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DATA MINING-BASED ASSESSEMENT OF THE RISK OF USING FINANCIAL INTERMEDIARIES FOR MONEY LAUNDERING

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ОЦІНЮВАННЯ РИЗИКУ ВИКОРИСТАННЯ ФІНАНСОВИХ ПОСЕРЕДНИКІВ З МЕТОЮ ЛЕГАЛІЗАЦІЇ КРИМІНАЛЬНИХ ДОХОДІВ НА ОСНОВІ ІНТЕЛЕКТУАЛЬНОГО АНАЛІЗУ ДАНИХ

The paper deals with the mathematical economic modeling of the neural network describing the dependence of the risk of using financial intermediaries for money laundering on factors. Implementation of the proposed approach involved a multilayer perceptron (MLP) and a network based on radial basis functions (RBF). The BFGS algorithm was used to build a neural network based on the multilayer perceptron (MLP). The RBFT algorithm was used to construct a neural network based on radial basis functions (RBF). Data mining in the context of identifying key factors of the investigated risk was based on the collinearity study by applying sigma-limited parameterization and correlation analysis of the dependence of both the regressand on each of the regressors, as well as the factors among themselves. It is proposed to use the Statistica software,

the Analysis package, the Advanced Methods tab, the GLM General Linear Models tab for data mining. A data set was generated for 215 countries of the world for 2017 to conduct the study. It was implemented the ranking of the predictors by the degree of their influence on the response: 1) Corruption Perceptions Index; 2) internally displaced persons, new displacement associated with conflict and violence (number of cases) 3) Happy Planet Index; 4) claims on the central government; 5) bank secrecy; 6) Global Terrorism Index; 7) gross domestic product per capita. The constructed models of neural networks are represented by architecture (the number of layers and hidden neurons), performance and error (training, control, test), learning algorithm, as well as error functions, active hidden and active output neurons. The reliability of the presented models is based on the following criteria: the criteria given in the columns "Training Performance", "Control Performance", "Test Performance". The risk of using financial intermediaries for money laundering for the period 2019 - 2023 has been predicted, showing its gradual growth since 2020. It is proved that the predicted risk values of using financial intermediaries for money laundering, regardless of the rather low predicted level for 2019, tend to increase rapidly in the near term.

В статті побудовано економіко-математичні моделі нейронної мережі залежності ризику використання фінансових посередників з метою легалізації коштів, отриманих незаконним шляхом, від факторних ознак. Реалізація запропонованої методики відбувалась у вигляді багатошарового перцептрону MLP та мережі на основі радіальних базисних функцій.

Для побудови нейронної мережі типу багатошарового перцептрону MLP використано алгоритм BFGS. Для побудови нейронної мережі на основі радіальних базисних функцій RBF використано алгоритм RBFT. Інтелектуальний аналіз даних в розрізі виявлення ключових факторів досліджуваного ризику проведений на основі дослідження колінеарності шляхом застосування сигма-обмеженої параметризації та кореляційного аналізу залежності як регресанда від кожного із індикаторів регресорів, так і факторів між собою. Проведене ранжування факторів за ступенем їх впливу на відгук: 1) індекс сприйняття корупції; 2) внутрішньо переміщені особи, нові переміщення, пов'язані з конфліктом та насильством (кількість випадків); 3) світовий індекс щастя; 4) позови до центрального уряду; 5) банківська таємниця; 6) глобальний індекс тероризму; 7) валовий внутрішній продукт на душу населення.

Побудовані моделі нейронних мереж представлені архітектурою (кількістю шарів та прихованих нейронів), продуктивністю та помилкою (навчальною, контрольною, тестовою), алгоритмом навчання, а також функціями помилки, активних прихованих та активних вихідних нейронів. Достовірність представлених моделей доведена на основі критеріїв: «Продуктивність навчання», «Контрольна продуктивність», «Тестова продуктивність». Проведено прогнозування ризику використання фінансових посередників з метою легалізації кримінальних доходів на період 2019 – 2023 рр., яка засвідчило його поступове зростання починаючи з 2020 р. Доведено, що прогнозні значення ризику використання фінансових посередників з метою легалізації кримінальних доходів, незалежно від досить низького прогнозного рівня 2019 року, мають тенденцію до стрімкого зростання в найближчій перспективі.

Keywords: *money laundering risk; neural network; multilayer perceptron; network based on radial basis functions; prediction.*

Ключові слова: *ризик легалізації кримінальних доходів; нейронна мережа; багатошаровий перцептрон; мережа на основі радіальних базисних функцій; прогнозування.*

Statement of the problem in general terms and its relationship with important scientific and practical tasks. In the modern economic world, which is characterized by the rapid development of the global financial system and the rapid growth of information technologies for the implementation of financial transactions, the problems of global shadowing of economic processes, as well as money laundering, are becoming more acute. The solution to this problem requires the introduction of an effective system for assessing the risk of using financial intermediaries for money laundering. Data mining is of particular importance among modern developments against money laundering.

