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ANTI-MONEY LAUNDERING IN THE DIGITAL ECONOMY: INSTITUTIONAL, FINANCIAL, AND EDUCATIONAL CHANNELS

Anton Boyko, Andrew Zimbroff, Serhii Mynenko, and Yang Chen

Abstract. This paper aims to address the practical challenge of enhancing the effectiveness of anti-money laundering systems within the context of the digital economy. Specifically, it examines how institutional, financial, and educational channels can be optimised to combat illicit financial activities. This research responds to the growing need for a comprehensive anti-money laundering framework that can adapt to the evolving dynamics of the digital economy, where financial crimes are becoming increasingly sophisticated. A methodological framework is proposed to assess and forecast the effectiveness of these channels, employing the principal component method and Saaty hierarchy analysis. The study incorporates both linear and nonlinear regression models to provide medium-term forecasts for the channels' characteristics and their contribution to anti-money laundering effectiveness. An integral indicator is developed to quantify the impact of these channels in combating illicit financial activities. Historical data are utilised to project trends up to 2025, revealing the expected influence of institutional, financial (investment), and educational channels on the anti-money laundering system. The results indicate that, without targeted interventions, the effectiveness of institutional and financial channels gradually decreases, whereas the educational channel maintains a positive trajectory. This analysis underscores the importance of strengthening institutional frameworks and financial oversight to ensure the sustainability of anti-money laundering measures in the digital economy.

Keywords*:* anti-money laundering; institutional channel; investment channel; tax channel; educational channel; Saati hierarchy analysis method; forecast integral indicator

Authors:

Anton Boyko
Sumy State University, Sumy, Ukraine
E-mail: a.boiko@uabs.sumdu.edu.ua
https://orcid.org/0000-0002-1784-9364

Andrew Zimbroff
College of Education and Human Sciences, University of Nebraska-Lincoln, Lincoln, USA
E-mail: zimbroff@unl.edu
https://orcid.org/0000-0002-4535-879X

Serhii Mynenko
Sumy State University, Sumy, Ukraine
E-mail: s.mynenko@biem.sumdu.edu.ua
https://orcid.org/0000-0003-3998-9031

Yang Chen
Fujian Normal University, Fuzhou, China
E-mail: cheny3598@gmail.com
https://orcid.org/0000-0002-4801-4036

Corresponding author: Anton Boyko, a.boiko@uabs.sumdu.edu.ua

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1. Introduction

In the modern era, combating crime, particularly financial crime, has become a central focus for governments and international institutions. As economies become increasingly digital and interconnected, financial crimes, including money laundering, have evolved in complexity. Money laundering, which enables the concealment of illegally obtained wealth, remains a significant threat to global economic stability and security. Criminals leverage the opportunities provided by globalized financial systems to obscure the origins of illicit funds, undermining economic transparency and facilitating other criminal activities.

To counteract these threats, a variety of frameworks and institutions have been established at both the national and international levels. Anti-money laundering systems now encompass a broad range of strategies, legal frameworks, asset protection mechanisms, and risk management tools. However, the rise of the digital economy and the widespread adoption of digital financial technologies have added new layers of complexity to the anti-money laundering process.

This paper focuses on the role of institutional, financial, and educational channels in enhancing the effectiveness of anti-money laundering efforts within the digital economy. By decomposing the anti-money laundering system into these key channels, it becomes possible to assess their individual impacts and forecast future trends. This approach allows for a more precise understanding of how each channel contributes to combating illicit financial activities in a rapidly digitalizing world. The ability to forecast the effectiveness of these channels is crucial for designing policies and interventions that ensure long-term success in anti-money laundering efforts, particularly as financial crimes continue to adapt to new technological realities. This research makes several significant contributions to the field of anti-money laundering. First, it introduces a novel methodological framework that combines principal component analysis and Saaty hierarchy analysis to assess the effectiveness of institutional, financial, and educational channels in anti-money laundering systems. Second, it provides medium-term forecasts of the effectiveness of these channels, offering practical insights for policymakers and stakeholders in adapting anti-money laundering strategies to the evolving digital economy. Third, this paper highlights the need for targeted interventions to maintain the effectiveness of institutional and financial channels while recognizing the positive role of educational channels in sustaining anti-money laundering efforts. Finally, it emphasizes the broader role of digitalization in shaping the future of anti-money laundering systems, linking anti-money laundering efforts to sustainable development goals and economic security.

