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FORECASTING THE RISK OF MONEY LAUNDERING THROUGH FINANCIAL INTERMEDIARIES

Abstract. The increase in international trade, the active development of integration and convergence processes in the global financial market, the rapid implementation of digital technologies in various spheres of life, as well as the growth of cross-border organized crime have led to increased shadow economic activity and improved forms and methods of money laundering. Under these conditions, it is essential to assess the risk of money laundering adequately through financial institutions and determine its dynamics in the future. The primary purpose of the study is to build a predictive neural network model to define the dynamics of the risk of using banking institutions to legalize criminal funds. The methodological tools of the study were methods of exponential smoothing (using exponential trend, linear Holt model and decaying trend), artificial neural network model (multilayer perceptron MLP-architecture using BFGS algorithm, radial basis function of RBF-architecture usage). Assessment and forecasting of money laundering risk through financial institutions is based on 13 relevant indicators, the source of which is internal financial statements. The object of research is the chosen 20 Ukrainian banks. Investigation of the forecast model in the paper is carried out in the following logical sequence: the forecast values of relevant factors influencing the risk of using financial institution in shadow operations are determined; training of neural networks according to the formed sample of indicators; forecasting the risk of using financial intermediaries of Ukraine for the legalization of criminal proceeds for the period 2020-2025 based on constructed neural networks. The calculations showed that by 2025 only 40% of the analyzed banks in Ukraine would be able to reduce their participation in the legalization of illegally obtained funds. The quality of the constructed forecasts is high, as the efficiency coefficient for most constructed models ranges from 0.9 to 1.0. The results of the study can be useful for the management of financial institutions to take a set of preventive measures in the system of internal financial monitoring, as well as scientists who deal with this issue.

Keywords: risk, money laundering, bank, neural network, financial monitoring, forecast.

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ПРОГНОЗУВАННЯ РИЗИКУ ВИКОРИСТАННЯ ФІНАНСОВИХ ПОСЕРЕДНИКІВ ДЛЯ ЛЕГАЛІЗАЦІЇ КРИМІНАЛЬНИХ ДОХОДІВ

Анотація. Збільшення обсягів міжнародної торгівлі, активний розвиток інтеграційний та конвергентних процесів на світовому фінансовому ринку, стрімке впровадження цифрових технологій у різні сфери життя, а також зростання масштабів транскордонної організованої злочинності призвели до нарощення обсягів тіньової економічної діяльності та удосконалення форм і методів відмивання незаконно отриманих коштів. За цих умов украй важливим є адекватна оцінка ризику легалізації кримінальних коштів за посередництва фінансових установ і визначення його динаміки в майбутньому. Основною метою проведеного дослідження є побудова прогнозної нейромережевої моделі для визначення динаміки ризику використання банківських установ для легалізації кримінальних коштів. Методичним інструментарієм проведеного дослідження стали методи експоненційного згладжування (з використанням експоненційного тренду, лінійної моделі Хольта і затухаючого тренду), моделі штучної нейронної мережі (багатошаровий персептрону MLP-архітектури з використанням алгоритму BFGS, радіальна базисна функція RBF-архітектури з використанням алгоритму RBFT). Об'єктом дослідження обрано 20 банків України. Побудову прогнозної моделі здійснено в такій логічній послідовності: визначено прогнозні значення релевантних факторів впливу на ризик залучення фінансової установи в тіньові операції; навчання нейронних мереж за сформованою вибіркою показників; прогнозування ризику використання фінансових посередників України для легалізації кримінальних доходів

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на період 2020—2025 рр. на основі побудованих нейронних мереж. Проведені розрахунки засвідчили, що до 2025 року лише 40 % аналізованих банків України зможуть зменшити їх участь у легалізації незаконно отриманих коштів. Якість побудованих прогнозів є високою, оскільки коефіцієнт ефективності для більшості побудованих моделей коливається в межах 0,9—1,0. Результати проведеного дослідження можуть бути корисними для менеджменту фінансових установ з метою вжиття комплексу превентивних заходів у системі внутрішнього фінансового моніторингу, а також науковцям, які займаються цією проблематикою.