Such innovations include neural networks that are adapted to the study of the complex dependencies inherent in modern financial transactions in the context of information constraints. Consequently, the solution to the problem of assessing the risk of using financial intermediaries for money laundering with new, non-standard methods of analysis and modeling of economic processes is becoming more relevant.

Analysis of recent studies and publications, which initiated the search for the solution to this problem and on which the author relies, highlighting previously unresolved parts of the general problem, which are discussed in this paper. Scientists V. Bilous [17], S. Hurzhii, A. Kopylenko, Ya. Yanushevych [18], R. Marchuk, A. Popov, V. Onisiev [19], V. Zakharov [22] and other scientists study the general theoretical, organizational and legal issues of combating money laundering and terrorist financing. Some aspects of the assessment and management of the risk of money laundering and terrorist financing are highlighted in the works of the following scientists: V. Kadnichanska, T. Romas [24], N. Moskalenko, N. Klimchuk [27] and other. Global issues of the analysis of international experience in using a risk-based approach against money laundering in the foreign economic activity are revealed in their studies by N. Vnukova, A. Kolodiziev, I. Chmutova [20], O. Smahlo [30]. The solution to more specialized problems of assessing and managing risks of money laundering with the help of banks is described by A. Berezhnyi [16] S. Dmytrov, A. Merenkova, T. Medvid, O. Vashchenko [21], V. Rysin [28], M. Khudokormova [31], I. Chmutova [32].

Such scientists as H. Setlak [29], M. Mozolevska, A. Stavytskyi [26], D. Ivanov [23], A. Matviichuk [25] work in the area of specific issues on the use of neural networks as a method of prediction in the financial sphere.

Research objective. The purpose of the paper is the mathematical economic modeling of the neural network describing the dependence of the risk of the use of financial intermediaries for money laundering and predicting the possible values of this risk in the short term. Achievement of this goal requires solving a number of tasks: identification of key risk factors; description of architecture, performance, error (training, control, test), learning algorithm, error functions, active hidden and active output neurons of a multilayer perceptron and a network based on radial basis functions; risk prediction; estimation of statistics of predicted values and sensitivity analysis of neural network models.

Statement of basic research materials with full justification for the scientific results. The study of the risk of using financial intermediaries for money laundering involved the selection of the most relevant indicators and formation of a certain sequence of its calculation. Thus, we will consider the steps of the proposed scientific and methodological approach in more detail.

Step 1. Formation of the statistical base of the study. A data set was generated for 215 countries of the world for 2017 to conduct the study. These figures represent statistical information that has been obtained from official websites of the world organizations. Thus, the authors selected 1 regressand – the level of risk of using financial intermediaries for money laundering from the results of previous studies [33] and 7 regressors: from the official website of the World Bank - gross domestic product per capita (GDP); claims on the central government; internally displaced persons, new displacement associated with conflict and violence (number of cases) [3]; based on the data from the Organization for Economic Cooperation and Development – banking secrecy [4]; from the website of Transparency International – Corruption Perceptions Index [5]; from research materials of the Institute of Economics and Peace – Global Terrorism Index [6]; according to Happy Planet Index [7].

The rationale for the inclusion of the specified set of indicators is the results of collinearity studies by applying sigma-limited parameterization (Figure 1) and correlation analysis of the dependence of both the regressand on each of the regressors, as well as the factors among themselves (Figure 2). It is proposed to use the Statistica software, the Analysis package, the Advanced Methods tab, the GLM General Linear Models tab for such data mining as identifying key factors.

Effect	Collinearity statistics for members in the equation Sigma-limited parameterization							
	Toleran	Dispersi Infl fac	R square	Risk of mor laundering Beta	Risk of mor laundering Private	Risk of mon laundering Semi-privat	Risk of mor laundering t	Risk of mor laundering p
GDP per capita (current)	0,916	1,092	0,084	-0,033	-0,044	-0,032	-0,432	0,667
Bank Secrece	0,500	2,000	0,500	0,099	0,098	0,070	0,962	0,338
Claims on central gover	0,878	1,138	0,122	-0,151	-0,195	-0,142	-1,944	0,055
Internally displaced per	0,719	1,390	0,281	-0,222	-0,255	-0,188	-2,579	0,011
Corruption Perceptions	0,399	2,506	0,601	-0,588	-0,461	-0,371	-5,092	0,000
Global Terrorism Index	0,722	1,385	0,278	0,087	0,103	0,074	1,014	0,313
Happy Planet Index	0,450	2,220	0,550	-0,186	-0,172	-0,125	-1,713	0,090

Figure 1 - Statistics of collinearity of indicators of the statistical base

An analysis of Figure 1 (beta coefficients – the Risk of money laundering graph) indicates the feasibility of ranking the predictors by the degree of their influence on the response as follows: 1) Corruption Perceptions Index; 2) internally displaced persons, new displacement associated with conflict and violence (number of cases) 3) Happy Planet Index; 4) claims on the central government; 5) bank secrecy; 6) Global Terrorism Index; 7) gross domestic product per capita; but only the first two have a strong influence, while the others have a moderate one.