This paper first discusses the literature on anti-money laundering practices, with a focus on the role of digitalization and its impact on the effectiveness of anti-money laundering systems. It then presents the models and methodologies used to assess and forecast the effectiveness of institutional, financial, and educational channels in combating money laundering. Following that, the paper details the data collection process and the statistical techniques applied for analysis. The empirical results of the analysis are presented next, highlighting the performance of each channel. The paper concludes with a discussion of the forecasted trends in the effectiveness of these channels and offers recommendations for improving anti-money laundering strategies in the context of the digital economy.

2. Literature Review

The issue of anti-money laundering has been extensively studied by the scientific community. Most researchers concentrate on anti-money laundering within the financial sector, examining topics such as the competence of bank employees [1], the operational characteristics of banks as integrated systems [2], and the impact of new legal frameworks on banking expenses [3], among others. The regulation of virtual currencies, which are increasingly used for laundering illicit income, is also a pressing issue. This has led to a growing body of research focusing on monitoring the activities of virtual currency service providers and adapting national legislation to meet the latest international standards and regulations for virtual currency circulation [3–8].

Recently, many scholars have focused on the role of artificial intelligence and digital technologies, both as tools for driving economic and business processes [9,10] and for managing social and environmental transformations [10–14]. The application of these technologies to anti-money laundering efforts [15] has also gained attention. While the rise of digital technologies in the financial sector has introduced new methods for laundering money, such as "dropping," it has also significantly increased the tools available for combating money laundering. The authors of [16] noted an increase in the level of accountability in the economy with an increase in the level of digitalization [17]. Increasing the level of digitalization reduces corruption in various areas of the public sector [18–21]. In addition, the increase in the level of digitalization and accountability at the enterprise level facilitates the verification of control bodies for the organization’s involvement in legalization schemes [22–24].

Another group of researchers [25] focused their attention on the dynamic stability of the financial monitoring system as the main means of combating money laundering, using a vector autoregression model and identifying the main factors influencing the financial monitoring of transactions. Criminals disguise illegal transactions as legal ones, forming a part of global money circulation [26], which can lead to a decrease in the level of economic security of the country [27].

Scientists have demonstrated the adverse impact of the shadow economy on the investment climate and the country’s investment attractiveness [28]. The sources of illicit income accumulation can include drug dealing, prostitution, fraud [29], tax fraud [30], cybercrime [31,32], corruption, smuggling [33], etc. Thus, with the development of blockchain technology and the introduction of cryptocurrencies, criminals have gained more tools [34] to hide and disperse illegal income [35].

Within the framework of achieving the goals of sustainable development, which has recently received special attention among scientists [36–41], anti-money laundering is also of key importance. Thus, taking into account the large volume of money laundered (2–5% of the world GDP) (UNODC) [42], the question of an effective antlaundering system becomes relevant [43]. Combating money laundering corresponds to Target 16.4 Sustainable development goals (United Nations) [44] aimed at reducing illicit financial flows and arms trafficking and fighting all forms of organized crime. Achieving sustainable development goals is a priority of all civilized countries [45–47].

An important issue when analysing the causes and consequences of the legalization of illegal income is the level of education in the country [48]. Since the main reason for the accumulation of illegal income lies in the well-being of the population [49,50], institutions of higher education have a special influence on the formation of a conscious society, which not only educates its conscious members but also increases the average income due to improvements in worker qualifications [51–54].

While identifying the components of the anti-money laundering system, it is appropriate to single out the following elements: institutional, tax, educational and investment channels for anti-money laundering. These four channels cover the entire spectrum of influence on the anti-money laundering system currently available in Ukraine. Examining each component in more detail, the authors should note that the institutional channel of anti-money laundering is a channel of direct influence since it includes a set of bodies whose activities are aimed at detecting money laundering facts, proving them and bringing criminals to justice. The activity of this channel is monitored after the crime has been committed and is aimed at compensating for the damage caused by criminals and demonstrating the inevitability of punishment, thus reducing the number of potential criminals.

