	Serbia	Romania	Spain	Singapore
Nepal	Sri Lanka	Russian Federation	Tunisia	Sweden
Nigeria	Suriname	South Africa	Uruguay	Switzerland
Pakistan	Tajikistan	Syria		Taiwan, China
Rwanda	Trinidad and Tobago	Thailand		United Arab Emirates
Senegal		Turkey		United Kingdom
Sierra Leone		Ukraine		United States
Swaziland		Venezuela		
Tanzania		Vietnam		
Timor-Leste				
Uganda				
Yemen				
Zambia				
Zimbabwe				

The results of the Scheffe tests conducted are presented in Table 4. For each pillar and sub-pillar different colours for different average values of the clusters are used. For a given pillar or sub-pillar, starting with the Laggers, each change in colour corresponds to an increase or decrease for a cluster in the corresponding pillar or sub-pillar with 5% level of significance. Notice that the Laggers have the lowest values in almost all pillars. On the other hand, the Developing Ones have statistically significantly higher average values with respect to the Laggers in 11 out of 21 pillars. The Runners Up have higher average values in 10 pillars with respect to the Developing Ones. The Followers have relatively higher pillar averages in 20 pillars when compared to Runners Up. Finally, the Leaders have higher averages in 17 pillars with respect to Followers.

5. Development of the BN

As mentioned earlier, BNs will be used here to discover the dependency structure between the pillars and sub-pillars of the WEF competitiveness model (Figure 1) and to evaluate their effect on innovation performance of countries.

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Table 4. The results of the Scheffe tests.

		1A. Public institutions	1B. Private institutions	2A. Transport infrastructure	2B. Electricity and telephony infrastructure	3. Macroeconomic environment	4A. Health	4B. Primary education	5A. Quantity of education	5B. Quality of education	5C. On-the-job training
Cluster 1	The Laggers	3.48	3.81	2.89	2.28	4.11	4.33	3.65	1.97	3.13	3.38
Cluster 2	The Developing Ones	3.37	3.83	3.14	3.40	4.19	6.23	4.57	3.95	3.53	3.58
Cluster 3	The Runners-Up	3.46	3.89	3.56	3.91	4.82	6.35	4.66	4.76	3.66	3.80
Cluster 4	The Followers	4.39	4.62	4.27	4.86	4.82	6.71	5.27	5.37	4.47	4.31
Cluster 5	The Leaders	5.31	5.51	5.51	5.75	5.38	6.84	5.73	5.59	5.17	5.13

	6A. Competition	6B. Quality of demand conditions	7A. Labour market flexibility	7B. Efficient use of talent	8A. Financial market efficiency	8B. Trustworthiness and confidence	9. Technological readiness	10A. Domestic market size	10B. Foreign market size	11. Business sophistication	12. Innovation
Cluster 1	4.02	3.44	4.42	3.94	3.00	4.12	2.75	2.55	3.11	3.33	2.74
Cluster 2	4.12	3.75	4.61	3.77	3.26	4.46	3.30	2.66	3.42	3.59	2.74
Cluster 3	3.94	3.90	4.18	3.80	3.42	4.27	3.57	4.50	5.15	3.85	3.09
Cluster 4	4.58	4.19	4.63	4.27	3.84	4.86	4.44	3.07	4.14	4.22	3.45
Cluster 5	5.11	4.97	4.99	4.96	4.64	5.35	5.39	4.49	5.47	5.14	4.73

BN is a directed acyclic graph where nodes represent the variables, and arcs represent the conditional dependencies between the variables. If there is a directed arc from a variable X_1 to a variable X_2, then we call X_1 as the parent of X_2 and X_2 as the child of X_1. As given in Equation (1), each variable in a BN, $X_1, \ldots, X_N$ possess a probability distribution given its parents and the product of these conditional probability distributions constitute the joint probability distribution of the network:

$$P(X_1, \ldots, X_N) = \prod_{i=1}^{N} P(X_i|\mathrm{Pa}(X_i)), \tag{1}$$

where $\mathrm{Pa}(X_i)$ denotes the set of parents of X_i. In table based BN, the probabilistic part of the BN is represented by the conditional probability tables of each of the variables. Figure 2 gives a small example of a BN with four variables X_1, X_2, X_3, and X_4 and their conditional distributions. In this network, X_2 and X_4 are the children of the same parent; X_1 and X_3 is the only child of its parent X_2.

One of the main advantages of BNs is that the inference process is not solely based on one output variable. Making inferences in a BN is about finding posterior probabilities once evidence is observed. The ability to reflect the complex dependency structure between the variables without compromising on any of the variables is the main incentive for us to use BN for our analysis.

Previously, Kim and Park (2008) used BNs for analysing the impact of R&D collaboration in Korean firms on their innovative performance. They compared the BN model they obtained with the probit model and neural networks in predicting innovation. Their comparison for these methods was in terms of the classification accuracy. Accordingly, the results indicated that though neural networks obtained the best results, it was only slightly better compared to BNs. Considering that neural networks have the weakness of being difficult to interpret they suggested to use the BNs as the most useful in analysing and predicting innovation.

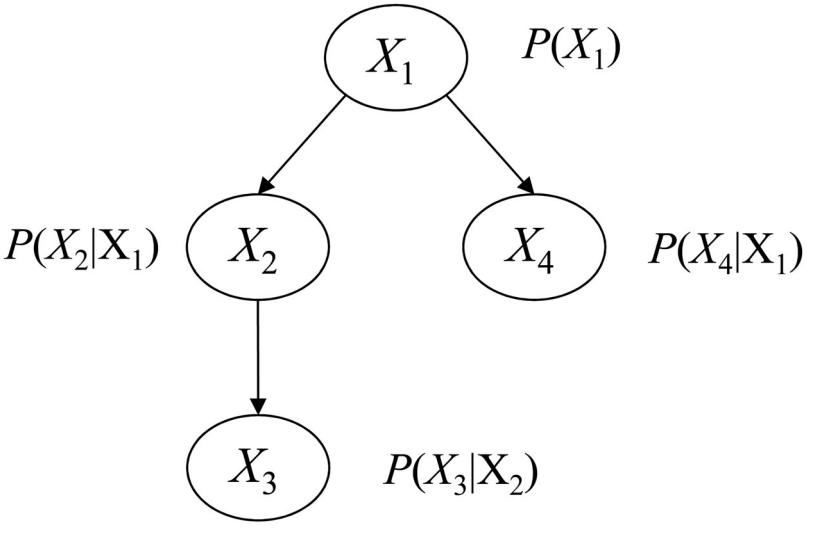


Figure 2. A small BN example with four variables.

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For executing the BN analysis, the data released by WEF for the 2009–2012 period will be employed as the dataset. The dataset used to learn the BN constitute the data for the 21 variables considered for all 148 countries participating in the WEF study over the four years indicated. Additionally, one more variable indicating the cluster is added to the dataset. To learn the corresponding BN, the GCI data are first transformed into a form where the range of each variable is discretized with seven states, each state having equal width of range. In each variable, this 1–7 discretization scheme represents the status of the corresponding variable from worst level (state 1) to the best level (state 7). The WinMine software is used to learn the structure of the BN from data. Using WinMine we first divide the data into a 70%/30% train and test split. All 21 variables are used both to predict and be predicted. As the model is built, the granularity of the learned network is determined by using a factor called Kappa. The values for Kappa range between 0 and 1.0. As Kappa value approaches 1.0, a much denser network is obtained. In this analysis, we want to evaluate the effect of all the different factors on countries' innovation performance and also see the dependencies between them. For that reason, in order to see the complete dependency structure between the variables, the Kappa value is taken as 1.0.

In our analysis, we evaluate the accuracy of the learned BN model using the log score. Log score is a quantitative criterion, which evaluates how the provided model learned from the training data performs on the test set. The formula for the log score is given in Equation (2), where n is the number of variables and N is the number of cases in the test set:

$$\text{Score}\,(x_1,\ \ldots,\ x_N) = \sum_{i=1}^{N} \log_2 p(x_i|\text{model})/nN. \tag{2}$$

In our case, the provided model resulted in a log score of –0.9886, meaning on the average, the log probability that each variable assigns to the given value in the test case, given the value of other variables, is 50.40%. By using WinMine, the lift over the marginal value can be found as well, which is the difference between the log scores of the provided model and marginal model. A positive difference indicates that the provided model outperforms the marginal model on the test set. In the same way that a regression model is more accurate than a simple baseline model chosen in the form of a mean dependent value, the 'lift over marginal' log score provides information on how well the model fits the data (Scuderi and Clifton 2005). The lift over marginal value obtained by our model is 0.7009, meaning that the predictive capacity of the provided model is about 19.39% better than the marginal model. The lift over marginal, varies according to the data characteristics, such as the number of variables, cases presented in data and the states corresponding to variables. In sparse datasets where a big number of variables are presented through a low number cases, this improvement rate may increase to such small values as 1% which is an indication that variable selection should be performed in BN (Cinicioglu and Shenoy 2016). In that instance, an improvement rate of 19.39% may be considered as an excellent outcome.