Ключові слова: ризик, легалізація коштів, банк, нейронна мережа, фінансовий моніторинг, прогноз.

Формул: 2; рис.: 0; табл.: 2; бібл.: 34.

Introduction. The COVID-19 pandemic has given impetus to the even more intensive use of digital technologies by both businesses and the public, allowing a massive and rapid shift to remote work, online administrative services, online payments and the use of electronic payment instruments. These processes have led to the active exchange of personal information between different entities and the accumulation of data on the network, which increases the burden on the security of the infrastructure of financial institutions, as well as increases the risk of unauthorized use of this data for illegal activities. In particular, in May 2020, the FATF (Financial Development Team) based on reports from national financial regulators published a document indicating an increase in transactions with virtual assets to move and conceal illegal funds, fundraising for counterfeit charities, unauthorized use of personal data to obtain medical care, etc.

The primary forms of illegal money laundering activities include the creation of fictitious companies to perform the functions of a conversion centre, phishing, payment card fraud, screening (obtaining data from the magnetic stripe of a bank payment card and password to it), speculative transactions with securities, making «phantom» investments, illegal cryptocurrency transactions, withdrawing funds through sports betting and online casinos, etc. Despite the awareness of possible forms of money laundering and the adoption of the relevant legislation at the national and international levels aimed at combating these shady transactions, every year there is an increase in the amount of money laundering. According to experts, in the post-war period, rapid growth in global money laundering is projected from $ 2.2 billion in 2020 to $ 4.5 billion in 2025 [1]. In this regard, there is a growing demand for improved anti-money laundering solutions, including the use of the latest smart methods for data collection, risk assessment of money laundering and modelling of factors influencing it, which will take preventive measures to minimize the destructive impact of illegal financial transactions on the macroeconomic stability of the country.

Literature review and the problem statement. There is a growing demand for improved anti-money laundering solutions, including the use of the latest smart methods for data collection, risk assessment of money laundering and modelling of factors influencing it, which will take preventive measures to minimize the destructive impact of illegal financial transactions on the macroeconomic stability of the country [2]. On the work of J. Dean [3], on the contrary, the influence of the country's economic development on the level of terrorism and legalization of criminal proceeds is analyzed.

A key role in combating money laundering is the timely identification of this risk. Among the scientists involved in assessing the risk of money laundering the works of S. Dmytrov et al. [4], P. Berzin [5; 6], V. Levchenko et al. [7], A. Boyko and V. Roienko [8], M. Hopkins and N. Shelton [9], Y. Isa et al. [10], M. Riccardi et al. [11] are worth noting.

Research on the study of factors influencing the risk of money laundering through the services of financial institutions are considered in the works of O. Lebid et al. [12], M. Subeh et al. [13], E. Evana [14], L. Kirichenko et al. [15], X. Chao et al. [16], M. Naheem [17]. In [12], the influence of FinTech innovations on the risk of using banking services to legalize dubious income was investigated. M. Subeh et al. [20] used neural networks to detect fraud with bank card accounts. E. Evana et al. [14] proved based on the ANOVA test that the basis of a significant number of financial scams is the manipulation of corporate financial statements. One of the forms of legalization of criminal proceeds is a foreign economic activity with the conclusion of fictitious contracts between trading partners [19].

Using gravitational modeling in S. Lyeonov et al. [18], the degree of attractiveness of a country for money laundering by another country was determined. A. Kerimov et al. [19] analyzed cyclical fluctuation of the environment in different countries, which forms there the preconditions for the money laundering using methods of decomposition and harmonic analysis.

The development of systems to counter shadow transactions in the financial sector is covered in the works of such scientists as M. Subeh et al. [20], V. Levchenko et al. [21], T. Vasylieva et al. [22]. The principles and methodology of queuing theory were used to assess the effectiveness of state supervision and control over operations to legalize dubious income [20].

