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APPLICATION OF BAYESIAN NETWORKS TO DETERMINE THE IMPACT OF HIGHER EDUCATION ON ECONOMIC DEVELOPMENT

БАЙЕС ЖЕЛІЛЕРІН ҚОЛДАНУ АРҚЫЛЫ ЭКОНОМИКАЛЫҚ ДАМУҒА ЖОҒАРЫ БІЛІМ БЕРУДІҢ ӘСЕРІН АНЫҚТАУ

ПРИМЕНЕНИЕ БАЙЕСОВСКИХ СЕТЕЙ ДЛЯ ОПРЕДЕЛЕНИЯ ВЛИЯНИЯ СОСТОЯНИЯ ВЫСШЕГО ОБРАЗОВАНИЯ НА ЭКОНОМИЧЕСКИЕ РАЗВИТИЕ

Abstract. *In modern society, higher education institutions not only serve as educational and research centers but also exert a certain influence on the economy, politics, and social sphere of their presence region. Therefore, the question of evaluating the functioning of universities in a specific region in the interest of its sustainable development becomes relevant.*

In this article, the authors propose a model for analyzing the influence of factors characterizing the state of the education system on the gross domestic product (GDP) of the country, based on the mathematical apparatus of Bayesian networks. The advantage of using Bayesian networks (BNs) lies in the robustness of these networks to incomplete, inaccurate, and noisy information. BNs are used for forecasting, direct and inverse modeling of complex relationships, and decision-making. The proposed model predicts the GDP based on factors such as funding for higher education, research activity, the number of students, and staff. The constructed Bayesian network allows not only direct forecasting of the GDP level based on factors characterizing the state of higher education but also inverse modeling, that is, determining which parameters need to be changed to achieve a certain level of GDP.

Keywords: *Bayesian Networks, gross domestic product, higher education, economic development of the region, computer modelling.*

Аңдатпа. *Қазіргі қоғамда жоғары оқу орындары білім беру және ғылыми-зерттеу орталықтары ретінде ғана емес, сонымен аймақтың экономикасына, саясатына, әлеуметтік саласына белгілі бір әсер етеді. Сондықтан, аймақтардағы университеттердің жергілікті ортаның тұрақты дамуы үшін жұмыс істеуін бағалау мәселесі өзекті болып отыр.*

Мақалада авторлар Байес желілерінің математикалық аппаратына негізделген білім беру жүйесінің күйін сипаттайтын факторлардың елдің жалпы ішкі өніміне (ЖІӨ) әсерін талдау моделін ұсынды. Байес желілерін (БЖ) пайдаланудың артықшылығы – олардың толық емес, дәл емес, шулы ақпарат жағдайыны төзімділігі. БЖ күрделі қатынастарды болжау, тікелей және кері модельдеу және шешім қабылдау үшін қолданылады. Ұсынылған модель жоғары білім беруді қаржыландыру, ғылыми-зерттеу қызметі, білім алушылар мен қызметкерлер саны сияқты *факторларға байланысты ЖІӨ мөлшерін болжайды. Құрастырылғаг Байес желісі ЖІӨ деңгейінің жоғары білім беру жағдайын сипаттайтын факторларға тәуелділігін тікелей болжауға ғана емес, сонымен қатар кері модельдеуге, яғни ЖІӨ-нің Белгілі бір деңгейіне жету үшін қандай параметрлерді өзгерту керектігін болжауға көмектеседі.*

Түйін сөздер: *Байес желілері, жалпы ішкі өнім, жоғары білім, аймақтың экономикалық дамуы, компьютерлік модельдеу*

Аннотация. *В современном обществе высшие учебные заведения не только выступают в качестве образовательных и научно-исследовательских центров, но и оказывают определенное влияние на экономику, политику, социальную сферу региона своего присутствия. В связи с этим актуальным становится вопрос оценки функционирования университетов определенного региона в интересах его устойчивого развития.*

В статье авторами предложена модель анализа влияния факторов, характеризующих состояние системы образования, на валовой внутренний продукт (ВВП) страны, основанная на математическом аппарате байесовских сетей. Преимущество использования байесовских сетей (БС) заключается в их устойчивости к неполной, неточной, зашумленной информации. БС используются для прогнозирования, прямого и обратного моделирования сложных взаимосвязей и принятии решений. Предложенная модель прогнозирует величину ВВП в зависимости от таких факторов, как финансирование высшего образования, научно-исследовательская деятельность, численность обучающихся и сотрудников. Построенная байесовская сеть позволяет проводить не только прямое прогнозирования зависимости уровня ВВП от факторов, характеризующих состояние высшего образования, но обратное моделирование, то есть какие параметры нужно изменить для достижения определенного уровня ВВП.