As the next step of the research, the same BN is created using Netica software (Norsys Software Corp. 2016). This way we can enter evidence for variables and observe the consequential change in the posterior probabilities. Additionally, by using Netica software,

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sensitivity analysis may also be performed, which allows the decision maker to identify the variables affecting the target variable most. The BN created from the whole dataset using Netica software and the marginal probabilities of the variables in the network can be seen in Figure 3. As explained before, each variable possesses seven states and the corresponding number for each state indicates the probability of observing that state for the corresponding variable.

Examining Figure 3, we see that Innovation has its highest probability for state 3 with 39.1% and the lowest probability for state 1 with 3.23%. Looking at the structure of the network, on the other hand, we see that Innovation has Business Sophistication as its parent and Efficient Use of Talent as its child variable. However, the effect a variable has on other variables in a BN is not only restricted to its child variable. On the contrary, it can expand up to the whole network depending on the probabilistic dependency structure of the network and the observed evidences. For that reason, BNs can be considered as a perfect choice for exploring the complex relationship between Innovation and competitiveness, since via the BN structure the effect of a change in any of the variables can be observed and thus, the analysis conducted may represent the dynamic and multidimensional structure of the problem.

For illustration of the capability of BNs to represent different scenarios under evidence observation, consider the case illustrated in Figure 4. An evidence observation is made for Business Sophistication for state 7, accordingly the posterior probability of its child variable Innovation increases to 69.2% for state 7 and to 26.9% for state 6. However, the effect of Business Sophistication is not only limited to Innovation. An easy comparison of the variables' probabilities before and after the evidence observation given in Figures 4 and 5, respectively, reveals that Business Sophistication has an impact on all the variables in the network. In Figure 5, on the other hand, we observe the state 7 for Efficient Use of Talent. Accordingly, the posterior probability of its parent Innovation increases to 51.7% for state 7 and to 31% for state 6. Still, that change is not only limited to Innovation. Though Efficient Use of Talent does not have any child we see that its impact is widespread and a change in posterior probabilities can be observed in all the variables of the network, similar to the case of Business Sophistication in Figure 4. Another interesting finding, which may be observed in Figures 4 and 5, respectively, is the change in posterior probabilities of the Followers and Leaders. We see that given that 'Business Sophistication = 7', the posterior probability of the Followers and Leaders increases to 14.1% and 85.4%, respectively. Moreover, observing 'Efficient Use of Talent = 7' increases the posterior probability of the Followers and Leaders to 18.8% and 76.6%, respectively. Both these changes occur along with the positive increase in Innovation level, explained as before. This finding is in parallel with the Acemoglu, Aghion, and Zilibotti (2002), who underline that when a country is closer to the technology frontier, the selection of high-skill managers will be more important.

Notice that the network in Figure 3 is learned from the complete dataset, including the data of all countries for the four years considered. This network is beneficial in giving us a complete picture of the interdependencies between the considered pillars. On the other hand, in order to provide strategic guidelines for improving the innovation performance of the countries, it is necessary to analyse the interdependencies inherent in each of the clusters. For that reason, the dataset is partitioned into five new datasets according to the cluster sets identified previously. For each new dataset, the corresponding BN is

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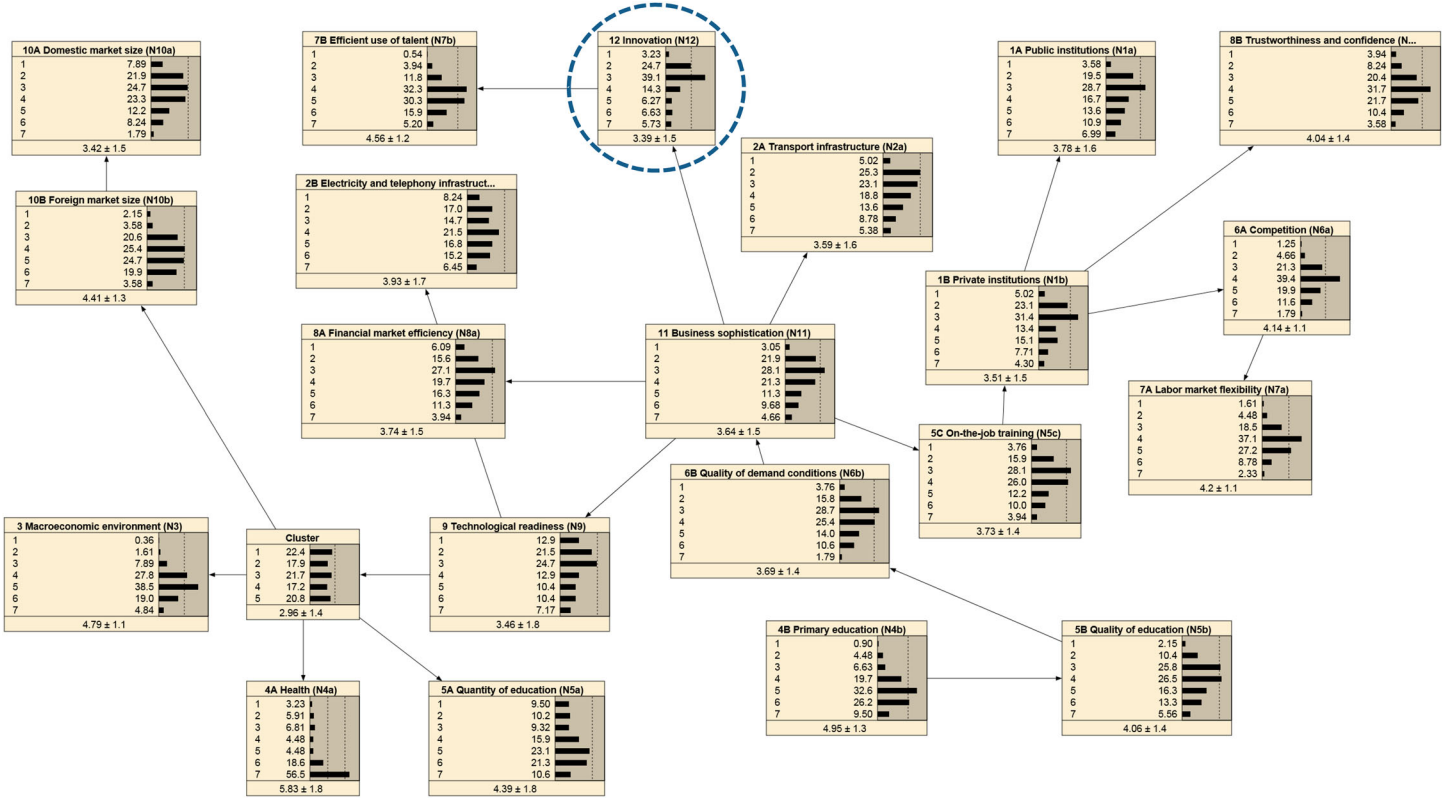


Figure 3. The BN created using Netica software.

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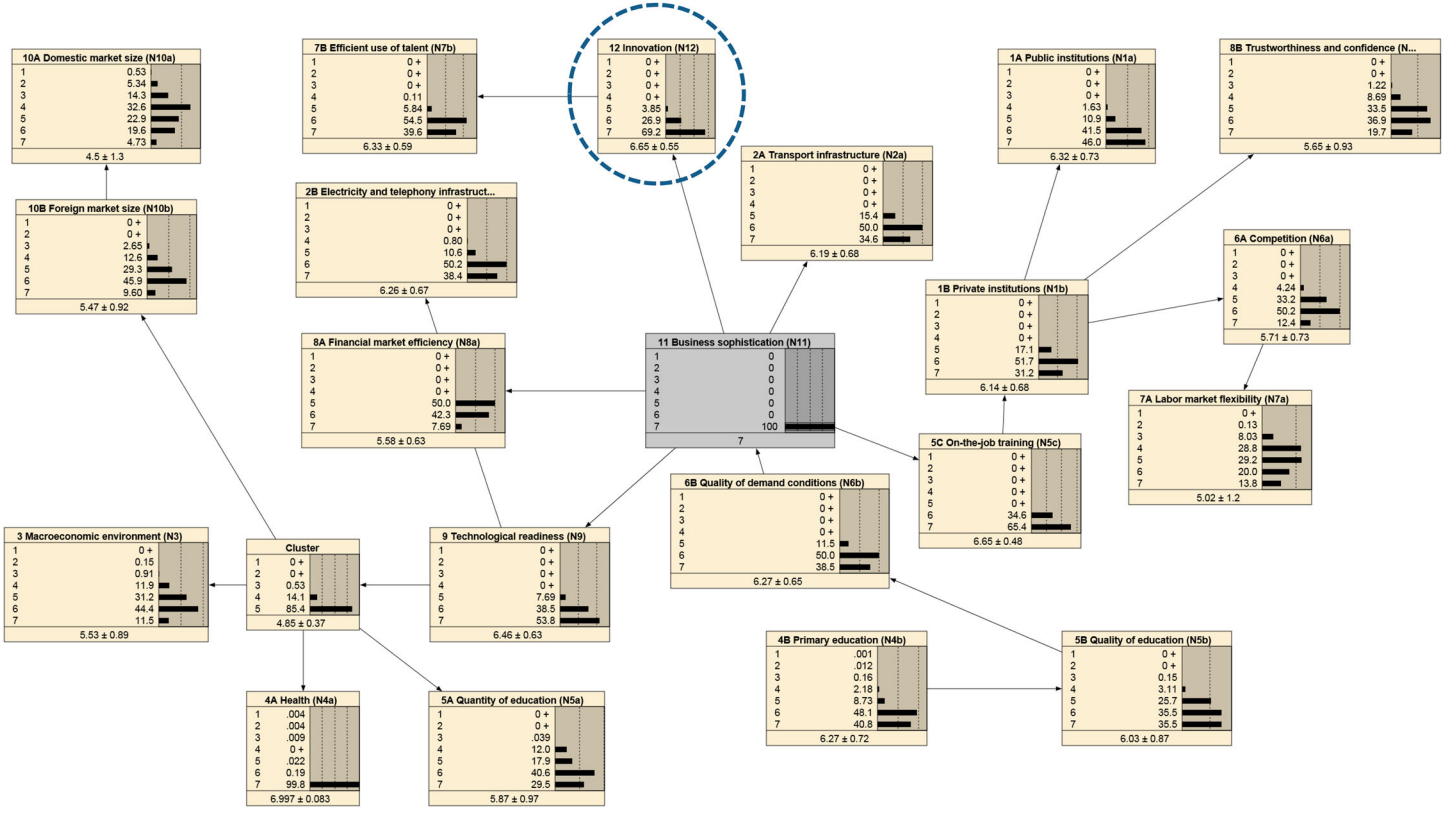