In the digital age, banks and other financial institutions accumulate more and more data about their customers [23; 24], which allows the use of personalized management decisions for the provision of banking services. Various machine learning algorithms for modelling the risk of money laundering have been analyzed comprehensively in [25—27].

The following approaches are used to predict the dynamics of economic processes: autoregressive model (ARIMA) [28], exponential smoothing and extrapolation based on average level characteristics [28], neural networks, etc. Today, to build a qualitative forecast, it is advisable, first, to take into account the behavioural aspects of economic entities [30], to use artificial neural networks [30] and trend analysis [31]. To identify and determine the predicted level of risk of money laundering, it is not enough to use traditional research methods, and there is an objective need to use innovative ways.

Research results. The authors of this article in their previous work [33] assessed the risk of using the services of financial institutions of Ukraine for money laundering by gravity modelling. It was found that to identify the risk of involving financial intermediaries in illegal transactions, the following significant 13 of the 18 indicators are included: the share of transactions that have signs of legalization of income from internal financial monitoring (p_1); the percentage of income in the form of commissions from settlement and cash transactions, which falls on one customer bank (p_3); the number of violations of the Law of Ukraine «On Prevention and Counteraction to Legalization (Laundering) of Proceeds from Crime, Financing of Terrorism and Financing of the Proliferation of Weapons of Mass Destruction» (p_5); the number of violations of the Law of Ukraine «On Banks and Banking» (p_6); the amount of cash issued for the purchase of agricultural products, which is per customer of the bank (p_9); the amount of money allocated from accounts on deposits of individuals, which is per customer of the bank (p_{10}); the amount of cash issued for other purposes, which is per customer of the bank (p_{11}); share of money in the total amount of cash receipts (p_{12}); the share of non-cash funds in the total amount of revenues (p_{13}); the share of cash expenditures on deposits of individuals from the total amount of spending of individuals (p_{14}); the amount of foreign currency transfer operations to a country belonging to the offshore zone (p_{16}); number of foreign currency transfer operations abroad without a foreign economic contract (p_{17}); the amount of transfers abroad of foreign currency, which was made without a foreign trade contract (p_{18}). While 5 out of 18 indicators turned out to be insignificant: a share of financial transactions in respect of which it was decided not to send to the State Financial Monitoring Service in all financial transactions that were registered based on internal financial monitoring (p_2); the total number of violations by the bank of the Resolutions of the Board of the National Bank of Ukraine (p_4); the share of customers who did not carry out financial transactions, which falls on one customer of the bank (p_7); the percentage of issued cash to purchase agricultural products, issuing cash from accounts on deposits of individuals and issuing for other purposes, which is per unit of the total amount of issued cash (p_8); the number of foreign currency transfer transactions to a country belonging to an offshore zone (p_{15}).

As the source of most data on the above indicators is internal reporting, the input statistical information is not presented in the article, based on the obligation not to disclose trade secrets.

65 banks of Ukraine were ranked according to the level of risk of money laundering and 10 best (1—9, 23) and 10 worst (35, 36, 38, 42, 43, 51, 52, 54, 58, 60) banks were identified, which served as objects for forecasting at the preparatory stage.

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In continuation of the previous study, it is proposed to determine the forecast level of this risk by building a neural network for the next five years — 2020—2025.

The neural network contains the properties of artificial intelligence, which allows determining the predicted values of the studied indicator with a small error, and also has a high level of adaptation to changing conditions. The construction of neural networks is based on the principle of learning from real data, which involves the recognition of images, as well as the establishment of complex relationships between factors and performance. The trained neural network allows defining the trend in the future based on the analysis of historical data, while independently ranking the factor variables according to the degree of their impact on the performance indicator.

Mathematical calculations for the development of methods for forecasting the risk of using financial intermediaries of Ukraine to legalize criminal proceeds based on artificial neural networks were performed in the software package Statistica 6.0 in four stages.