Ключевые слова: *Байесовские сети, валовый внутренний продукт, высшее образование, экономическое развитие региона, компьютерное моделирование.*

Introduction. Education has long been recognized as a crucial factor in economic development and dynamics. Higher education is widely regarded as a driving force behind growth and development in knowledge societies, as it contributes to stimulating research, knowledge, and economic growth.

An analysis of international and Kazakhstani publications dedicated to studying the relationship between education and the pace of economic growth has enabled the identification of the most interesting concepts and models.

It is necessary to note that most studies on the impact of higher education indicators on economic growth are based on the following approaches:

– traditional economic-based approach;

– skill-based approach;

– assessment of the university's contribution as a facilitator of regional innovation activity.

In addition, the above approaches are used to assess the contribution of higher education to various areas of the country's social life, such as economics, science and innovation, and human capital.

In (Valero & Reenen, 2019), based on the analysis of 15,000 universities from 1,500 regions, it is shown that universities have a positive impact on geographically proximate neighboring regions. The relationship between GDP per capita and universities is determined not only by the direct expenditures of the university, its staff, and students. In part, the impact of universities on economic growth is mediated by the increase in the supply of human capital and the growth of innovation.

The impact of education on economic growth in ASEAN-5 countries is evaluated in (Paravee & Woraphon, 2021) using various education indicators, including government spending on higher education per student, the level of coverage of primary, secondary, and higher education, the educated workforce, and a new indicator of unemployment rate with higher education. In this study, nonlinear regression models are being created – time series regression and panel regression – to study the impact of education breakpoints on the economic growth of individual countries and the ASEAN-5 region, respectively.

In the study by Kazakhstani scientists (Ashimova et al., 2021), an analysis of the competitiveness of the economies of several countries and the impact of innovation activity on this indicator is presented. The authors of the study examined the following parameters for 43 countries: the science intensity of GDP, the number of scientists per million people, education spending as a percentage of GDP, the number of national patent applications, high-tech exports as a percentage of industrial exports, and ICT exports as a percentage of total exports.

According to recent research, educational services have become the most in-demand commodity, which means that education directly affects the formation of GDP, as it affects the quality of human capital and, as a result, the amount of income received from it. In general, education can be considered one of the main factors of economic growth and technological progress (Lehikoinen et al., 2019).

After studying the relationships between various factors influencing economic growth within the education system, key indicators selected for analysis include: funding for higher education, research activity, the number of students, and employees.

Currently, econometric methods are widely used to analyze the relationship between education factors and economic growth rates. However, traditional methods cannot handle large volumes of data, which are often unstructured and stored in various data sources. To successfully solve such tasks, it is necessary to use machine learning methods, neural networks, and other artificial intelligence methods.

In this study, the authors propose to use Bayesian networks to identify dependencies between GDP dynamics and factors such as research activity, the number of employees engaged in higher education, the number of students in higher education universities, education expenditures, and the number of organizations conducting scientific research. The advantage of using Bayesian networks lies in their resilience to incomplete, inaccurate, and noisy information, as even in such cases, the obtained result will reflect the most probable outcome of events.

BNs are a powerful tool for modeling probabilistic dependencies between variables and making decisions based on these dependencies. The probabilistic models used in Bayesian networks allow for uncertainty and working with limited knowledge. Such models play a key role in the development and application of artificial intelligence (AI), where uncertainties and causal relationships are common features of the problems under study (Litvinenko et al., 2020; Caprio et al., 2023; Shayahmetova et al., 2020).