Figure 4. The posterior probabilities of the BN after observing 'Business Sophistication = 7'.

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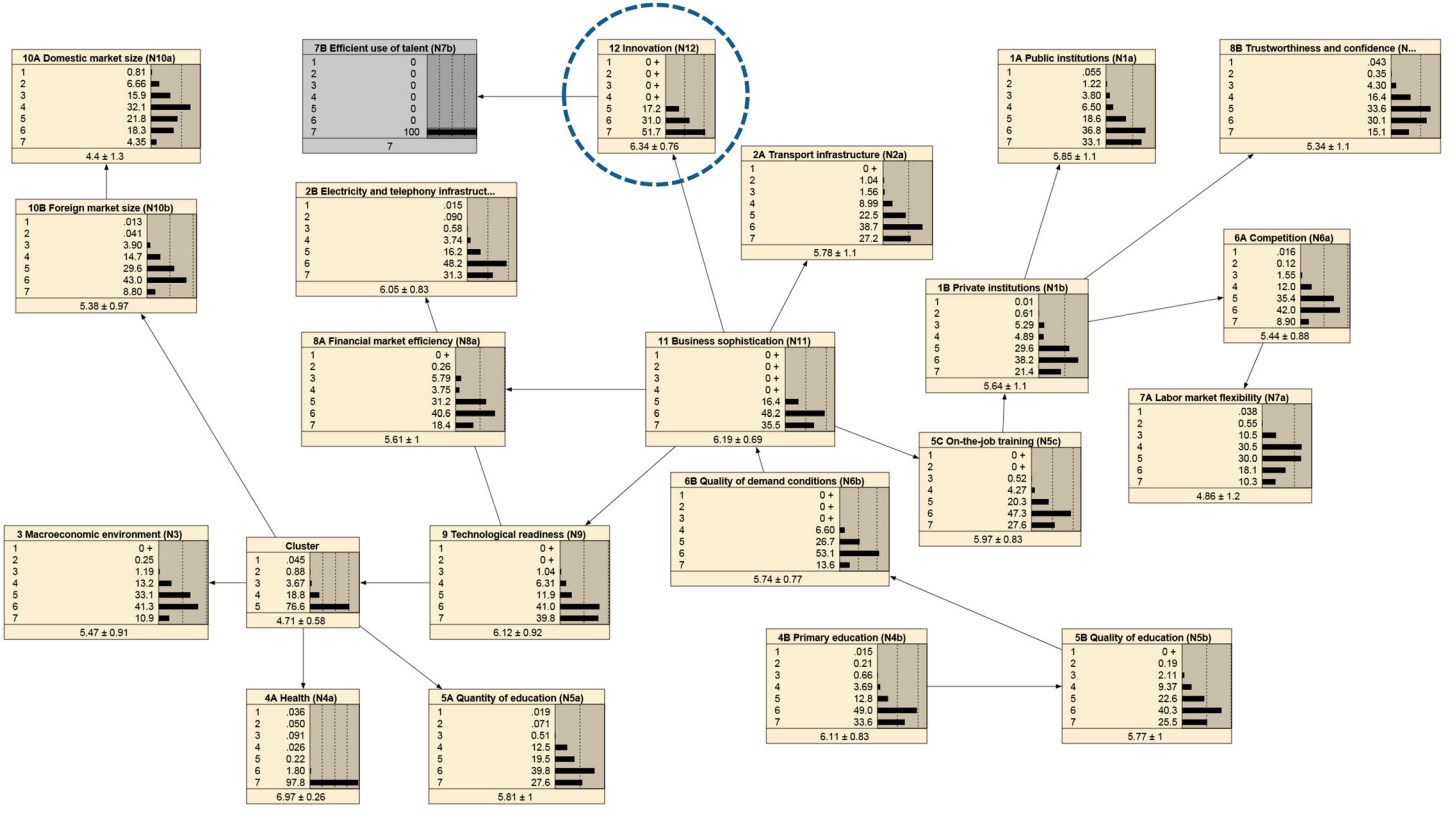


Figure 5. The posterior probabilities of the BN after observing 'Efficient Use of Talent = 7'.

Table 5. Log scores and lift over marginal values of the BNs created.

BN	Log score	Lift over marginal	Improvement obtained (%)
The Laggers	−0.807413	0.487418	16.3822
The Developing Ones	−0.769154	0.409844	14.5103
The Runners Up	−0.788488	0.515584	17.3969
The Followers	−0.66602	0.487645	18.1763
The Leaders	−0.659827	0.527949	19.3975
All Countries	−0.988644	0.70088	19.3922

learned, which can be seen in Figure A1–5 given in the Appendix. As a result, six different BNs are created for our analysis, one for the whole dataset and one for each of the five country clusters. The corresponding log scores and lift over marginals of all BNs learned are reported in Table 5. As can be seen in Table 5, there is an improvement obtained for all the BNs created indicating that these cluster-based BN models can be used efficiently in analysing the interdependencies between pillars and sub-pillars.

Section 6 provides sensitivity analysis and evidence observation conducted for the specific interest. Varying results of the clusters and their posterior outcomes are interpreted to constitute a strategic guideline for how to improve the innovation performance of a country.

6. Sensitivity and scenario analyses for innovation enhancement

6.1. On how to reach an improved stage of innovation

After creating the BN structure from the dataset, a sensitivity analysis is performed to determine the competitiveness indicators (variables) that have the greatest effect on the Innovation variable. The results of the sensitivity analysis are in terms of the variance reduction (VR) rates corresponding to indicators. VR is the expected reduction in the variance of the output variable due to the value of an input variable. When information is supplied about the state of an input node, the output node distribution may shrink towards more probable values, reducing its variance (Nash et al. 2013). The variable with the greatest VR rate is expected to be the one that has the highest explanatory power over the output variable.

Table 6 lists the results of the sensitivity analysis performed on the five different cluster BNs for the Innovation variable. In each column, the indicators are listed in decreasing order of the per cent VR (VR%). According to Table 6, it can be seen that Business Sophistication and On-the-Job-Training are the two variables that appear in each of the clusters as one of the top five indicators affecting the Innovation level of countries the most. This points out the fact that solid levels of Business Sophistication and On-the-Job-Training are essential for improving the Innovation level of a country regardless on the level of current competitiveness of that country. Additionally, notice that Business Sophistication is listed as the top variable affecting the Innovation level for a country belonging to the Leaders, Followers, and Laggers. Thus, the same finding is obtained for the best two country clusters as well as the worst one. Though this may seem as surprising at first glance, a closer look reveals that these countries are similar to each other in the sense that they represent a homogenous structure within their clusters, in terms of the low variation present among their competitiveness indicators. In Leaders and Followers, this low variation shows itself

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Table 6. Results of the sensitivity analysis[a] performed for the innovation variable on each cluster BN.