At the first stage, a training sample was formed, consisting of 13 financial performance indicators of 20 pre-selected banks of Ukraine for the period 2015—2019.

The second stage involves the construction of neural network models that describe the dependence of the risk of using financial intermediaries of Ukraine to legalize criminal proceeds from significant factors using a multilayer perceptron MLP-architecture using BFGS algorithm and by determining the radial basis functions of RBF-architecture using RBF-architecture.

The input data for the construction of neural networks of two types (multilayer perceptron MLP-architecture and basic radial functions of RBF-architecture) are not only actual data in terms of selected factors, which probably indicate shadow financial transactions but also the calculated level of money laundering risk by the method of gravitational modelling [33]. 11—12 models were built for each bank based on actual risk data and impact factors, among which the most effective neural network model was selected according to performance indicators, error, correlation coefficients of actual and forecast values, descriptive statistics indicators for forecast values and sensitivity are presented in *Table 1*.

Table 1

Results of selection of the best neural network models for forecasting the risk of using financial intermediaries of Ukraine in money laundering

	Bank 1	**Bank 2**	**Bank 3**	**Bank 4**	**Bank 5**	**Bank 6**	**Bank 7**
Model	model 6 RBF 11-5-1	model 7 RBF 10-4-1	model 6 RBF 13-5-1	model 4 RBF 12-4-1	model 3 MLP 11-4-1	model 7 MLP 11-6-1	model 9 MLP 10-7-1
Learning algorithm	RBFT	RBFT	RBFT	RBFT	BFGS 10000	BFGS 21	BFGS 17
Productivity	1,0000	1,0000	1,0000	0,9944	1,0000	1,000	0,9997
	Bank 8	*Bank 9*	*Bank 23*	*Bank 35*	*Bank 36*	*Bank 38*	*Bank 42*
Model	model 9 RBF 13-4-1	model 6 RBF 13-5-1	model 3 RBF 11-4-1	model 6 RBF 8-5-1	model 4 MLP 9-9-1	model 11 MLP 9-4-1	model 6 MLP 7-6-1
Learning algorithm	RBFT	RBFT	RBFT	RBFT	BFGS 421	BFGS 60	BFGS 53
Productivity	1.0000	0.9997	1.0000	1.0000	1.0000	1,000	1.0000
	Bank 43	*Bank 51*	*Bank 52*	*Bank 54*	*Bank 58*	*Bank 60*	
Model	model 1 RBF 7-4-1	model 3 MLP 8-5-1	model 8 MLP 7-6-1	model 6 MLP 9-8-1	model 7 RBF 9-5-1	model 5 MLP 6-4-1	
Learning algorithm	RBFT	BFGS 0	BFGS 25	BFGS 2	RBFT	BFGS 42	
Productivity	1,000	0.3252	0.9148	0.5644	1.0000	0.9103	

Source: own calculations.

As a result of mathematical experiment it was found that for bank 1 with the lowest level of risk the best is the neural network model, the structure of which is represented by a three-layer perceptron, consisting of 11 common and 5 hidden layers. At the same time, for the bank 36 with the highest level of risk among the studied banks of Ukraine, it is advisable to choose the fourth model of MLP 9-9-1 architecture (total number of layers 9, number of hidden layers 9).

The mathematical model of the sixth neural network with the RBF 11-5-1 architecture of the risk of using the bank №1 for legalization of criminal financial resources can be presented as follows:

$$\begin{gathered} sn_1^{(2)} = f(0{,}1351p_1 + 0{,}1351p_3 + 0{,}1351p_5 + 0{,}1351p_9 + 0{,}1351p_{10} + 0{,}1351p_{11} \\ +\ 0{,}1351p_{12} + 0{,}1351p_{13} + 0{,}1351p_{14} + 0{,}1351p_{17} + 0{,}1351x_{18} + 0{,}4482); \\ sn_2^{(2)} = f(p_1 + p_3 + p_5 + p_9 + p_{10} + p_{11} + p_{12} + p_{13} + p_{14} + p_{17} + x_{18} + 0{,}2678); \\ sn_3^{(2)} = f(4{,}4712); \\ sn_4^{(2)} = f(0{,}9193p_1 + 0{,}9193p_3 + 0{,}9193p_5 + 0{,}9193p_9 + 0{,}9193p_{10} + 0{,}9193p_{11} \\ + 0{,}9193p_{12} + 0{,}9193p_{13} + 0{,}9193p_{14} + 0{,}9193p_{17} + 0{,}9193x_{18} + 0{,}2678); \\ sn_5^{(2)} = f(0{,}9193p_1 + 0{,}9193p_3 + 0{,}9193p_5 + 0{,}9193p_9 + 0{,}9193p_{10} + 0{,}9193p_{11} \\ + 0{,}9193p_{12} + 0{,}9193p_{13} + 0{,}9193p_{14} + 0{,}9193p_{17} + 0{,}9193x_{18} + 0{,}2678); \\ \tilde{R} = h^{(3)} = f(-3{,}7621sn_1^{(2)} - 0{,}0040sn_2^{(2)} + 4{,}4712sn_3^{(2)} - 0{,}0127sn_4^{(2)} + 0{,}0113sn_5^{(2)} + \\ 0{,}3913), \end{gathered} \tag{1}$$

where *f*(-) — specification of the activation function of latent neurons, in our case the Gaussian function;

$sn_1^{(2)}$ — output of the first hidden neuron in the section of the second layer of the neural network, the inputs of which are hidden neurons of the first layer $v_{11}^{(1)}p_1, v_{13}^{(1)}p_3, \dots, v_{117}^{(1)}p_{17}, v_{118}^{(1)}p_{18}$ *та* $s_1^{(1)}$. Others $sn_1^{(2)}$, $sn_2^{(2)}$, $sn_3^{(2)}$, $sn_4^{(2)}$, $sn_5^{(2)}$, $sn_6^{(2)}$, $sn_7^{(2)}$ — similarly;

$sn^{(3)}$ — the output of hidden neurons in the section of the third layer of the neural network; the inputs for these outputs are the weighted outputs of the hidden neurons of the second layer of the neural network $sn_1^{(2)}, sn_2^{(2)}, sn_3^{(2)}, sn_4^{(2)}, sn_5^{(2)}$.

Mathematical representation of the fourth neural network with MLP 9-9-1 architecture of the risk of using bank 36 for money laundering is as follows:

$$\begin{gathered} sn_1^{(2)(2)} = f(2{,}9260p_1 + 2{,}8879p_3 + 2{,}8110p_5 + 2{,}8564p_6 + 2{,}8574p_{10} + 2{,}8540p_{11} \\ + 2{,}8884p_{12} + 2{,}7917p_{13} + 2{,}7996p_{14} + 1{,}3515); \\ sn_2^{(2)} = f(0{,}8277p_1 + 0{,}8061p_3 + 0{,}7950p_5 + 0{,}7946p_6 + 0{,}7983p_{10} + 0{,}7755p_{11} \\ + 0{,}7876p_{12} + 0{,}7809p_{13} + 0{,}8084p_{14} - 0{,}0012); \\ sn_3^{(2)} = f(-1{,}5814p_1 - 1{,}5970p_3 - 1{,}5895p_5 - 1{,}5909p_6 - 1{,}5821p_{10} - 1{,}4648p_{11} \\ - 1{,}5630p_{12} - 1{,}5696p_{13} - 1{,}5233p_{14} - 0{,}0932); \\ sn_4^{(2)} = f(-0{,}4963p_1 - 0{,}4874p_3 - 0{,}5341p_5 - 0{,}4882p_6 - 0{,}4992p_{10} - 0{,}5335p_{11} \\ - 0{,}5130p_{12} - 0{,}5552 - 0{,}5037p_{14} - 0{,}0518); \\ sn_5^{(2)} = f(-4{,}2394p_1 - 4{,}2457p_3 - 4{,}1700p_5 - 4{,}1700p_6 - 4{,}1460p_{10} - 4{,}2286p_{11} - \\ 4{,}2177p_{12} - 4{,}2313p_{13} - 4{,}1796p_{14} - 0{,}3955); \\ sn_6^{(2)} = f(6{,}3942p_1 + 6{,}3520p_3 + 6{,}3808p_5 + 6{,}3934p_6 + 6{,}3228p_{10} + 6{,}3822p_{11} \\ + 6{,}3155p_{12} + 6{,}3764p_{13} + 6{,}3877p_{14} - 0{,}7124); \\ sn_7^{(2)} = f(0{,}5129p_1 + 0{,}5126p_3 + 0{,}5544p_5 + 0{,}4729p_6 + 0{,}4775p_{10} + 0{,}5058p_{11} + \\ + 0{,}4949p_{12} + 0{,}5252p_{13} + 0{,}5301p_{14} - 0{,}0151); \\ sn_8^{(2)} = f(0{,}6517p_1 + 0{,}7410p_3 + 0{,}63990p_5 + 0{,}5891p_6 + 0{,}6636p_{10} + 0{,}6731p_{11} \\ + 0{,}7275p_{12} + 0{,}6581p_{13} + 0{,}6723p_{14} - 0{,}2772); \\ sn_9^{(2)} = f(-0{,}0130p_1 + 0{,}0219p_5 - 0{,}0001p_6 + 0{,}0131p_{10} + 0{,}0140p_{11} - 0{,}0100p_{12} - \\ - 0{,}0164p_{13} - 0{,}0088p_{14} + 0{,}0240); \\ \tilde{R} = h^{(3)} = f\Big(-7{,}1785sn_1^{(2)} - 2{,}1895sn_2^{(2)} + 2{,}7843sn_3^{(2)} + 4{,}0501sn_4^{(2)} - 11{,}9282sn_5^{(2)} \\ + 2{,}1587sn_6^{(2)} - 1{,}7474sn_7^{(2)} + 7{,}0218sn_8^{(2)} - 12{,}0050sn_9^{(2)} - 2{,}8903\Big). \end{gathered} \tag{2}$$

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The next step is to determine the forecast values of significant factors influencing the risk of involving banking institutions in money laundering based on the use of methods of exponential smoothing (exponential trend, linear trend (Holt method), decaying trend). The choice of this mathematical tool is because the predictive assessment of trend parameters to a greater extent allows taking into account the value of the process at the end of the study period.

The final stage is forecasting the risk of using financial intermediaries of Ukraine to legalize criminal financial resources for the period 2020—2025. The results of the forecast on the money laundering risk through financial institutions are presented in *Table 2*. The limits of the calculated level of risk of legalization of illegally obtained funds range from [0; 1].

Table 2

Forecast values of the risk of using financial intermediaries in Ukraine for the money laundering for the period 2020—2025