In addition, the partial correlation coefficients (Risk of money laundering graph in Figure 1) show the degree of influence of one predictor on the response, assuming that other predictors are fixed at a constant level. The calculated

values of this indicator confirm the above conclusion that there is a significant influence of only the Corruption Perceptions Index and the indicator of internally displaced persons, new displacement associated with conflict and violence (number of cases) on the risk of using financial intermediaries for money laundering, as well as moderate influence of other indicators.

In terms of the analysis of the determination coefficient (column R in Figure 1), i.e. the square of the coefficient of multiple correlations between this variable and others variables, we note the moderation of all indicators, but the relationship between the three predictors (bank secrecy, Corruption Perceptions Index, Happy Planet Index) and all others is much greater than for four unspecified predictors.

Effect	Correlations of vectors in the plan matrix X Corelate. matrix for vectors in the plan X							
	GDP pe capita (curren LCU)	Bank Secrec	Claims or central governme etc. (% GDP)	Internally displaced persons, new displacement associa with conflict and viole (number of cases)	Corrup on Percep ions Index	Global Terrori m Inde	Happy Planet Index	Risk of money laundei ng
GDP per capita (current LCU)	1,000	0,110	-0,117	0,032	-0,090	0,086	-0,014	0,052
Bank Secrece	0,110	1,000	0,291	-0,255	0,611	-0,100	0,583	-0,368
Claims on central government	-0,117	0,291	1,000	-0,113	0,134	-0,008	0,177	-0,206
Internally displaced persons, r	0,032	-0,255	-0,113	1,000	-0,242	0,484	-0,215	-0,006
Corruption Perceptions Index	-0,090	0,611	0,134	-0,242	1,000	-0,259	0,716	-0,646
Global Terrorism Index	0,086	-0,100	-0,008	0,484	-0,259	1,000	-0,200	0,158
Happy Planet Index	-0,014	0,583	0,177	-0,215	0,716	-0,200	1,000	-0,545
Risk of money laundering	0,052	-0,368	-0,206	-0,006	-0,646	0,158	-0,545	1,000

Figure 2 – Correlation matrix of indicators of statistical base of the study

At the same time, studies of the correlation matrix (Figure 1) suggest that there is moderate reverse causality between the level of risk studied and the Corruption Perceptions Index and the Happy Planet Index, as evidenced by the corresponding correlation coefficients of -0.6466 and -0.5454. In addition, there is a weak reverse causality between the effective attribute and factor attribute banking secrecy. In the context of other regressors, namely: gross domestic product per capita (GDP), claims on the central government, internally displaced persons, new displacement associated with conflict and violence (number of cases), Global Terrorism Index, Happy Planet Index, the relationship is not confirmed at 95% significance.

In terms of the analysis of the multicollinearity of regressors, we observe only one case of a high degree of dependence between the Corruption Perceptions Index and the Happy Planet Index since the corresponding correlation coefficient is 0.71. Despite the need to remove one of these factors from the model to mitigate the collinearity problem of the corresponding vectors, we propose leaving both indicators, since, from an economic point of view, both indicators are of considerable interest in terms of the study of the risk of using financial intermediaries for money laundering.

Step 2. Formation of research methodology. Justification of the methods of mathematical formalization of the problem. Risk assessment of financial intermediaries for money laundering using the principles of data mining is proposed to be carried out by building a neural network. It is proposed to present mathematical economic models of the neural network describing the risk of using financial intermediaries for money laundering on factors in the form of a multilayer perceptron and a network based on radial basis functions.

Thus, the mathematical economic model of the neural network of the risk under study takes the following form [2]:

$$f(x) = F \left(\sum_{i_N} w_{i_N/N} x_{i_N} - \theta_{j_N} \right) - \theta_{j_{N-1}} - \dots - \theta_{j_1} \quad (1)$$

$$F \left(\sum_{i_1} w_{i_1/1} x_{i_1} - \theta_{j_1} \right) \quad \text{-- layer 1;}$$

$$\sum_{i_2} w_{i_2/2} F \left(\sum_{i_1} w_{i_1/1} x_{i_1} - \theta_{j_1} \right) - \theta_{j_2} \quad \text{-- layer 2;}$$

$$F \left(\sum_{i_N} w_{i_N/N} \dots \sum_{i_2} w_{i_2/2} F \left(\sum_{i_1} w_{i_1/1} x_{i_1} - \theta_{j_1} \right) - \theta_{j_2} - \dots - \theta_{j_N} \right) \quad \text{-- layer N;}$$

i – input number;

j – the number of the neuron in the layer;

$x_{i,j,1}$ – the i -th input signal of the j -th neuron in layer 1;

$w_{i,j,N}$ – the weighting factor of the i -th input signal of the j -th neuron in layer N ;

$\theta_{j,N}$ – threshold level of j -th neuron in layer N .

In turn, the mathematical economic model of the neural network of the risk of using financial intermediaries for money laundering in the form of a network based on radial basis functions takes the following form [8, 9]:

$$f(x) = \sum_{i=1}^N w_i \varphi(\|x - x_i\|) \quad (2)$$

where - w_i – the weighting coefficient of the i -th input signal;

x_i – centers of radial basis functions.