Leaders (Cluster 5)		Followers (Cluster 4)		Runners up (Cluster 3)		Developing ones (Cluster 2)		Laggers (Cluster 1)	
Indicator	VR%	Indicator	VR%	Indicator	VR%	Indicator	VR%	Indicator	VR%
11 Business sophistication	56.0	11 Business sophistication	45.4	5B Quality of education	46.0	8A Financial market efficiency	34.9	11 Business sophistication	39.3
5C On-the-job training	35.1	5C On-the-job training	42.7	5C On-the-job training	43.1	8B Trustworthiness and confidence	23.8	8A Financial market efficiency	21.5
5A Quantity of education	32.8	2B Electricity and telephony infrastructure	33.8	9 Technological readiness	29.5	5C On-the-job training	12.1	6B Quality of demand conditions	19.4
2B Electricity and telephony infrastructure	21.1	9 Technological readiness	22.9	8B Trust worthiness and confidence	26	11 Business sophistication	7.51	5C On-the-job training	17.2
6B Quality of demand conditions	19.3	6B Quality of demand conditions	14.6	11 Business sophistication	22	6B Quality of demand conditions	4.51	5B Quality of education	17
7B Efficient use of talent	18.9	3. Macroeconomic environment	13.6	6B Quality of demand conditions	14.8	10B Foreign market size	2.02	8B Trustworthiness and confidence	14.3
5B Quality of education	10.8	2A Transport infrastructure	6.78	4B Primary education	11.9	1B Private institutions	1.8	9 Technological readiness	11.6
9 Technological readiness	10.7	1B Private institutions	3.9	4A Health	11.3	10A Domestic market size	1.09	1B Private institutions	7.94
4B Primary education	5.99	7A Labour market flexibility	3.81	8A Financial market efficiency	10.8	2A Transport infrastructure	0.98	1A Public institutions	4.92
10B Foreign market size	5.84	1A Public institutions	3.47	1B Private institutions	10.6	4B Primary education	0.883	2A Transport infrastructure	3.61
1B Private institutions	3.87	6A Competition	2.92	10A Domestic market size	8.27	6A Competition	0.695	6A Competition	3.39
3. Macroeconomic environment	3.7	8A Financial market efficiency	2.41	2B Electricity and telephony infrastructure	7.91	9 Technological readiness	0.559	10B Foreign market size	2.67
10A Domestic market size	2.33	5A Quantity of education	0.962	7B Efficient use of talent	5.6	5A Quantity of education	0.344	4B Primary education	2.43
2A Transport infrastructure	2.31	10A Domestic market size	0.766	6A Competition	5.52	2B Electricity and telephony infrastructure	0.199	7B Efficient use of talent	2.12
7A Labour market flexibility	1.03	10B Foreign market size	0.321	1A Public institutions	5.34	5B Quality of education	0.189	10A Domestic market size	1.7
8B Trustworthiness and confidence	0.802	4B Primary education	0.3	5A Quantity of education	5.2	3. Macroeconomic environment	0.116	2B Electricity and telephony infrastructure	1.37
1A Public institutions	0.559	8B Trustworthiness and confidence	0.175	2A Transport infrastructure	4.45	7B Efficient use of talent	0.0527	4A Health	0.61
6A Competition	0.183	5B Quality of education	0.169	10B Foreign market size	4.39	1A Public institutions	0.0245	5A Quantity of education	0.268
8A Financial market efficiency	0.0572	7B Efficient use of talent	0.0808	7A Labour market flexibility	2.98	7A Labour market flexibility	0.00289		
				3 Macroeconomic environment	0.614				

Note: [a]In Table 6, only the competitiveness indicators with a VR% >0 are reported.

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as advancement in all of the competitiveness indicators, whereas in Laggers, in all of the indicators a lack of development is observed. Thus, for these three clusters, Business Sophistication turns out to be the most important factor to scale up for higher levels of Innovation.

The next step necessary is to analyse how to improve the Innovation level of the cluster under consideration in order to scale up to the subsequent cluster's Innovation level. The logic of the proposed approach here is to identify the competitiveness indicators, which most affect the Innovation level of the subsequent cluster and then to investigate the impact of an improvement obtained for these competitiveness indicators on the Innovation level of the current cluster. The benchmark procedure, which is used in the selection of the variables, is summarized in Figure 6. This figure illustrates the selection of the variables for evidence observation for the case of the Laggers and how to read the effect of an improvement obtained in these variables for the posterior probabilities of Innovation for that cluster.

The analysis procedure is as follows: To determine competitiveness indicators, where improvement is necessary for scaling up, the top five competitiveness indicators of Innovation in the subsequent cluster are considered. In Table 6, the ranking of the indicators for each cluster according to their explanatory power on Innovation level are provided. Subsequently, referring to Table 4, from the top five indicators, those ones will be omitted where the competitiveness indicator mean values of the current and the subsequent cluster do not differ statistically significantly (Table 4). For instance, among the top five indicators of the Developing Ones, On-the-Job-Training has a similar mean with that of the Laggers and for this reason it is not considered further in the analysis. Afterwards, evidence observation is conducted for each of the selected indicators in the cluster under consideration by improving the state of each pillar to the next higher level and observing its effect on the posterior distribution of Innovation.

The described analysis is conducted for each of the first four clusters with the fifth one ignored, since it corresponds to the best one. In Figure 7(a)–(d), the results for each of these four clusters are presented where the first stacked column represents the marginal distribution of Innovation for the cluster under consideration. The remaining columns present the posterior distributions of Innovation after improving selected pillar to the next higher state. The idea is to see the effect of an improvement obtained in one of the selected pillars on the Innovation level for that cluster.

Consider the case illustrated in Figure 7(a) for the Laggers (Cluster 1). According to the original values, the Laggers cluster on the Innovation variable has its highest probability for state 2, which is 50.2%. When we improve the state of the variable Trustworthiness and Confidence from its original state 4 to the higher state 5, for example, then Innovation has its highest probability for state 3 with 44.7%. In fact, Fawcett, Jones, and Fawcett (2012) introduce four levels of trust within a maturity trust framework and elaborate on the impact of trust in general and collaborative trust in particular on the collaborative innovation capability. Similarly, Murphy (2002) analyses the social dimensions of innovation and reveals that trust is especially important for innovation.

As it can be seen from Figure 7(a), the same type of analysis is valid also for the three indicators Quality of Demand Conditions (fifth column), Financial Market Efficiency (second column), and Business Sophistication (fourth column). When, for example,

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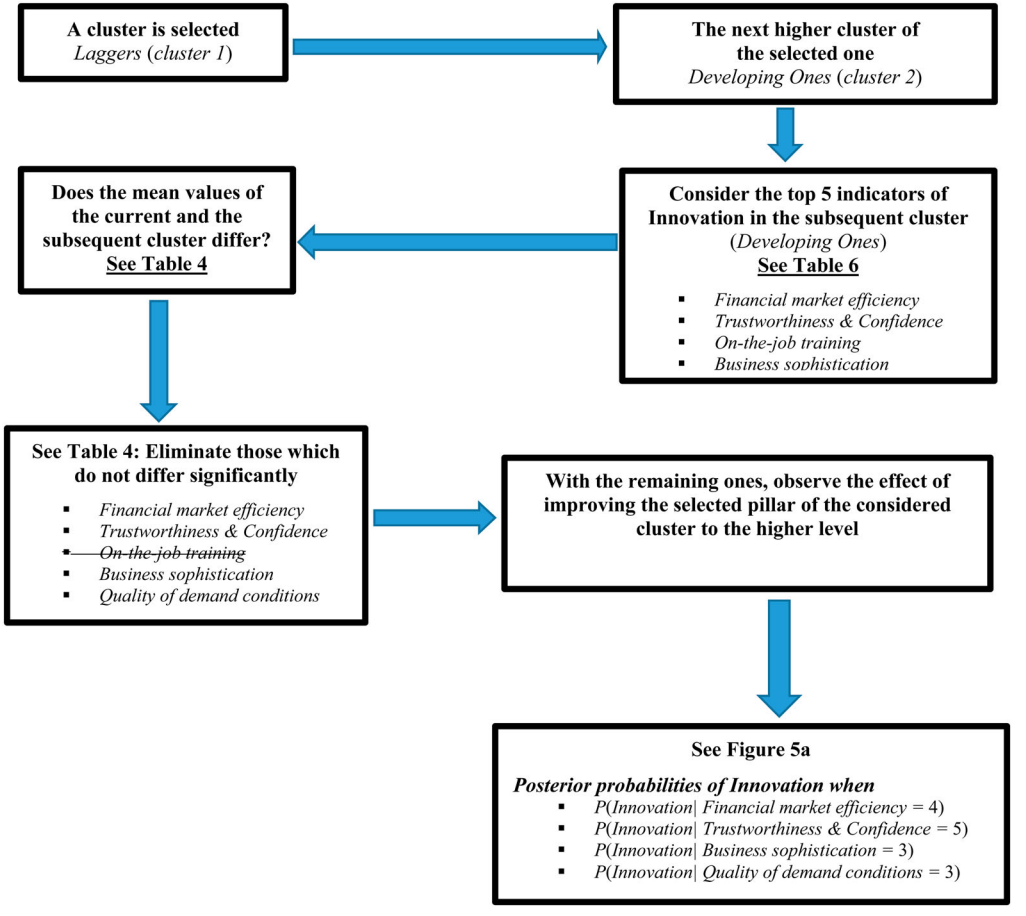


Figure 6. Benchmark procedure for each cluster (Laggers (*cluster 1*)).