The educational channel of anti-money laundering indirectly affects the money laundering process, but it cannot be neglected. Education has several directions of influence on the money laundering process. First, the education system forms highly qualified specialists who ensure the functioning of the institutional channel of anti-money laundering. Specialists in economics and finance are needed to identify the money laundering facts. Legal experts form the basis of investigative bodies and the judicial system. In addition, legal experts are the generating factor of normative legal acts, including in the anti-money laundering field. Second, quality education allows people to realize their life goals in the legal sector of public life without committing crimes. Third, a high level of education and financial literacy will allow law-abiding citizens to become more protected from criminals and reduce the risk of their crime involvement [55]. Fourth, a high level of education and knowledge of one's rights and duties reduce the level of corruption as a source of illicit income accumulation.

Several factors characterize the tax channel of anti-money laundering. On the one hand, tax fraud is a source of illicit income as a basis for legalization. Thus, it is necessary to build such a taxation system to prevent opportunities to carry out tax scams. On the other hand, excessive tax burdens and complexity in tax administration push business entities to shadow schemes of their activities [56]. As a result, part of the shadow economy is growing, in which funds for laundering are accumulated. The essence of the tax channel of anti-money laundering has led to the development of a fair, convenient taxation system that encourages business entities to conduct their activities openly. Therefore, the risks for business entities are reduced, the volume of the shadow economy is reduced, and ultimately, the money laundering volume is reduced [57,58]. Investments constitute the main tool for the cross-border movement of financial resources [59]. Some income obtained illegally is disguised as an investment. Money laundering is carried out through obtaining investment income. The investment channel of anti-money laundering aims to create favourable investment conditions and ensure investment process transparency. On this basis, investments should be controlled, but excessive bureaucratization of the investment process will complicate their administration. The anti-money laundering investment channel must maintain a balance between the freedom of a competitive investment market and control over the risk of money laundering.

Effective management of the anti-money laundering system involves improving each channel. However, in terms of economic instability caused by military actions or other factors, the issue of rational distribution of financial and human resources to ensure the functioning of the state is acute. Accordingly, the issue of prioritizing the distribution of available resources arises. Thus, it is necessary to determine the current state of anti-money laundering channels and forecast their development in the near future. This problem can be solved by forecasting socioeconomic processes. Adequate forecasts of the effectiveness of anti-money laundering channels will allow the identification of weak points at the current moment and in the future and, therefore, the allocation of resources with their maximum effectiveness.

3. Materials and methods

A scientific and methodical approach to forecasting the effectiveness of anti-money laundering channels, consisting of five stages, is suggested. In the first stage, a database of statistical indicators is collected. The main goal is to select data that accurately characterize the effectiveness of each anti-money laundering channel: investment, tax, educational, and institutional

In the second stage, preliminary data processing is conducted, and the data are prepared for use in subsequent stages. Since the collected set contains missing values, they need to be processed by replacing them with the arithmetic mean if the missing value is inside the variation series (Formula 1) and with the average growth rate if the missing value is at the beginning (Formula 2) or at the end of the variation series (Formula 3).

$$x_i = \frac{x_{i-1} + x_{i+1}}{2} \tag{1}$$

where x_i is the missing value of the variation series; x_{i-1} is the previous value to the missing value of the variation series; and x_{i+1} is the next value to the missing value of the variation series.

$$x_1 = \frac{x_2}{\sqrt[n]{\frac{x_n}{x_2}}} \tag{2}$$

where x_1 is the first missing value of the variation series; x_n is the last value of the variation series; x_2 is the second value of the variation series; and n is the number of units in the variation series.

$$x_n = x_{n-1} \sqrt[n]{\frac{x_{n-1}}{x_1}} \tag{3}$$

where x_n is the last missing value of the variation series; x_{n-1} is previous to the missing value of the variation series; x_1 is the first value of the variation series; and n is the number of units in the variation series.

When considering the third stage of the scientific and methodological approach to forecasting the effectiveness of anti-money laundering channels, it is reasonable to divide this stage into three parts.

First, the input indicators must be standardized by converting them into a comparable form, eliminating the influence of measurement units. To achieve this, natural normalization is applied. For the stimulator indicators, the normalization formula is as follows:

$$x_{i_{norm}} = \frac{x_i - \min_i x}{\max_i x - \min_i x} \tag{4}$$

where $x_{i_{norm}}$ is the normalized feature value; x_I is the initial feature value; $\min_i x$ is the minimum feature value; and $\max_i x$ is the maximum feature value.