The Broyden—Fletcher—Goldfarb—Shanno (BFGS) algorithm is used to build a neural network such as the MLP multilayer perceptron. It is one of the most comprehensive quasi-Newton methods that consists in implementing an iterative procedure of numerical optimization to search for a local extremum of a nonlinear function without restrictions. The BFGS algorithm involves the implementation of the following sequence of steps [15]:

- 1) determining the weighting coefficients by random small quantities and the initial approximation value of the inverse Hessian V – a matrix of size $n \times n$, where n is the length of the gradient vector g .
- 2) calculation of the gradient g .
- 3) calculating the correlation of weighting coefficients $\Delta W = g \cdot \tau, W_{k+1} = W_k - \Delta W$, where τ is the parameter of the learning rate.
- 4) defining a new gradient value $g = g(W)$ given the previous value g_p , and calculating the gradient change $\Delta g = g - g_p$.
- 5) calculation of inverse hessian (r gradient change, s weight change):

$$V_{k+1} = V_k - \frac{V_k \cdot s \cdot s^T \cdot V_k}{s^T \cdot V_k \cdot s} + \frac{r \cdot r^T}{s^T \cdot s}, \quad (3)$$

$$r = \Delta g_k = g_k - g_{k-1}$$

$$s = \Delta W_k = W_k - W_{k-1}$$

- 6) calculation of change of weighting coefficients $\Delta W = W \cdot g$ and corresponding adjustment of parameters $W_{k+1} = W_k - \Delta W$.
- 7) determining the value of the error. If the error exceeds the value of the specified accuracy, it is necessary to repeat the algorithm, starting from step 4. Otherwise, the algorithm stops.

The RBFT algorithm is used to construct a neural network based on the radial basis functions (RBF).

It is suggested to use the Statistica software, Analysis package, Neural Network tab, Regression tab to implement this stage. It is feasible to determine weighting coefficients using the least-squares method.

Step 3. Practical testing of design calculations. We will carry out mathematical economic modeling of two types of neural networks (MLP multilayer perceptron and networks based on radial basis functions (RBF)) describing the regression dependence of the risk of using financial intermediaries for money laundering on relevant regressors and will systematize the results in a tabular form (Figure 3).

Model results											
N	Architecture	Productivity, training	Productivity, control	Test. productivity	Learning error	Control error	Test error	Learning algorithm	Error function	Function of active hidden neurons	Function of active output neurons
1	MLP 7-4-1	0,866524	0,76818E	0,809887	0,006050	0,011037	0,01871	BFGS 26	Sums. squares.	Hyperbolic	Hyperbolic
2	MLP 7-7-1	0,78895E	0,840554	0,819724	0,00923E	0,007807	0,01150E	BFGS 13	Sums. squares.	Logistic	Sin
3	MLP 7-6-1	0,86851E	0,732577	0,84199E	0,005977	0,01281E	0,01020E	BFGS 21	Sums. squares.	Logistic	Hyperbolic
4	MLP 7-6-1	0,808654	0,85048E	0,83823E	0,00840E	0,007230	0,01028E	BFGS 13	Sums. squares.	Logistic	Sin
5	MLP 7-4-1	0,84542E	0,72861E	0,81917E	0,00694E	0,01258E	0,01143E	BFGS 12	Sums. squares.	Logistic	Exponential
6	MLP 7-10-1	0,795541	0,795391	0,81381E	0,00889E	0,01009E	0,01142E	BFGS 9	Sums. squares.	Exponential	Identical
7	MLP 7-8-1	0,82827E	0,82610E	0,84880E	0,00764E	0,00829E	0,00922E	BFGS 19	Sums. squares.	Logistic	Hyperbolic
8	RBF 7-20-1	0,827427	0,69191E	0,80893E	0,007637	0,014047	0,012504	RBFT	Sums. squares.	Logistic	Identical
9	RBF 7-20-1	0,855934	0,71694E	0,804731	0,00647E	0,01282E	0,01242E	RBFT	Sums. squares.	Gaussian	Identical
10	MLP 7-9-1	0,79078E	0,83773E	0,84621E	0,00913E	0,007997	0,00975E	BFGS 12	Sums. squares.	Logistic	Identical

Figure 3 – The results of the modeling of neural networks of regression dependence of the risk of using financial intermediaries for money laundering on regressors

The analysis of Figure 3 shows a much larger spectrum of constructed neural networks in the form of MLP multilayer perceptron (80% of models) than networks based on radial basis functions RBF (20% of models). All presented models are characterized by a high level of adequacy as evidenced by the criteria given in the columns “Training Performance”, “Control Performance”, “Test Performance”. At the same time, the performance of MLP models has a much larger range of variation of correlation coefficients – from 0.7890 to 0.8685 (training sample), from 0.7286 to 0.8505 (control sample), from 0.8099 to 0.8448 (test sample) than RBF models – respectively, from 0.8274 to 0.8559 (training sample), from 0.6919 to 0.7169 (control sample), from 0.8047 to 0.8089 (test sample). The reliability of 10 constructed models of neural networks is confirmed by the error indicator within the framework of the training, control and test samples, which takes values close to zero.