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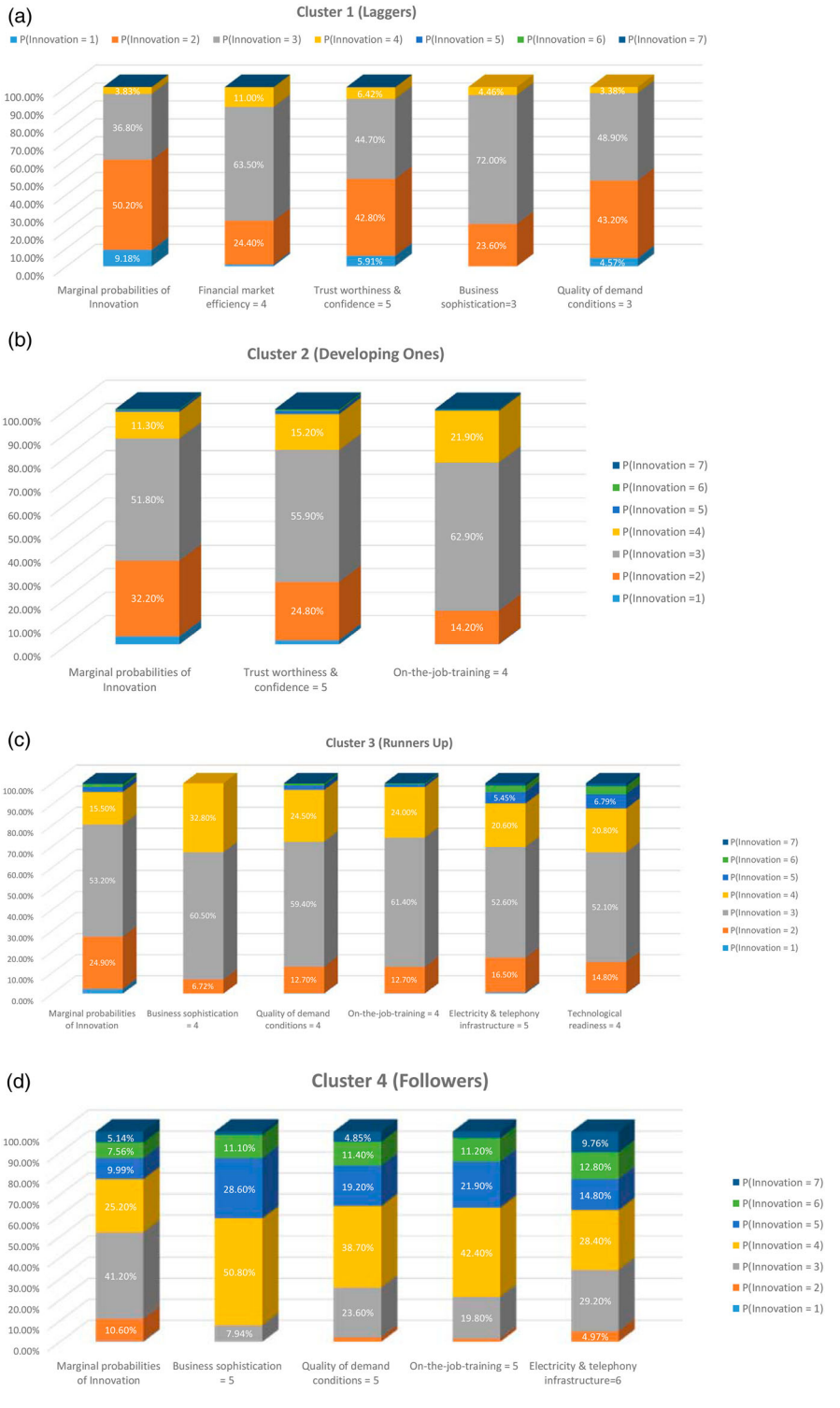


Figure 7. (a) Posterior probabilities of Innovation for the Laggers (Cluster 1). (b). Posterior probabilities of innovation for Cluster 2. (c) Posterior probabilities of innovation for Cluster 3. (d) Posterior probabilities of innovation for Cluster 4.

the state of Business Sophistication is improved to state 3 from its original value of 2, we observe that the probability of Innovation occurring in state 3 increases from 36.8% to 72%. In fact, the quality of a country's overall networks and the quality of individual firms' operations and strategies are especially important for countries at an advanced stage of development. Note that Business Sophistication includes local supplier quantity and quality and state of cluster development among others. Parallel to our finding, Lai et al. (2014) explore the relationships among firms in a cluster on innovation performance and reveal that participation in industrial clustering is important for sustainable corporate development and that geographical proximity influences firms' innovation performance.

As given in Figure 7(b), in Cluster 2 (The Developing Ones) the marginal probability of the Innovation variable is highest for state 3 with a value of 51.8%. When we improve the state of the On the Job Training variable from its original state 3 to the higher state 4, then Innovation has its highest probability for state 3 again but with a higher probability of 62.9%.

On-the-job training ensures a constant upgrading of employees' skills. It is interesting to note that On-the-job training appears as a more influential indicator than Quantity of education and Quality of education. This finding is in line with Lewis (2004) claim that regardless of the institutional education level, workers around the world can be adequately trained on-the-job for high productivity and hence, competitiveness. Koellinger (2008) shows the importance of employment development for the improvement of innovation. This result is also in line with Ruth and Deitmer (2010) who underline the importance of the technical and vocational education as well as training on innovation. On-the-job training is important as a means of providing a career opportunity in the countries at the lower innovation levels while it serves as a means of adaptation to technology at higher levels.

Figure 7(c) illustrates the third cluster (Runners Up), which has higher average values in all of the five most important pillars with respect to the developing ones and for that reason posterior probability changes are analysed for all the top five indicators. In this cluster, the marginal probability of Innovation variable for state 4 is 15.5%, which increases to 32.80% after improving the level of Business Sophistication to the state of 4 from its original most likely state of 3.

As can be seen in Figure 7(d) the Innovation level has its biggest jump in Cluster 4 when the state of Business Sophistication is improved to five from its current mostly likely state of 4. Before evidence observation, Innovation has its highest probability for the state of 3 with 41.2%. After improving the state of Business Sophistication to state 5 Innovation shows a significant increase: The Innovation state with the highest probability is 4, with 50.8% probability. Also notice that at the same time, the posterior probability of Innovation for state 5 is increased to 28.6%. This result parallels the findings of the sensitivity analysis conducted for Innovation in Table 6. In Table 6, notice that the top indicator of Innovation for the Followers is Business Sophistication with 45.4% VR rate. These analyses propose that the above indicators are the most influential ones, where special attention is required in order to raise a country in that cluster to a higher state of Innovation.

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6.2. The interaction among innovation, cluster, and competitiveness

The analyses provided in the previous sections are essential to develop policy tools for the policy-makers in their attempt to develop strategies for improving the innovation level of their country. On the other hand, it is also important to realize that the relationship between competitiveness indicators and a country's Innovation level is a two-way rather than a one-way relationship, where innovativeness and competitiveness interact. Therefore, in addition to the analysis based on Figure 7(a)–(d) it is also necessary to explore the impact of an improvement obtained in the Innovation level in a cluster to the other competitiveness indicators. With that purpose in this section we will conduct a new analysis where we observe the posterior probabilities of variables for all possible combinations of evidences for the cluster and Innovation variables, which is given in Table 7. The formation of Table 7 and along with the description of this new analysis is provided in Figure 8 given.

The procedure is as follows: To see the complete picture of this effect and understand the trends of improvement in the competitiveness indicators depending on the Innovation state and the cluster observed, we need to perform the same analysis for all possible combinations of evidences for the cluster and Innovation variables. Since we are only interested in observing the posterior probabilities of the variables, where the Innovation state has an essential impact, we first performed sensitivity analysis for all the variables in the network and identified those variables where Innovation is one of the top five variables with the greatest VR rates.

If the results of the sensitivity analysis of a variable indicate Innovation as one of the top five variables with the highest VR rates, that variable is included in Table 7. Accordingly, nine competitiveness indicators are included in Table 7, which form the columns after Cluster and Innovation. Subsequently, after evidence observation for each possible combination of states of Cluster and Innovation, which are listed as rows in Table 7, the state of the variable with the highest posterior probability for that variable is observed and included to Table 7. The cases where an improvement in the posterior state with the highest probability is observed when the Innovation level is raised to the higher state, is coloured in red and marked in bold with an upward arrow ↑. That means, for example, for a country belonging to Cluster 3, if an increase is accomplished in its Innovation state from the third state to the fourth state, it will reflect itself as an increase in its Transport Infrastructure, On-the-Job-Training, Quality of Demand Conditions, Financial Market Efficiency, and Business Sophistication levels.

It is well known that demanding customers are one of the main drivers of innovation. For cultural reasons, customers may be more demanding in some countries than in others. For example, intense product competition and demanding customers encourage rising R&D spending and the development of new products and processes. However, this Quality of Demand Conditions in turn, depends upon the trust worthy and transparent financial markets with appropriate regulations to protect customers (Dobson and Safarian 2008). On the other hand, as is also stated by Vize et al. (2013), the institutional trust is of crucial importance for the firms, which are new to technology environment and likely to rely on an institutional trust mechanism to reduce their perceived risk and increase their technological readiness.

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Table 7. Posterior states with the highest probabilities of the competitiveness indicator variables after observing evidence for the variables cluster and innovation.