For destimulators, the natural normalization formula takes the form:

$$X_{i_{norm}} = \frac{\max_i x - x_i}{\max_i x - \min_i x} \tag{5}$$

where $x_{i_{norm}}$ is the normalized feature value; x_i is the initial feature value; $\min_i x$ is the minimum feature value; and $\max_i x$ is the maximum feature value.

The Saati hierarchy analysis method is used to determine the weighting factors for the integral indicators. This method involves constructing a pairwise comparison matrix, where each indicator is compared on the basis of its priority relative to others, and then the weighting factors are calculated through convolution. It is suggested that the principal component method be used to determine the priority of each indicator (formula 6):

$$\text{piority}_i = \frac{\sum_{j=1}^{n}(v_j * c_{ij})}{\sum_{j=1}^{n} v_j} \tag{6}$$

where piority_i is the evaluation of the i-variable priority; c_i is the contribution of the i-variable to the j-factor; v_j is the percentage of variance explained by the j-factor; and n is the number of factors.

For the pairwise comparison matrix, the k-weights are in the range of 1.n (where n is the number of variables), according to the rank in ascending order of piority_i.

The pairwise comparison matrix has the following form:

$$\begin{matrix} \frac{k_1}{k_1} & \frac{k_1}{k_2} & \cdots & \frac{k_1}{k_n} \\ \frac{k_2}{k_1} & \frac{k_2}{k_2} & \cdots & \frac{k_2}{k_n} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{k_n}{k_1} & \frac{k_n}{k_2} & \cdots & \frac{k_n}{k_n} \end{matrix} \tag{7}$$

Every element $v_{ij} > 0$ of the relative weight matrix (7) is the ratio of i-object weight a_i to j-object weight a_j, i.e., $v_{ij} = \frac{k_i}{k_j}$ for any I, j = 1. n. Elements of the matrix, located symmetrically to the main diagonal, are turned to each other: $v_{ij} = \frac{1}{v_{ji}}$.

Accordingly, matrix 3.8 is transformed into matrix 8:

$$\begin{matrix} v_{11} & v_{12} & \cdots & v_{1j} \\ v_{21} & v_{22} & \cdots & v_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ v_{i1} & v_{i2} & \cdots & v_{ij} \end{matrix} \tag{8}$$

The weighting coefficients for the integral indicator of each anti-money laundering channel's effectiveness are calculated according to the following formula:

$$w_i^* = \sqrt[n]{\prod_{j=1}^{n} v_{ij}} \tag{9}$$

$$w_i = \frac{w_i^*}{\sum_{j=1}^{n} w_j^*}$$

where w_i is the value of the weighting factor; v_{ij} represents the elements of matrix 8; and n represents the number of variables.

The modified Rasch model is used to implement this stage (10):

$$I_i = \frac{\sum_{i=1}^{n} e^{\mathrm{x}_{\mathrm{i}_{\mathrm{norm}}} * \mathrm{w}_{\mathrm{i}}}}{\sum_{i=1}^{n} (e^{\mathrm{x}_{\mathrm{i}_{\mathrm{norm}}}} + 1)} \tag{10}$$

where I_i is the integral evaluation of the i value of the integral indicator of the corresponding anti-money laundering channel; $x_{i_{norm}}$ is the normalized value of the variable; w_i is the weighting factor of the corresponding variable; and n is the number of observations of the variable.

The fourth stage of the scientific and methodological approach to forecasting the effectiveness of anti-money laundering channels involves forecasting the integral estimates for each channel. To forecast over a five-year period, it is necessary to select a model specification that minimizes error while ensuring the statistical significance of the results. For forecasting the effectiveness of institutional and investment channels, a hyperbolic dependence is suggested, as this curve more accurately captures the dynamics of these indicators. The general form of the model is provided in formula 11:

$$\hat{y} = \alpha + \frac{\beta}{x} \tag{11}$$

where y is the dependent variable value—the integral indicator of the anti-money laundering channel; x is the serial number of the model year; and α, β represents the regression coefficient.

A parabolic dependence is observed in the educational channel, and a general parabolic regression model (formula (12)) is suggested for selection:

$$y = \alpha + \beta \times x^2 \tag{12}$$

where y is the dependent variable value—the integral indicator of the anti-money laundering channel; x is the serial number of the model year; and α, β represents the regression coefficient.