AI uses BNs in various fields, including medicine, finance, bioinformatics, engineering, and more (Zhang et al., 2022; McLachlan et al., 2020; Shirali et al., 2022; Fedorova, 2022). In healthcare, BNs are used in disease forecasting, modeling complex interrelationships between diseases, providing personalized forecasts and diagnostic recommendations, assessing risk levels, and are utilized in other critical tasks (McLachlan et al., 2020; Kyrimi et al., 2020; Faruqui et al., 2020; Pescador et al., 2024). In finance, BNs play a crucial role in risk management and investment decision-making. Modeling market and economic indicators facilitates forecasting future market trends and investment portfolios, helping investors develop more effective strategies (Faruqui et al., 2020; Al-Azzawi et al., 2023; Bai et al., 2020; Zheng, 2024). In the industrial sector, BNs are used for preventive maintenance and optimization of production processes. By modeling equipment sensor data and production parameters, they enable early detection of equipment failure risks, thereby enhancing production efficiency (Shirali et al., 2022; Fedorova, 2022; Voronenko et al., 2020; Ebrahimi et al., 2024; Agnel et al., 2021; Shirali et al., 2022). In education, BNs are used in personalized learning, adaptive system development, academic performance forecasting, educational data analysis, and decision support for students and teachers, contributing to a more efficient and high-quality educational process (Chanthiran et al., 2022; Wang et al., 2024; Lytvynenko et al., 2019).

The aim of this article is to investigate the applicability of Bayesian networks in determining the relationship between indicators of higher education systems and the level of gross domestic product.

Materials and methods of research. The main stages of Bayesian network (BN) development are presented in Figure 1.

This section outlines the fundamental steps involved in constructing a Bayesian network (BN) for analyzing the relationship between education system indicators and GDP.

Data preparation: Defining the variables that are included in the model. These variables may include factors deemed significant for analysis or variables that could potentially impact the input data. In this study, the main factors are research activity, the number of education employees, the number of students in educational institutions, education expenditure, and the number of research institutions.

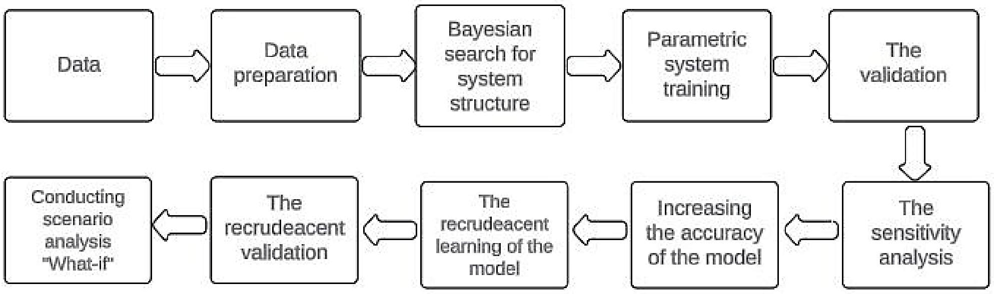

Figure 1. Generalized algorithm for developing a Bayesian network

Note – compiled by the authors on the basis of (Litvinenko N.G., 2020)

Building a network structure: Identifying relationships between variables and determining probabilities for each variable depending on its parents in the network. At this stage, it is determined which variables depend on others and which may be independent. This can be based on expert knowledge, statistical methods, or a combination of both. In this study, a conceptual model was built based on expert opinion and statistical data over a 10-year period.

Model training: At this stage, the network parameters are determined, allowing for refining the probabilities in the network and better matching real data.

Testing and evaluation: After building the model, it is necessary to conduct testing to ensure its effectiveness. This may include evaluating the model's quality on separate data sets, as well as testing its ability to predict new data.

Interpretation of results: Finally, the results of the model can be analyzed and interpreted to understand the influence of variables on the input data and identify possible ways to improve the model.