Evidence observation		Posterior states with the highest probabilities								
Cluster	Innovation	Transport infrastructure	Primary education	Quality of education	On-the-job training	Quality of demand conditions	Efficient use of talent	Financial market efficiency	Technological readiness	Business sophistication
1[a]	1	2	4	3	2	2	4	1	1	2
	2	2	**5↑**	3	2	2	4	**2↑**	1	2
	3	2	5	3	**3↑**	**3↑**	**4–5*↑**	**3↑**	**2↑**	**3↑**
	4	**4↑**	5	**4↑**	**4↑**	**4↑**	5	**4↑**	2	**4↑**
	5	**5↑**	**6↑**	**6↑**	**5↑**	**5↑**	**6↑**	**5↑**	**3↑**	**5↑**
	6	5	6	6	5	5	6	5	3	5
	7	5	6	6	5	5	6	5	3	5
2	1	2	4	3	2	2	4	2	2	2
	2	2	**5↑**	3	**3↑**	2	4	**3↑**	2	2
	3	**3↑**	5	**4↑**	3	**3↑**	**4–5*↑**	3	**3↑**	**3↑**
	4	**4↑**	5	4	**4↑**	**4↑**	5	**4↑**	3	**4↑**
	5	**5↑**	**6↑**	**6↑**	**5↑**	**5↑**	**6↑**	**5↑**	**4↑**	**5↑**
	6	5	6	6	5	5	6	**6↑**	4	5
	7	**6↑**	6	6	**6↑**	**6↑**	6	6	4	**6↑**
3	1	2	4	3	2	2	4	2	2	2
	2	2	**5↑**	3	**3↑**	**3↑**	4	**3↑**	**3↑**	2
	3	**3↑**	5	**4↑**	3	3	**4–5*↑**	3	3	3↑
	4	**4↑**	5	4	4↑	4↑	5	**4↑**	3	**4↑**
	5	**5↑**	**6↑**	**6↑**	**5↑**	**5↑**	**6↑**	**5↑**	**4↑**	**5↑**
	6	5	6	6	5	5	6	**6↑**	4	5
	7	**6↑**	6	6	**6↑**	**6↑**	6	6	4	**6↑**
4	1	2	5	3	2	2	4	2	3	2
	2	**3↑**	5	**4↑**	**3↑**	**3↑**	**4↑**	**3↑**	**4↑**	**3↑**
	3	3	5	4	**4↑**	**4↑**	**5↑**	**4↑**	4	**4↑**
	4	**5↑**	**6↑**	4	4	4	5	**5↑**	**5↑**	**5↑**
	5	5	6	**6↑**	**5↑**	**5↑**	**6↑**	**6↑**	5	5
	6	**6↑**	6	6	**6↑**	**6↑**	6	6	5	**6↑**
	7	6	6	6	6	6	6	6	**6↑**	**7↑**
5	1	2	5	3	2	2	4	2	3	2
	2	**3↑**	5	**4↑**	**4↑**	**3↑**	4	**3↑**	**4↑**	**3↑**
	3	**4↑**	5	4	4	**4↑**	**4–5*↑**	**4↑**	**5↑**	**4↑**
	4	**5↑**	**6↑**	4	**5↑**	**5↑**	5	**5↑**	**6↑**	**5↑**
	5	**6↑**	6	**6↑**	**6↑**	**6↑**	**6↑**	**6↑**	6	**6↑**
	6	6	6	6	6	6	6	6	6	6
	7	6	6	6	6	6	6	6	**7↑**	**7↑**

Note: *Both of the states possess the highest probability.

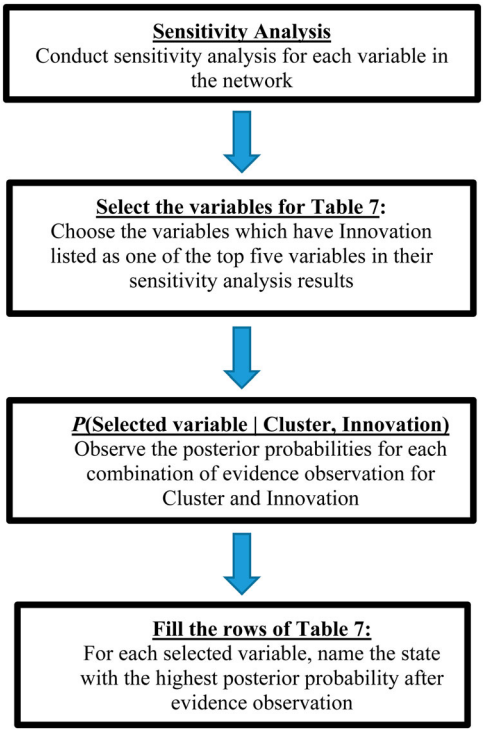


Figure 8. Description of the analysis for creation of Table 7.

7. Summary and conclusions

Innovation is a complex and multidimensional process, which involves many different players. A linear view of innovation has been replaced by the dynamic approach, which requires a complex interplay between all actors of an innovation system. A representation of the multi-faceted interaction of science, technology, and the economy is extremely useful for understanding the sources of and processes leading to technological innovation. In fact, although there are basic innovation drivers important for all the countries, the relative importance of those drivers differs with respect to the competitiveness level of the country. Therefore, it is also necessary to understand the main drivers of innovation to determine a country's competitiveness stage as well as the impact of increasing innovation level on the competitiveness of that country. Although there is abundant research on the impact of innovation on economic growth the research based on the analysis of the main ingredients of innovation is scarce in the literature (Castellacci 2011; Filippetti and Peyrache 2011; Castellacci and Natera 2013). To the best of our knowledge this research is the first attempt to analyse both the main drivers of Innovation for each different cluster of countries based on a wide spectrum of attributes and their impact on the competitiveness of a country.

As seen in the previous sections, in order to analyse the complex relationship between Innovation and the competitiveness indicators as well as to depict a country's innovation performance in its entirety, different analyses are conducted. These analyses include cluster-based identification of the competitiveness indicators most affecting Innovation

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(Table 6) and a posterior analysis of an improvement obtained in vital indicators to the Innovation performance of the considered cluster (Figure 7(a)–(d)).

In this paper we represent three main research questions and try to answer them through the conducted analysis made in this paper.

'What are the competitiveness factors that affect Innovation and how do they differ between different country groups?' which is explored via the sensitivity analysis performed for the Innovation variable on each cluster BN given in Table 6.

'To which factors should a country focus in order to scale up to higher levels of Innovation and how an improvement in those factors are going to affect the level of Innovation of the country?' The analysis conducted to explore this question is described in Section 6.1 via the benchmark procedure given in Figure 6. The results of the conducted analysis in terms of the posterior probabilities of Innovation in each Cluster are given in Figure 7 (a)–(d) and its implications are described in text.

'How does a change in Innovation level depending on the cluster the country belongs affect the other competitiveness factors?' The answer of this research question is explored in Section 6.2 where the analysis explained in Figure 8, results presented in Table 7 and observations are made in the same section.

Notice that all of these analyses are using the methods of sensitivity analysis and evidence observation in BNs. The BN created in this research contains 21 different variables (regarding the competitiveness indicators) each with seven states, plus one additional variable indicating the five different clusters. Henceforth, though we try to analyse different situations and present the relationship between the competitiveness indicators, the possible number of different combinations of observations correspond to precisely $5*7^{21}$ possible different situations, which makes it impossible to cover all the possible cases. However, that actually shows the real and foremost important contribution of the paper. The BN created in this research, which represents the multidimensional relationship between the competitiveness indicators and Innovation, is itself the strategy guideline for the policy-makers. Using this tool, the policy-makers can conduct different analyses and set their road map in order to scale up to higher levels of Innovation. Furthermore, it should also be noted that proposed approach is not only limited to Innovation variable, all the competitiveness indicators (hence variables) are subject for analysis in this network.

Since we operate with five different clusters and suggest policy measures for individual clusters, the heterogeneity within the clusters might appear as a limitation of this research in that it forces the inferences to be generalized to countries in the cluster. But although we cannot put an evidence for a particular country, the wide range of different combinations of observations allows us to put our evidences to each variable regarding the country of interest's placement in the competitiveness indicators. Thus, both in terms of generalizations of country groups and also for individual inferences regarding a country of interest, the BN created in this research can be used as a productive and decision support tool for policy-makers to form strategy guidelines for enhancing a country's Innovation level.

The use of WEF data can also be considered as a limitation of this research, since we are limited by the questions asked in the GCI questionnaire. Accordingly, only the variables, which are the set of pillars and sub-pillars in the Global Competitiveness Report can be included into the analyses.

As a further study, policy recommendations to build innovation capabilities of a specific country could be realized by taking into account the country-specific indicators

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or features that are not included in GCI indices such as production structure and participation in global value chains.

A further line of research could be the use of dynamic BNs in order to measure the temporal inertia in the economic behaviour of the variables in order to get additional information about the dynamics in the cluster.

Note

1. The sub-pillars 9A Technological Adaptation and 9B ICT have been first used in the Global Competitiveness Report 2010–2011. Since the data for the year of 2009 is not available for these sub-pillars, the 9th pillar is only considered with the main pillar Technological Readiness. Other than that all sub-pillars are included in the analysis.