To further use the constructed models for predicting the level of risk of using financial intermediaries for money laundering, we will choose two MLP perceptron models and RBF-based networks with better adequacy characteristics, namely: the first model with MLP 7-4- architecture 1 (a total of 7 layers, a number of hidden layers – 4), the third model with MLP 7-6-1 architecture (a total of 7 layers, a number of hidden layers – 6, Figure 4), the eighth model with RBF 7-20-1 architecture (a total of 7 layers, a number of hidden layers – 20), a ninth model RBF 7-20-1 architecture (a total of 7 layers, a the number of hidden layers – 20). The BFGS algorithm is used to build a neural network such as the multilayer perceptron MLP 7-4-1 and MLP 7-6-1, the RBFT algorithm is used, respectively, to build the neural network based on the radial basis functions RBF 7-20-1.

WeightID	Вари	
	Connection 1.MLP 7-6-1	Weight values 1.MLP 7-6-1
1	GDP per capita (current LCU) --> hidden neuron	0,2422
2	Bank Secrece --> hidden neuron	-3,5638
3	Claims on central government, etc. (% GDP) --> hidden neuron	-0,3559
4	Internally displaced persons, new displacement associated with conflict and violence (number of c hidden neuron	0,7627
5	Corruption Perceptions Index --> hidden neuron	-3,3600
6	Global Terrorism Index --> hidden neuron	2,8583
7	Happy Planet Index --> hidden neuron	-1,9071
8	GDP per capita (current LCU) --> hidden neuron	0,0960
9	Bank Secrece --> hidden neuron	-1,7483
10	Claims on central government, etc. (% GDP) --> hidden neuron	0,0107
11	Internally displaced persons, new displacement associated with conflict and violence (number of c hidden neuron	-0,2683
12	Corruption Perceptions Index --> hidden neuron	-3,0323
13	Global Terrorism Index --> hidden neuron	0,8873
14	Happy Planet Index --> hidden neuron	-2,6978
15	GDP per capita (current LCU) --> hidden neuron	0,1488
16	Bank Secrece --> hidden neuron	-1,7353
17	Claims on central government, etc. (% GDP) --> hidden neuron	-0,1046
18	Internally displaced persons, new displacement associated with conflict and violence (number of c hidden neuron	-0,5836

Figure 4 – Fragment of a seven-layer perceptron neural network architecture with 6 hidden layers MLP 7-6-1

A scatter diagram of theoretical (obtained by using four selected constructed neural networks) and the actual value of the risk of using financial intermediaries for money laundering is shown in Figure 5. Based on the visual correlation of neural networks built to predict the risk under study, it is necessary to note the high reliability of the selected model, as evidenced by a dense arrangement of actual values compared to theoretical (predictive ones found using the models).

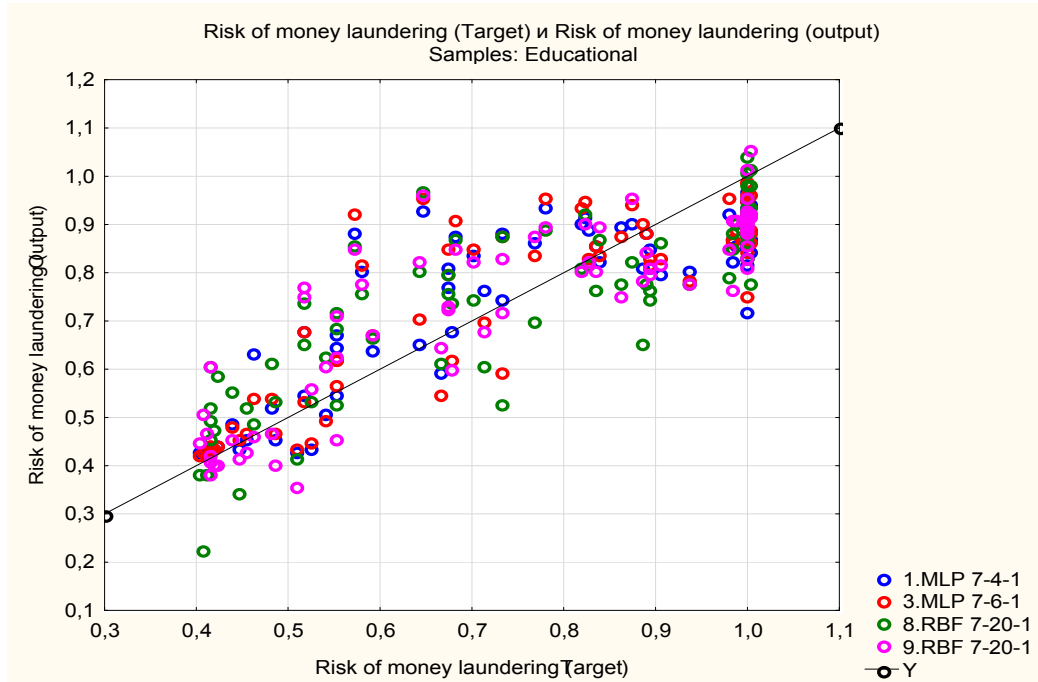


Figure 5 – Ratio of actual and projected levels of risk of using financial intermediaries for money laundering

A deep analysis of input predictors is important for the formalization of the risk of using financial intermediaries for money laundering using a neural network. Thus, we construct the corresponding scatterplots (Figure 6 – Figure 9).