BN is a probabilistic graphical model, or a directed acyclic graph, whose nodes represent variables, such as random variables, and have multiple states. The directed edges of the graph indicate the direct dependence relationship of one variable on another. Each edge corresponds to a table of conditional probabilities of transitioning from states of the upper-level node to the state of the lower-level node. For the upper-level nodes, unconditional probabilities obtained from observations are specified. Formally, a BN network can be represented as follows:

$$BNN = < U, T >, \tag{1}$$

where: $U=\{H_1,\dots,H_n\}$ is a finite ordered set of random variables such that for each $H_i \in U,\ i=\overline{1,n}$ satisfies the condition:

$$\exists\ \Pi_i \subseteq \{H_1,\ \dots,\ H_{i-1}\} \mid P(H_i \mid H_1,\ \dots,\ H_{i-1}) = P(H_i \mid \Pi_i)\ , \tag{2}$$

This condition defines the direction of the links between the nodes in the network, implementing the property of conditional independence of variables. Each variable takes amount from the ending set of values, i.e. $H_i=\{h_{i1},\ \dots,\ h_{ir_i}\}$, where $\sum_{j=1}^{r_i} P(h_{ij})=1$. $T=\{P(H_1 \mid \Pi_1),\ \dots,\ P(H_n \mid \Pi_n)\}$ is the set of dependent probability tables for each child variable H_i with parent variables Π_i. If the variable H_i has no parents, then unconditional probabilities $P(H_i)$ are used.

The foundation of the mathematical framework of Bayesian networks is the Bayes' theorem (3):

$$P(B \mid A)=\frac{P(A \mid B)\cdot P(B)}{P(A)}\ , \tag{3}$$

where:

$$P(A)=\sum_B P(A \mid B)\cdot P(B)\ . \tag{4}$$

Here, the sum is taken over all possible hypotheses *B*. It should be emphasized that all possible theories form a system of mutually exclusive events, i.e., $\sum_B P(B)=1$. The left-hand side of equation (3) $P(B \mid A)$ introduces the updated amount of the subjective probability of hypothesis *B*'s truth, obtained under observation *A*. This probability is called the posterior probability that hypothesis *B* is true [19,20]. The formula of total probability (4), the rule of generalized summation, and the chain rule. The first two have been discussed earlier. The power of generalized summary, or the sum rule, is called the equality:

$$P(A)=\sum_B P(A,B) \tag{5}$$

In the expression’s right-hand side (5), the factor *P(B)* represents the degree of our initial confidence that event *B,* which in this case is convenient to call a hypothesis, takes place. This probability is often referred to as the prior probability of the hypothesis *B* being true. $P(A \mid B)$ is the probability of obtaining observation *A*, given that hypothesis *B* is true [21,22]. The denominator *P(A)* can be considered as a normalizing term since the likelihood of observation *A* can be found applying the equality:

$$P(A)=\sum_B P(A \mid B)\cdot P(B) \tag{6}$$

The formula of total probability (7), the rule of generalized summation, and the chain rule. The power of generalized overview, or the sum rule, is called the equality:

$$P(A)=\sum_B P(A,B), \tag{7}$$

The chain rule plays an essential role in constructing Bayesian networks as a means of identifying the conditional independence of variables that determine the network structure.

$$P(H_1,\dots,H_n)=\prod_{i=1}^{n} P(H_i \mid H_1,\dots,H_{i-1})\ , \tag{8}$$

where $H_1, \ldots, H_n \in U$ is a finite set of variables corresponding to nodes of a BN.

Results. The relationship between the indicators is shown in the figure 2:

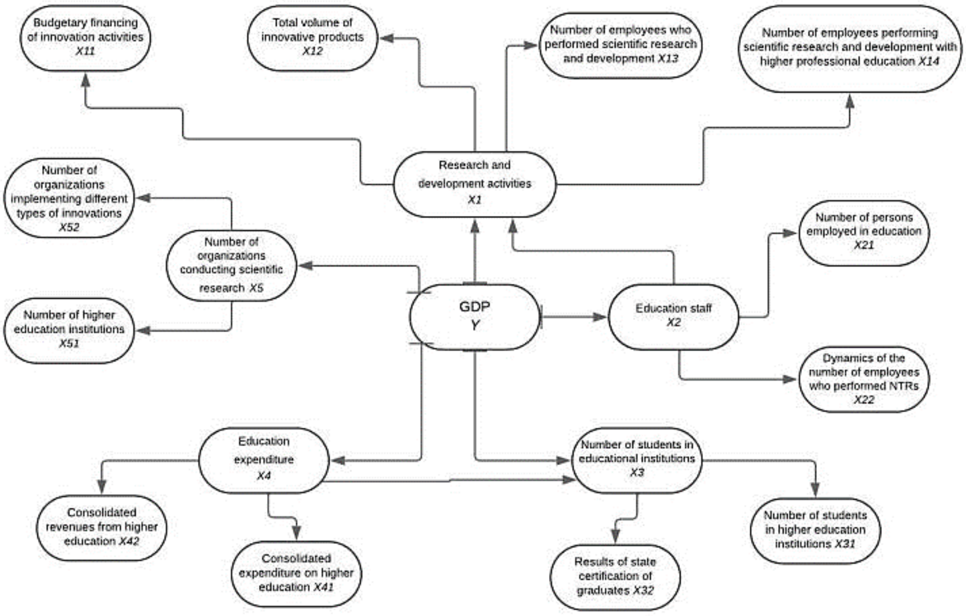

Figure 2. Conceptual model

Note – compiled by the authors

The presented model is based on expert knowledge and implemented in this work using GeNie 4.1 academic.

The original dataset for the study includes data on 18 indicators for the period from 2013 to 2022. Table 1 lists the indicators characterizing the state of higher education.

Table 1. Source Data

Indicator, unit of measurement.	Years									
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
X11, mln.tg	431 993,8	655 361,0	655 361,0	1 528 645,9	899 681,8	856 449,5	535 918,1	777 173,5	785 705,0	1 453 339,1
X12, mln.tg	578263	580386	377196,7	445775,7	844734,9	1064067,4	1113566,5	1715500,1	1438708,5	1879123,1
X13, person.	23 712	25 793	24 735	22 985	22 081	22 378	21 843	22 665	21 617	22 456
X14, person.	20 658	22 779	21 889	20 447	19 896	20 272	19 818	20 778	19 761	20 578
X21, unit.	41 635	40 320	38 087	38 241	38 212	38 275	38 470	36 307	36 378	36 404
X22, unit.	19 802	19 802	19 204	19 259	18 589	18 472	18 867	17 545	17 313	17 115
X31, person.	477 387	477 387	459 369	477 074	496 209	542 458	604 345	576 557	575 511	578 237
X32, person.	175 446	175 446	145 443	138 007	126 263	129 085	142 762	140 655	151 091	161 524
X41, mln.tg	250262159	281075710	291967572	15 043 245	322201246	379688945	421733204	428859784	532455069	640309147
X42, mln.tg	272851236	290460037	310740847	14987971	319010855	346934693	391410328	416744256	499890104	598983099
X51, unit.	128	126	127	125	122	124	125	125	122	116

X52, unit.	1 774	1 303	2 585	2 879	2 974	3 230	3 206	3 236	2 960	3 390
Y, mln.tg	35999025,1	39675832,9	40884133,6	46971150	54378857,8	61819536,4	69532626,5	70649033,2	83951587,9	103765518

Note – compiled by the authors

The structural model of the Bayesian network, presented in Figure 3, was built taking into account expert assessments from domain specialists based on the conceptual model of the study.

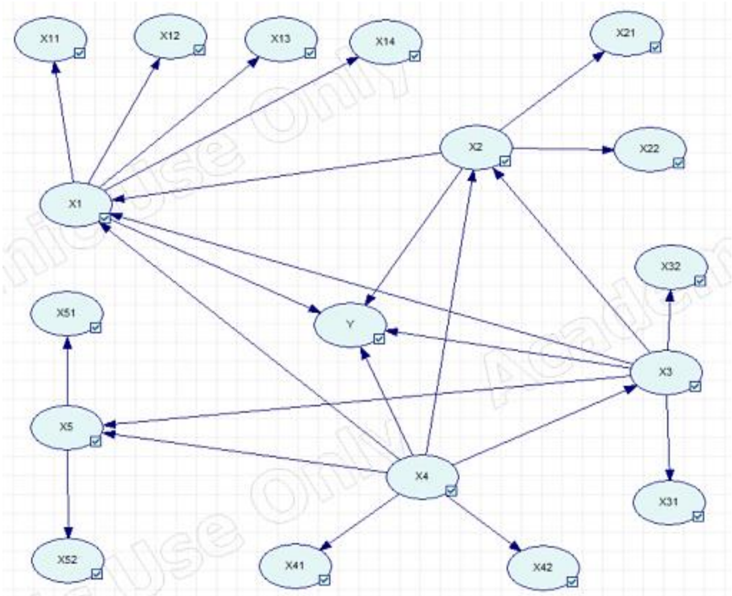

Figure 3. The structural model of the Bayesian network

Note – compiled by the authors

The model contains:

12 nodes of type GENERAL;

5 key nodes of type Noisy-MAX;

1 resulting node of type Noisy-MAX.

Each node has 5 states: from s1 to s5. The initial probabilities of the states are shown in Figure 4:

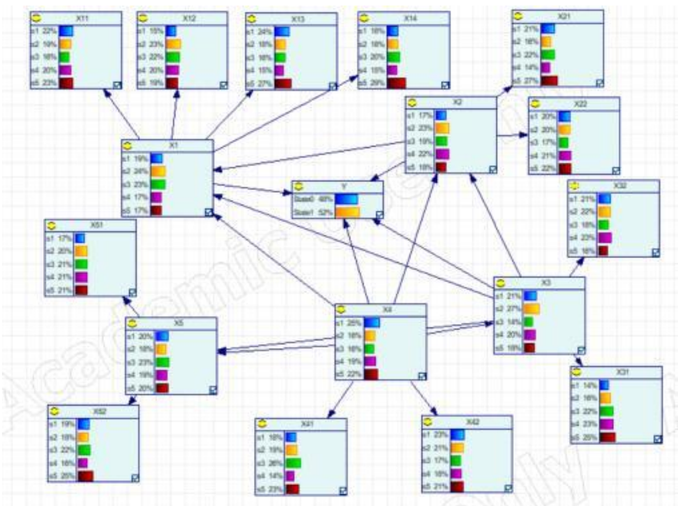

Figure 4. Initial probabilities of states

Note – compiled by the authors

After parameter training and initial network validation, the accuracy of the result was 64.86% (Figure 5). The next steps aim to increase the accuracy and adequacy of the model.

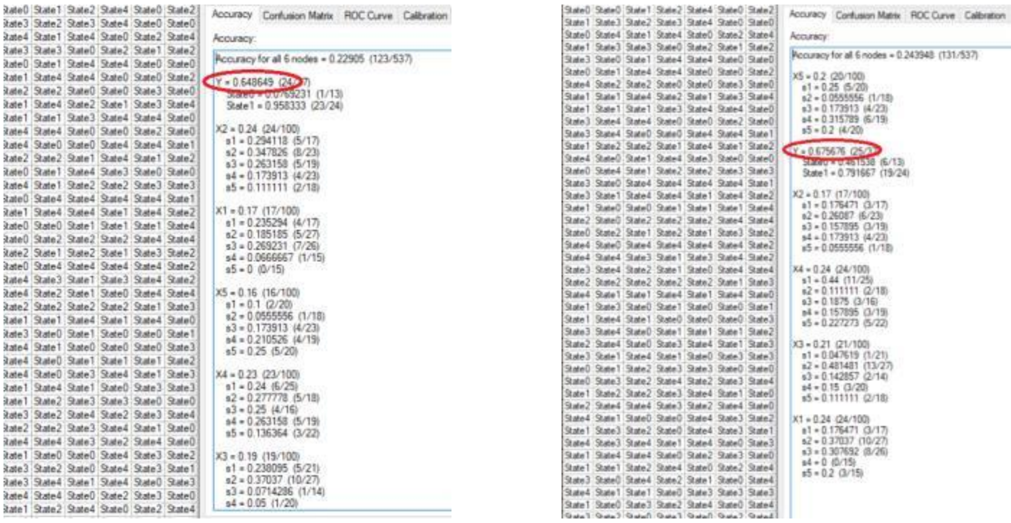

Figure 5. Initial and final accuracy of the resulting node

Note – compiled by the authors

The sensitivity analysis conducted revealed that all nodes are sensitive, indicating that the network responds to changes. Subsequently, aiming to increase the model accuracy, we replaced the key nodes: X1, X2, X3, X4, X5 of type GENERAL with Noisy-MAX. We are re-training the parameters and re-validating them. As a result, the accuracy of the resulting node was increased to 67.56% (Figure 5).