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Appendix

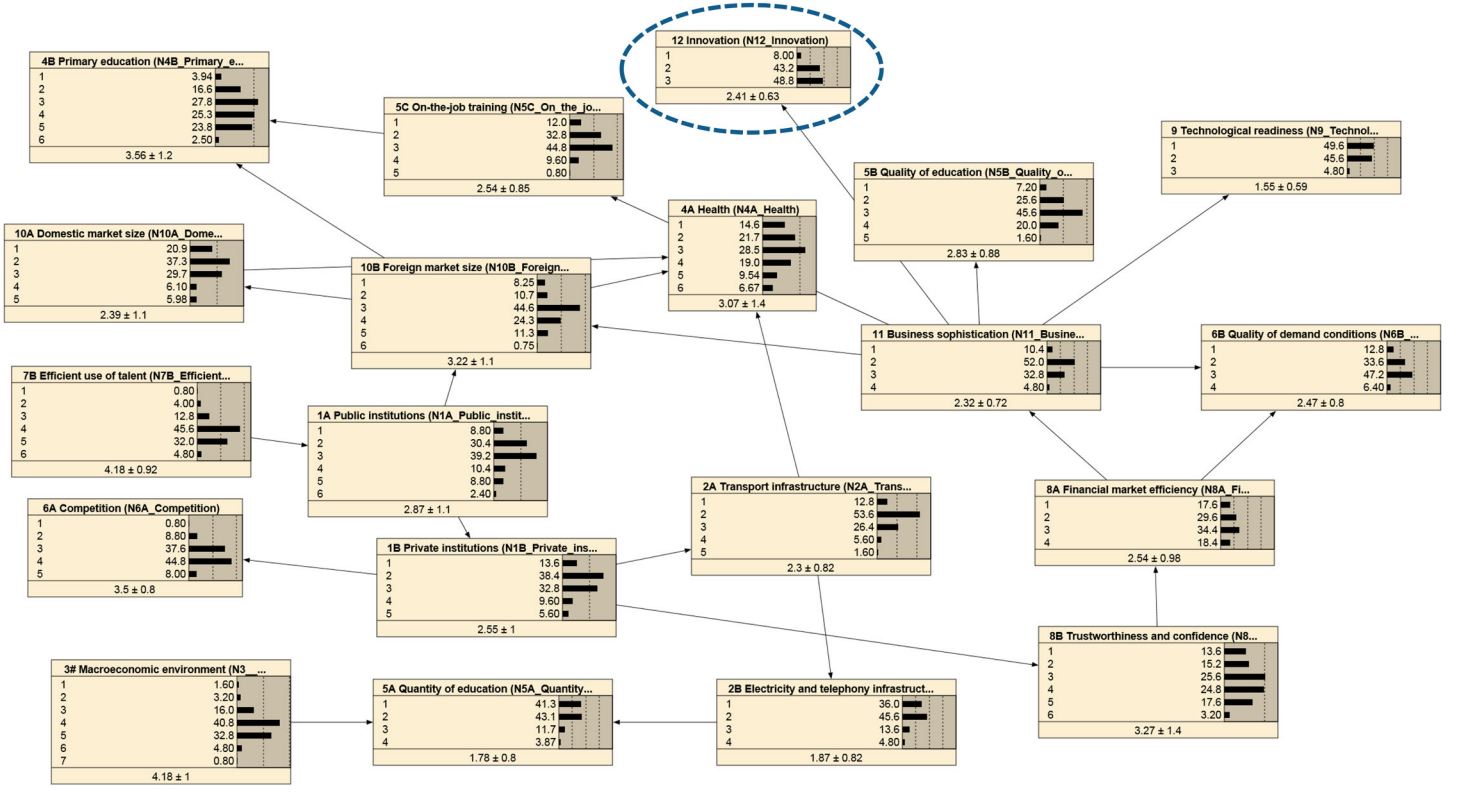


Figure A1. The learned BN for the partition of the dataset Cluster 1.

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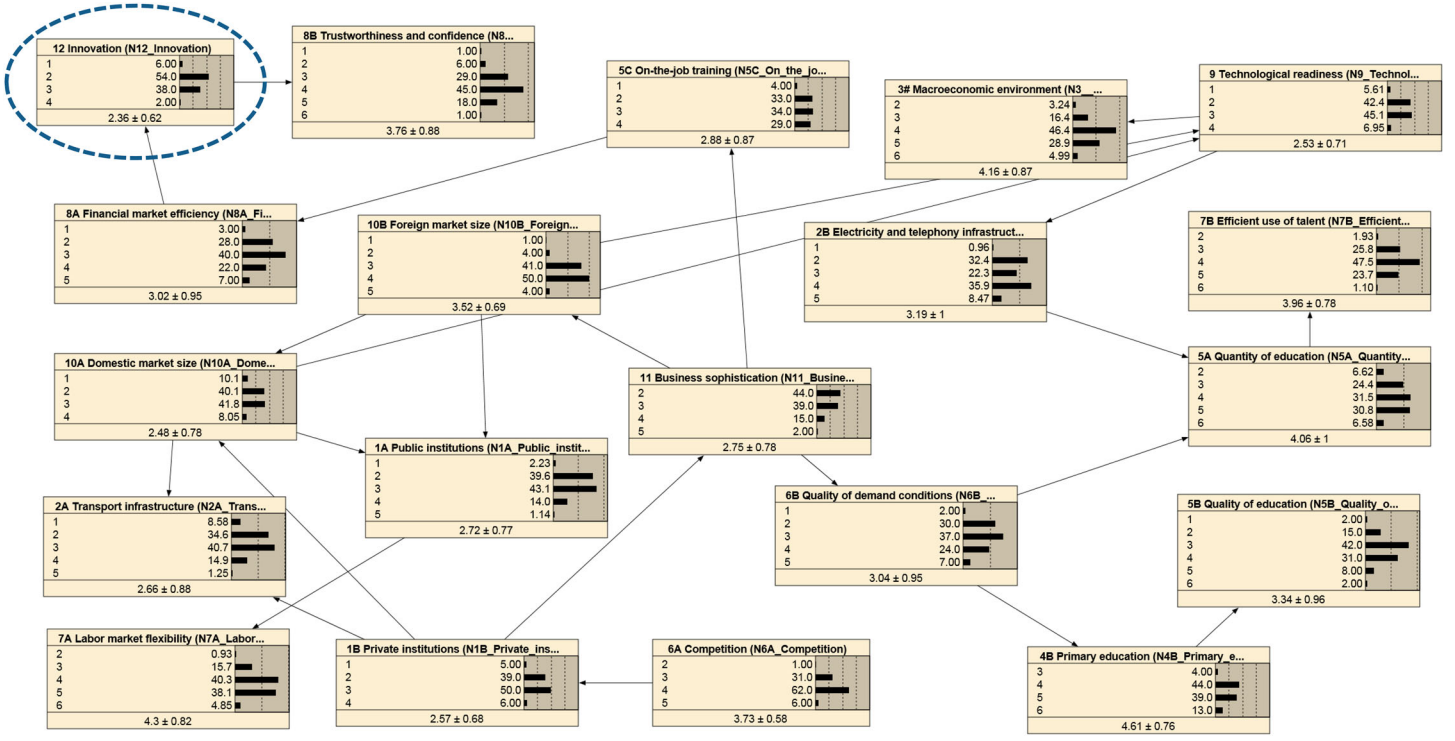


Figure A2. The learned BN for the partition of the dataset Cluster 2.

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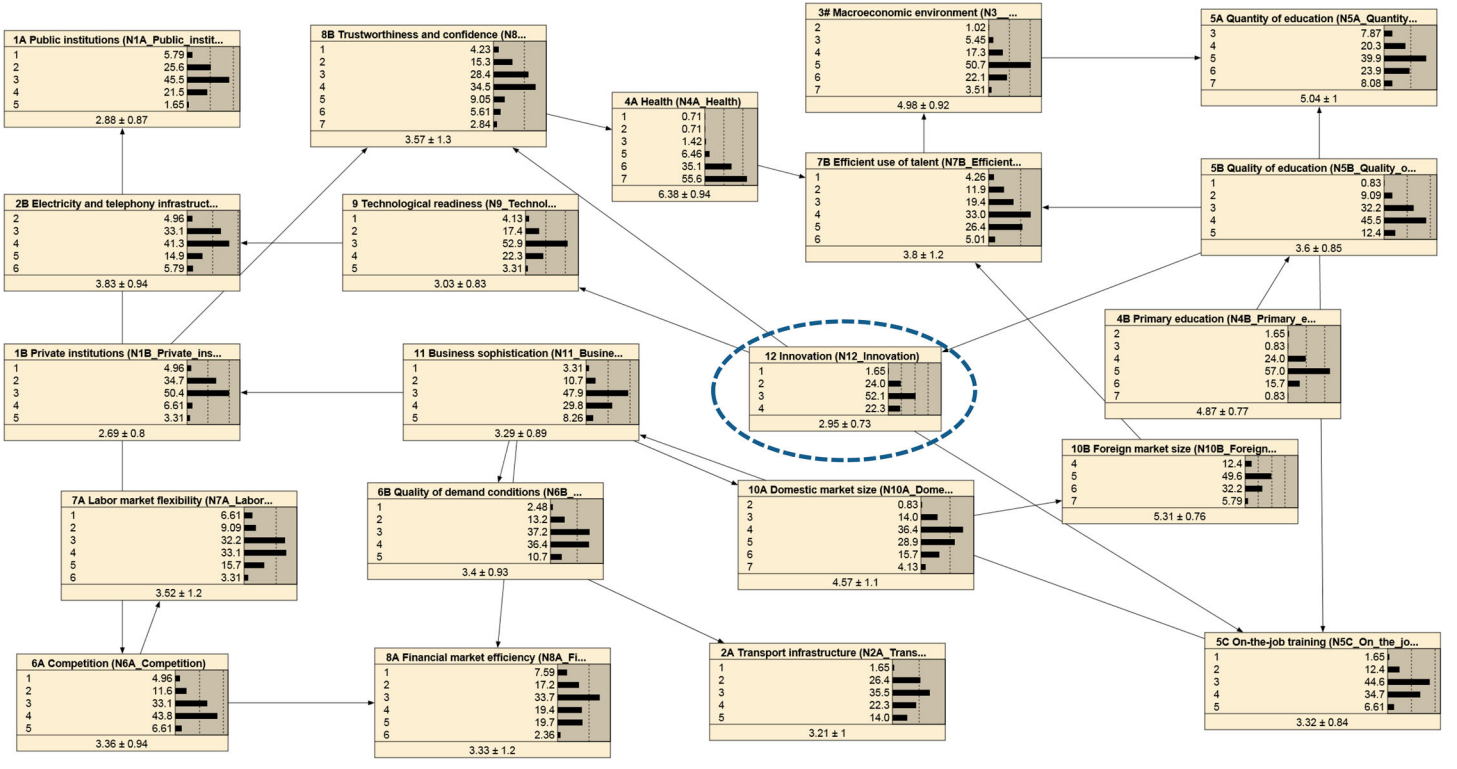