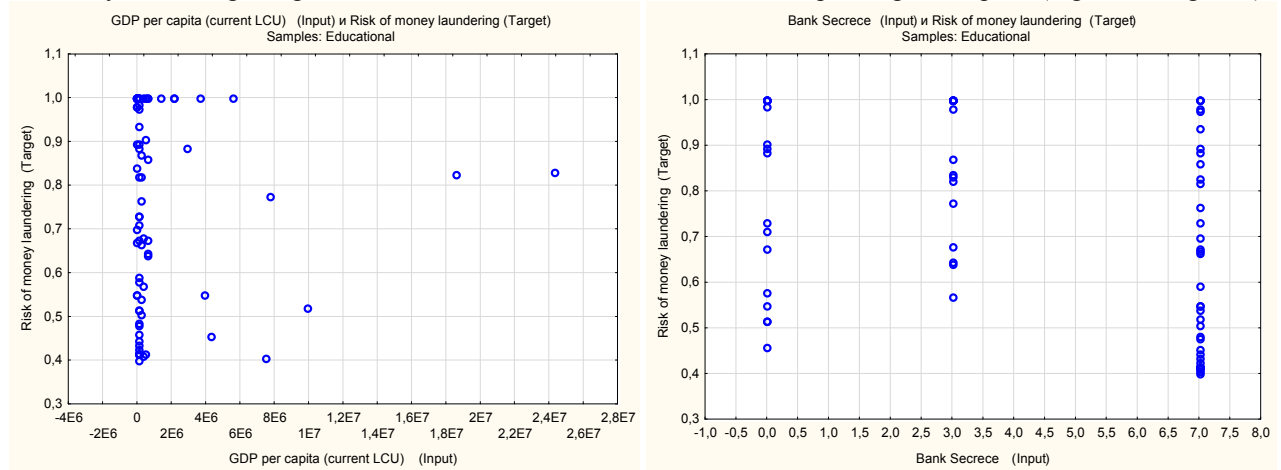


Figure 6 – Scatter diagrams of risk factors for the use of financial intermediaries for money laundering: gross domestic product per capita, bank secrecy

An analysis of the pairwise dependence of the effective attribute on gross domestic product per capita and bank secrecy indicates the following (Figure 6): the absence of a clear dependence of the risk of using financial intermediaries for money laundering on gross domestic product per capita, because despite the absence of a significant variation in the factor attribute, we observe a change in the effective one from 0.4 to 1.0; the value of the bank secrecy indicator is clearly grouped into 3 clusters, with the third cluster being the largest by volume, i.e. the increase of the value of this regressor will lead to the increase in the investigated level of risk.

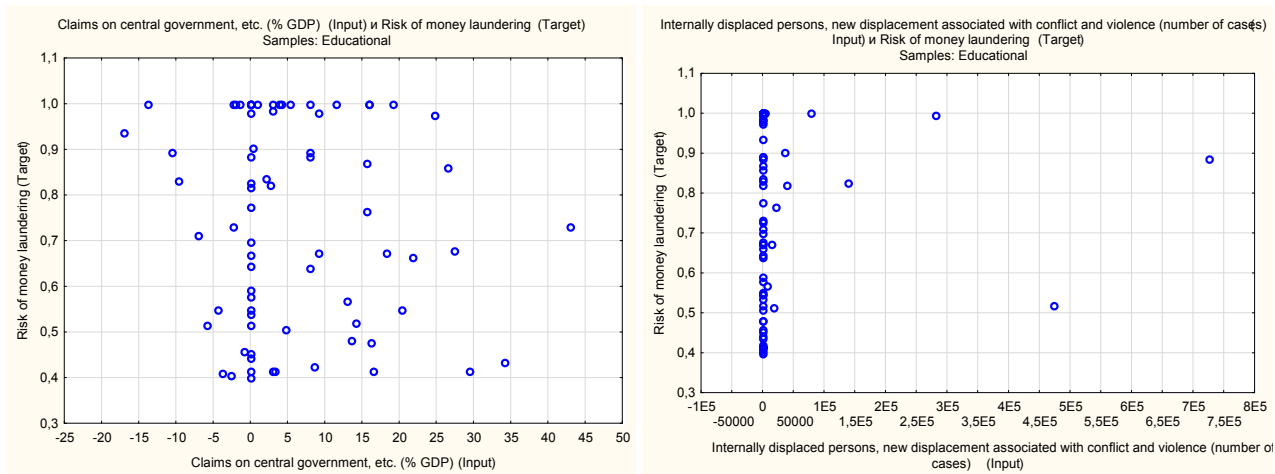


Figure 7 – Scatter diagrams of risk factors for the use of financial intermediaries for money laundering: claims to the central government, internally displaced persons, new displacement associated with conflicts and violence (number of cases)

In terms of the study of the dependence of the risk of using financial intermediaries for money laundering on claims on the central government (Figure 7), we observe a chaotic distribution, i.e. the absence of a clear relationship between the predictors under investigation. In terms of the indicator of internally displaced persons, new displacement associated with conflict and violence (the number of cases), similar to the case of GDP per capita, there is a lack of a clear dependence of the studied risk on this factor, because despite the absence of a significant variation in the factor characteristics, we observe change in the effective attribute from 0.4 to 1.0.