We analyze the relationship between indicators:

If the number of organizations engaged in scientific activities is increased to the maximum possible, the probability of an increase in the number of institutions implementing innovative technologies will increase by 19% (from the initial 25% to 44%), as shown in Figure 6.

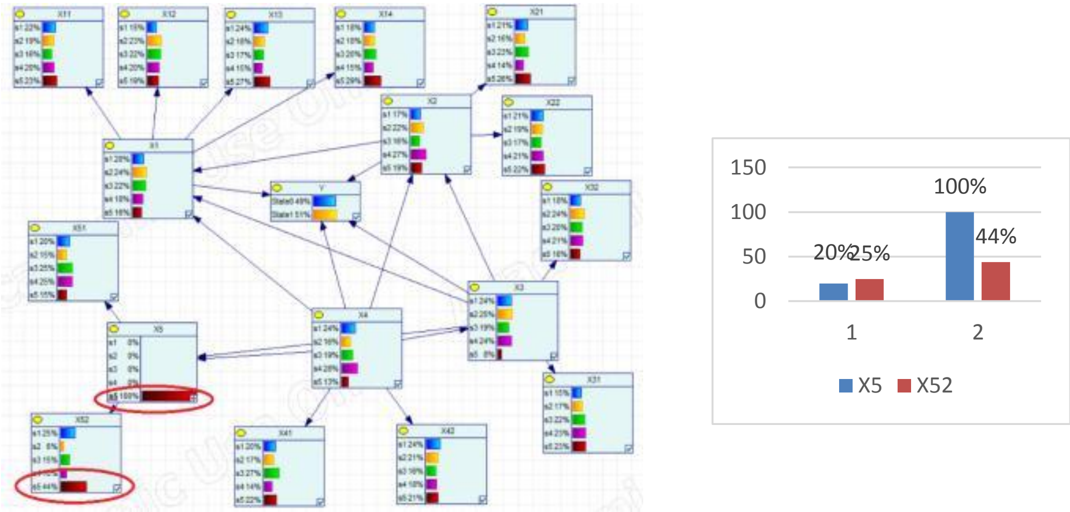

Figure 6. The effect of an increasing the number of organizations engaged in scientific activities

Note – compiled by the authors

Increasing scientific research activity will result in a 7% increase in the overall volume of innovative products (from 19% to 26%), as well as a 6% increase in employees engaged in scientific research (from 27% to 33%), as shown in Figure 7.