	Bank 1	**Bank 2**	**Bank 3**	**Bank 4**	**Bank 5**	**Bank 6**	**Bank 7**
Model	model 6 RBF11-5-1	model 7 RBF10-4-1	model 6 RBF13-5-1	model 4 RBF12-4-1	model 3 MLP11-4-1	model 7 MLP11-6-1	model 9 MLP10-7-1
Efficiency	1.0000	1.0000	1.0000	0.9944	1.0000	1,000	0.9997
2020	0.006028	0.027553	0.029034	0.066602	0.076735	0.097477	0.117444
2021	0.006066	0.035399	0.027695	0.083379	0.071023	0.096549	0.112108
2022	0.006067	0.036745	0.027225	0.102033	0.067189	0.096225	0.100761
2023	0.006067	0.036816	0.027651	0.113641	0.064715	0.096112	0.079903
2024	0.006067	0.036819	0.028751	0.118360	0.063144	0.096073	0.064233
2025	0.006067	0.036820	0.030224	0.119677	0.062151	0.096059	0.142801
	Bank 8	**Bank 9**	**Bank 23**	**Bank 35**	**Bank 36**	**Bank 38**	**Bank 42**
Model	model 9 RBF13-4-1	model 6 RBF13-5-1	model 3 RBF11-4-1	model 6 RBF8-5-1	model 4 MLP9-9-1	model 11 MLP9-4-1	model 6 MLP7-6-1
Efficiency	1.0000	0.9997	1.0000	1.0000	1.0000	1,000	1.0000
2020	0.235309	0.178785	0.176955	0,555566	0.786678	0.647084	0.727534
2021	0.328971	0.184734	0.180541	0.568438	0.778338	0.648106	0.730134
2022	0.372774	0.194389	0.180578	0.570665	0.772430	0.648539	0.732368
2023	0.382199	0.200636	0.180578	0.566978	0.767723	0.648769	0.734394
2024	0.383090	0.203054	0.180578	0.559892	0.763630	0.648914	0.736272
2025	0.383124	0.203668	0.180578	0.551011	0.759868	0.649017	0.738019
	Bank 43	**Bank 51**	**Bank 52**	**Bank 54**	**Bank 58**	**Bank 60**	
Model	model 1 RBF 7-4-1	model 3 MLP 8-5-1	model 8 MLP 7-6-1	model 6 MLP 9-8-1	model 7 RBF 9-5-1	model 5 MLP 6-4-1	
Efficiency	1,000	0.3252	0.9148	0.5644	1.0000	0.9103	
2020	0.625087	0.689277	0.665867	0.788050	0.693299	0.634956	
2021	0.610490	0.689916	0.665057	0.787761	0.700612	0.641141	
2022	0.591260	0.690247	0.664075	0.787478	0.708347	0.647668	
2023	0.572567	0.690336	0.663047	0.787200	0.715132	0.653603	
2024	0.557722	0.690250	0.662043	0.786930	0.720232	0.658540	
2025	0.547757	0.690047	0.661100	0.786666	0.723565	0.662434	

Source: own calculations.

According to estimates, only half of banking institutions in Ukraine in 2020 are projected to reduce the level of legalization of criminal income compared to 2019, with mostly positive changes occurred due to the selected top 10 banks. In particular, in 2020, positive changes aimed at counteracting the use of financial institutions in the money laundering were observed in such banks of Ukraine as 3, 5—7, 9, 23, 35, 36, 43.

Over the next 5 years, the forecast values of legalization risk obtained using the appropriate neural network models for each bank separately, only 40% of domestic banks will decrease slightly.

The obtained predictive values based on previously constructed neural networks are quite accurate and adequate, as evidenced by the high values of the efficiency factor. The only exceptions are banks 51 and 54, which have an efficiency ratio of 0.32 and 0.56, respectively.

In the context of growing risks and uncertainly it is important to improve the AML/CFT system in Ukrainian banks using a risk-based approach, tighten client disclosure equirements, refuse to cooperate with dummy, form financial intelligence for strategic and operational analysis [34].

Conclusions. Financial crime is a large-scale and globalized phenomenon that financial institutions around the world are trying to counter and minimize. Financial and credit institutions, regardless of their size, have an internal system of financial monitoring. At the same time, financial criminals are systematically exploring the various weaknesses of these anti-money laundering systems and actively using them to turn criminal income, into legal, financial resources. The paper proposes to use artificial neural networks to predict the risk of money laundering with the participation of financial institutions. The architecture of neural networks allows you to build linear and nonlinear functional relationships between variables. One of the critical disadvantages of neural network models for forecasting is its effectiveness in the event of a stable trend in the past and its likely preservation in the future. Thus, revision of forecast data taking into account the impact of the pandemic on the functioning of the financial sector in general and the risk of money laundering, in particular, is possible after receiving the actual data for 2020 and «retraining» on the updated training sample using the neuropackage. The priority areas for further research are to study the impact of COVID-19 on the processes of money laundering.

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