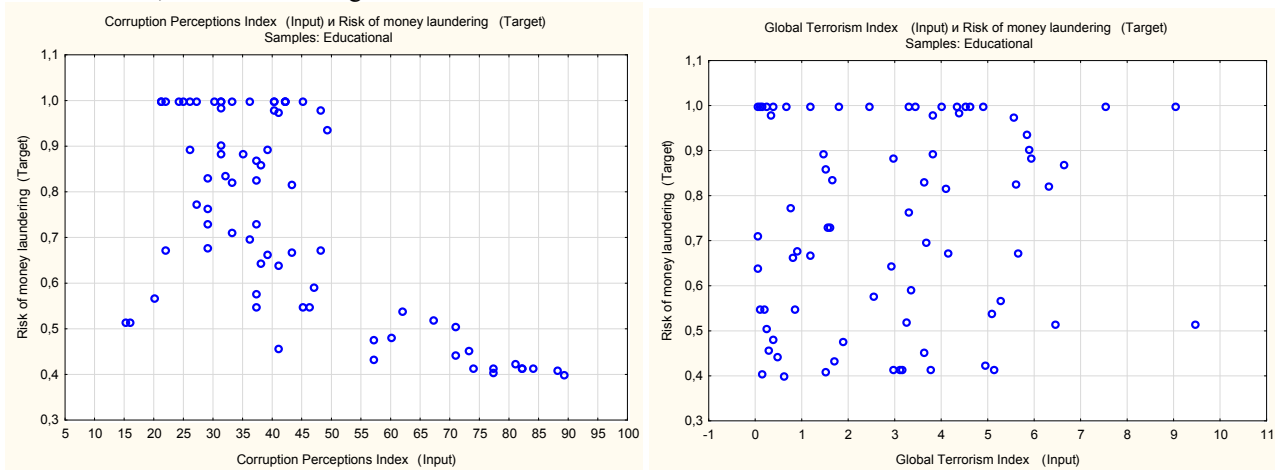


Figure 8 – Scatter diagrams of risk factors for the use of financial intermediaries for money laundering: Corruption Perceptions Index, Global Terrorism Index

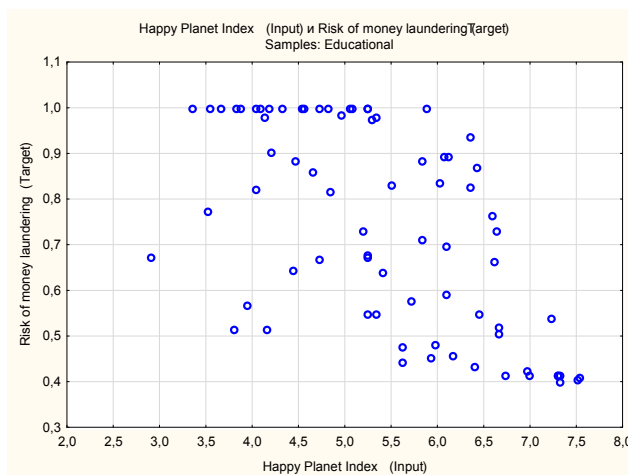


Figure 9 – Scatter diagrams of risk factors for the use of financial intermediaries for money laundering: Happy Planet Index

In terms of the study of the influence of the Corruption Perceptions Index (Figure 8) and the Happy Planet Index (Figure 9) on the risk of using financial intermediaries for money laundering, we observe an average inversely proportional relationship, i.e. an increase in the factor attribute lowers the value of the effective one and vice versa. In the context of the study of the impact of the Global Terrorism Index, we observe a chaotic distribution.

In terms of the last but one of the most important stages of the presented methodology – predicting the level of the risk under study, there is a need for a preliminary detailed analysis of quality of the four neural networks constructed and described above: the multilayer perceptron MLP 7-4-1, MLP 7-6-1, the network based on radial basis functions RBF 7-20-1, RBF 7-20-1. For this purpose, we consider the statistics of the predicted values (Figure 10) and the sensitivity of the models of selected neural networks in terms of input predictors (Figure 11).