Figure A3. The learned BN for the partition of the dataset Cluster 3.

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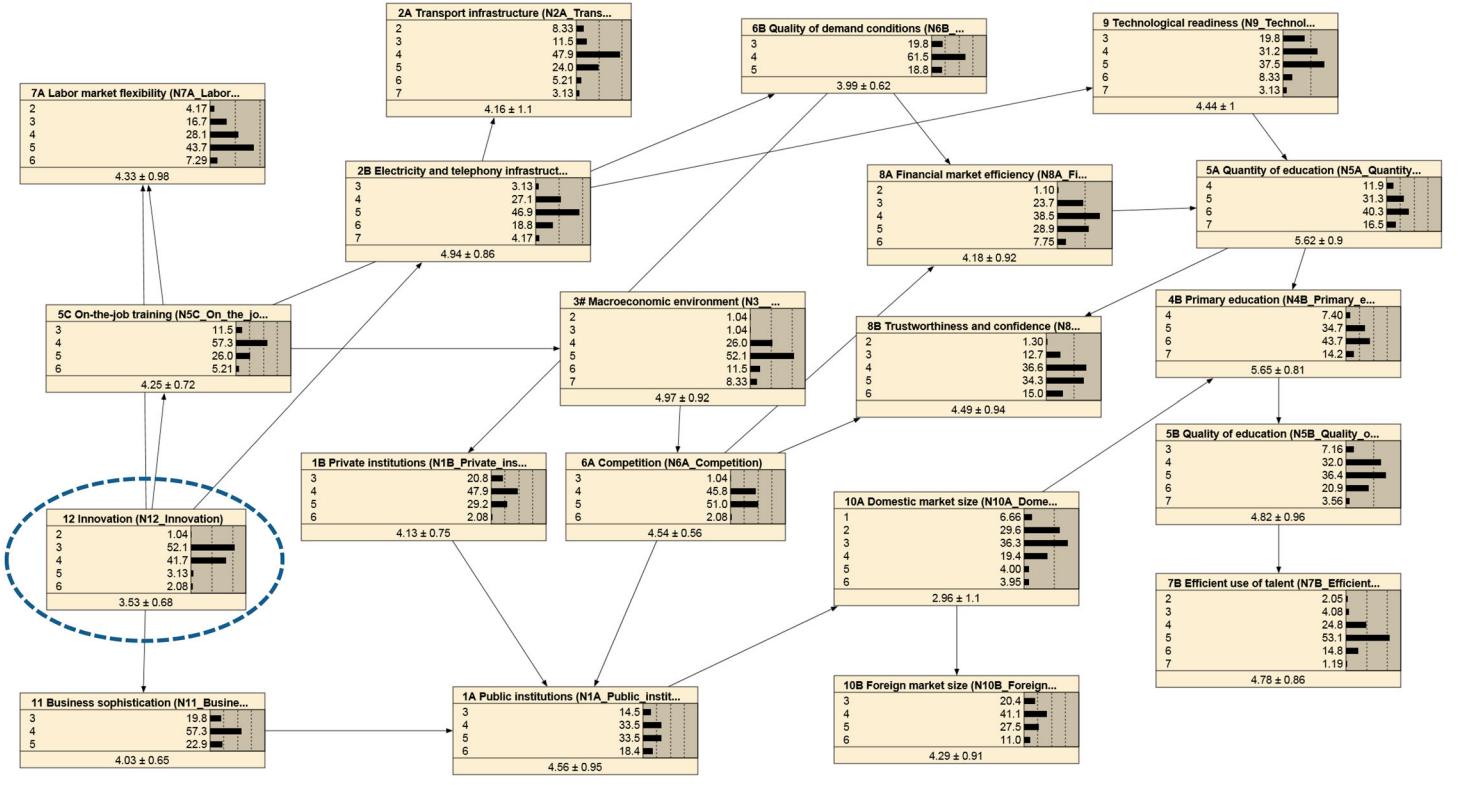


Figure A4. The learned BN for the partition of the dataset Cluster 4.

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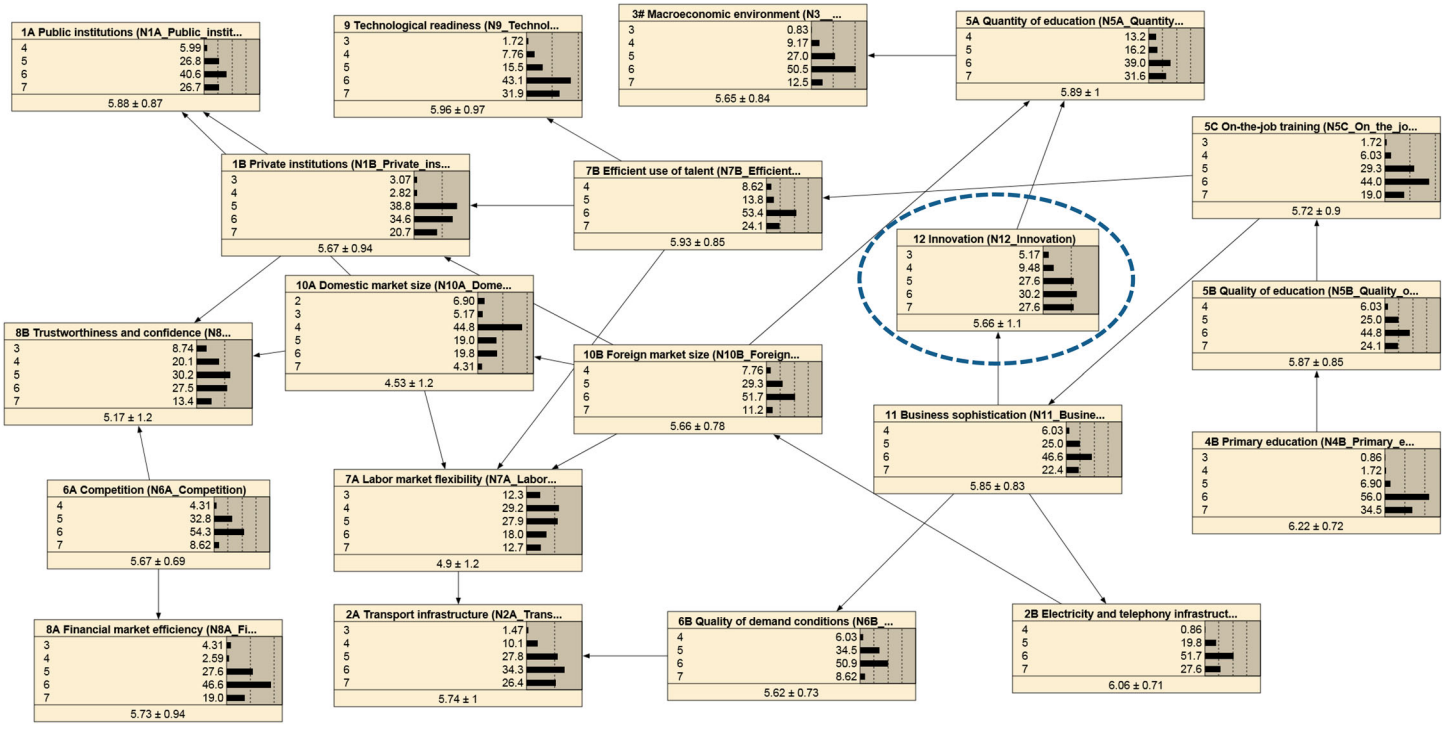


Figure A5. The learned BN for the partition of the dataset Cluster 5.