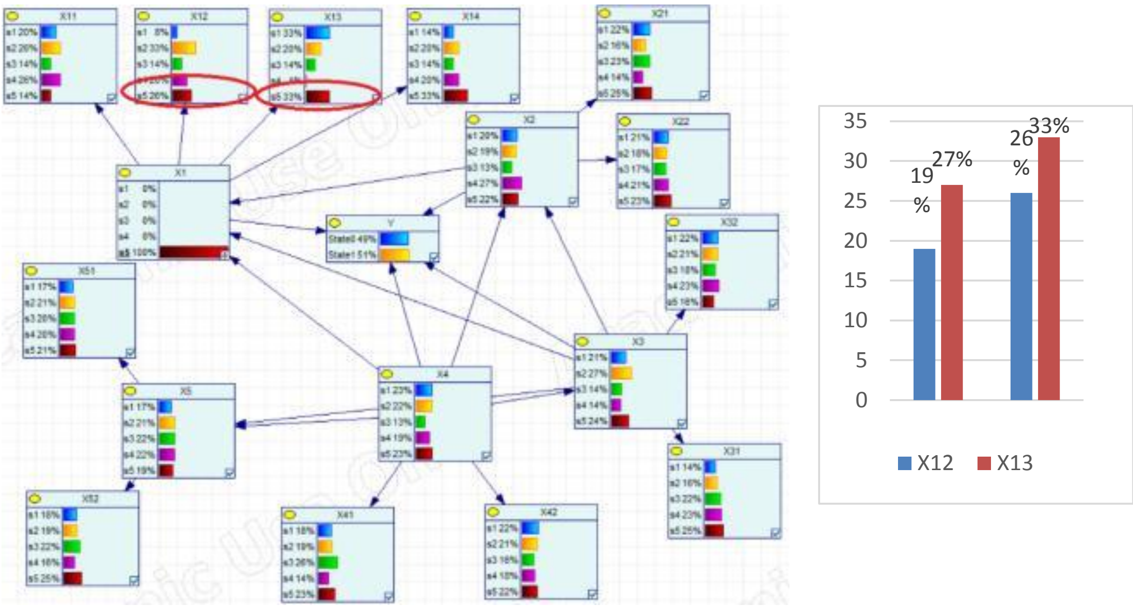

Figure 7. Effect of increasing scientific and technical activity

Note – compiled by the authors

As shown in Figure 8, increasing the number of education sector employees along with the growth in the number of students will lead to a 13% increase in the number of students in universities (from 25% to 38%), as well as a 7% increase in the country's GDP (from 52% to 59%):

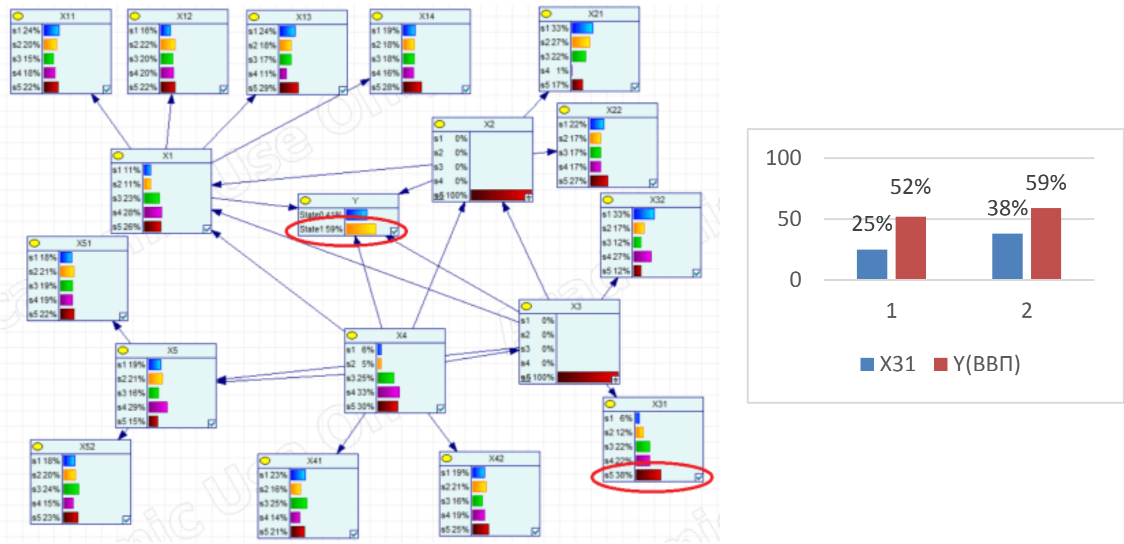

Figure 8. Factors Influencing GDP Growth

Note – compiled by the authors

The examples provided demonstrate that the tested method can be useful in assessing factors potentially influencing the state of indicators.

Conclusions. In conclusion, the findings of this study highlight the significance of Bayesian networks in analyzing indicators of higher education and their impact on economic outcomes. They offer insights into performance metrics, facilitate the integration of expert knowledge with empirical data, measure the impact of the higher education system on economic outcomes, and allow for "what-if" scenario modeling. The constructed Bayesian network enables not only direct forecasting of the GDP level based on factors characterizing the state of higher education but also reverse modeling, determining which parameters need to be altered to achieve a certain GDP level. This approach can play a crucial role in informing policy decisions and strategic planning in the education sector.

Further work aims to utilize the functionality of Bayesian networks with a broader range of indicators to investigate the influence of higher education on the economic development of the country.

Conflict of interest. The authors declare no conflict of interest.

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