Statistics	Statistics of predicted values Target : Risk of money laundering			
	1.MLP 7-4-1	3.MLP 7-6-1	8.RBF 7-20-1	9.RBF 7-20-1
Minimum predicted values. (Educational)	0,43035	0,42597	0,22755	0,36046
Maximum predicted values (Educational)	0,97322	0,99047	1,04531	1,05707
Minimum predicted values. (Control)	0,43214	0,42667	0,37610	0,45000
Maximum predicted values (Control)	0,96293	0,99084	0,92952	0,90805
Minimum predicted values. (Test)	0,42897	0,42666	0,42732	0,33787
Maximum prediction (Test)	0,92754	0,96464	0,96360	0,94910

Figure 10 – Statistics of the predicted values

Networks	Sensitivity Samples: Educational						
	Corruption Perceptions Index	Bank Secrece	Happy Planet Index	Global Terrorism Index	GDP per capita (current LCU)	Internally displaced persons, new displacement associated with conflict and violence (number of cases)	Claims on central government, etc. (% GDP)
1.MLP 7-4-1	2,083688	1,206860	1,499772	1,507157	1,022270	0,999329	1,037536
3.MLP 7-6-1	2,144036	1,459289	1,652610	1,628276	1,028311	1,000281	0,998251
8.RBF 7-20-1	1,712405	1,758827	1,459724	1,395042	0,980984	0,953876	0,913740
9.RBF 7-20-1	2,444216	2,132763	1,583271	1,480569	1,033622	0,971278	0,973889
Average	2,096087	1,639435	1,548844	1,502761	1,016297	0,981191	0,980854

Figure 11 – Sensitivity of the models of selected neural networks in terms of input predictors

An analysis of the statistical characteristics of neural network models shown in Figures 10 and 11 indicates a high quality of the models (insignificant variation of the minimum and maximum levels both in the training, control and test samples) and an insignificant level of sensitivity of the models to the input data scale.

In terms of predicting the risk of using financial intermediaries for money laundering for the period 2019-2023, we will form (based on an expert approach) promising areas for the development of 7 regressors: gross domestic product per capita (GDP), claims on the central government, internally displaced persons, new displacement associated with conflict and violence (number of cases); bank secrecy; Corruption Perceptions Index; Global Terrorism Index; Happy Planet Index presented in Table 1.

Table 1 – Predicted values of the input statistical data of the risk assessment of the use of financial intermediaries for money laundering

Series Name	2017	2018	2019	2020	2021	2022	2023
	70233.0	84190.3	105238	136809	177852	222315	277894
GDP per capita (current LCU)	26%	20%	25%	30%	30%	25%	25%
Bank Secrecy	3	3.0	3	3	3.0	3	3
Claims on central government, etc. (% GDP)	24.2	20.0	19	17	15	13	11
	-12%	-18%	-5%	-10%	-10%	-15%	-15%
Internally displaced persons, new displacement associated with conflict and violence (number of cases)	21000.0	12000.0	9600	8640	8208	7962	7882
	-81%	-43%	-20%	-10%	-5%	-3%	-1%
	30	32	28	22	17	13	10
Corruption Perceptions Index	3%	7%	-13%	-21%	-23%	-24%	-23%
Global Terrorism Index	6.54	6.05	5.5	4.5	3.5	2.5	1.8

	-8%	-7%	-9%	-18%	-22%	-29%	-28%
Happy Planet Index	4.25	4.41	4.65	4.71	5.95	5.11	5.25

Analysis of the predicted values of the risk of using financial intermediaries for money laundering (Figure 12, columns 2 – 5) for the period 2019 -2023 indicates fairly similar values (derived from the use of four neural networks): multilayer perceptron MLP 7- 4-1, MLP 7-6-1, radial basis function networks RBF 7-20-1, RBF 7-20-1. Therefore, it should be pointed out that the predicted risk values of using financial intermediaries for money laundering, regardless of the rather low predicted level for 2019, tend to increase rapidly in the near term.

Observation	User Values Table										
	1.Risk of money laundering _ (t)	3.Risk of money laundering _ (t)	8.Risk of money laundering _ (t)	9.Risk of money laundering _ (t)	GDP per capita (current LCU)	Bank Secre	Claims on central government, etc. (% GDP)	Internally displaced persons, new displacement associated with conflict and violence (number of cases)	Corrupti on Percepti ons Index	Global Terroris m Index	Happy Planet Index
1	0,446689	0,319165	0,604537	,776998	105238,0	3,000000	19,00000	9600,000	28,00000	28,00000	4,650000
2	0,917014	0,961509	0,889420	,901665	105237,8	3,000000	18,98612	9600,000	28,00000	5,50000	4,650000
3	0,918919	0,960774	0,903671	,909302	136809,2	3,000000	17,08751	8640,000	22,00000	4,50000	4,710000
4	0,933354	0,963849	0,910519	,958199	177851,9	3,000000	15,37876	8208,000	17,00000	3,50000	5,950000
5	0,930361	0,965438	0,942622	,918919	222314,9	3,000000	13,07194	7961,760	13,00000	2,50000	5,110000

Figure 12 – Alternative predictive values of the input and output predictors of assessing the risk of using financial intermediaries for money laundering

Conclusions of this study and prospects for further research in this area. Thus, it should be noted that risk assessment of the use of financial intermediaries for money laundering based on neural networks is a very relevant, powerful and flexible tool for ensuring an effective government control system, given the need to process large datasets. This method allows automatically identifying the complex dependencies of economic processes, predicting possible results and using them when making effective decisions in the field of public administration. The introduction of this approach will allow effectively predicting and combating crimes related to money laundering and terrorism financing, will contribute to the positive economic, financial, social, political, cultural development of the country, as well as increase the country's rating in the world.

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