For the tax channel of anti-money laundering, a regression model corresponding to the square root is selected:

$$y = \alpha + \beta \times \sqrt{x} \tag{13}$$

where y is the dependent variable value—the integral indicator of the anti-money laundering channel; x is the serial number of the model year; and α, β represents the regression coefficient.

In the fifth stage of the scientific and methodological approach, the four anti-money laundering channels are generalized into a single integral indicator of their effectiveness. To achieve this, stage 3 is repeated, but the integral estimates of the anti-money laundering channels, along with the forecast values, are used as input variables.

For the implementation of the proposed scientific and methodological approach to assess the effectiveness of anti-money laundering channels, the first stage requires the collection of a statistical base of indicators that characterize the effectiveness of these channels.

The information base for the research includes indicators of the effectiveness of the anti-money laundering channels. For the tax channel: income tax (% of profit) – T1, time spent paying taxes (hours per year) – T2, tax burden (% of profit) – T3, property registration costs (% of property value) – T4 and time spent on property registration (days) – T5. For the investment channel: gross capital formation (% of GDP) – Invest1, foreign direct investment, net outflow (% of GDP) – Invest2, foreign direct investment, net inflow (% of GDP) – Invest3, net portfolio investment (balance of payments, current USD) – Invest4, and the global competitiveness index (units) – Invest5. For the educational channel: State expenditure on education (% of state expenditure) – E1; participation in higher education (units) – E2; percentage of graduates of higher education institutions from business, administration and law programs (%) – E3. For the institutional channel, the number of reports taken into account by the State Financial Monitoring Service (units) – Inst1, amount of money, generalized materials related to money laundering and other criminal offenses (million UAH) – Inst2, amount of property seized and transferred to state income (million UAH) – Inst3, number of criminal proceedings that were opened or developed using new materials (units) – Inst4, number of indictments sent to court (units) – Inst5, and number of cases with a guilty verdict (units) – Inst6. The selected set of indicators characterizes the effectiveness of each anti-money laundering channel.

The data were collected for Ukraine from 2006-2020 from the official websites of the State Financial Monitoring Service [60] the World Bank [61], and the Doing Business Initiative [62]. The data are presented in Table 1.

Table 1. Input indicators of anti-money laundering channels

Year	Institutional						educational		
	Inst1	**Inst2**	**Inst3**	**Inst4**	**Inst5**	**Inst6**	**E1**	**E2**	**E3**
2006	841,589	47,110	**618.008**	163	8	1	13.923	2,740,342	38.143
2007	1,000,848	53,300	720.5	271	40	25	14.036	2,819,248	37.322
2008	1,062,373	65,200	59.1	354	117	77	13.558	2,847,713	37.163
2009	877,433	59,900	5561.4	504	150	119	15.055	2,798,693	36.416
2010	806,414	**57,050**	213.4	345	106	65	**14.270**	2,635,004	35.278
2011	1,079,451	54,200	344.9	203	142	37	13.484	2,566,279	33.236
2012	967,821	98,500	475.48	248	175	99	13.666	2,390,989	35.897
2013	982,141	**213,750**	598.68	813	177	115	13.868	2,205,595	**34.604**
2014	1,287,496	329,000	3070.22	540	79	156	13.121	2,146,028	**33.084**
2015	4,357,117	87,500	5492.61	356	58	70	13.341	1,776,190	32.017
2016	6,319,776	45,800	21,600	270	42	47	12.353	1,689,724	30.044
2017	8,013,029	59,400	3342.2	306	63	115	13.019	1,667,288	14.419
2018	9,969,792	347,400	**4356.1**	374	32	21	12.751	1,614,636	28.379
2019	11,437,374	92,200	5370	354	74	78	13.160	1,601,557	27.164
2020	4,725,537	68,000	2700	314	38	28	13.086	**1,536,736**	**26.464**

Year	Investment					Tax				
	Invest1	**Invest2**	**Invest3**	**Invest4**	**Invest5**	**T1**	**T2**	**T3**	**T4**	**T5**
2006	24.543	-0.119	5.009	-3,583,000,000	**57.695**	12.3	2085	57.3	5.6	113
2007	27.781	0.656	6.853	-5,753,000,000	57.64	12.4	2085	57	3.4	113
2008	27.393	0.424	5.688	1,280,000,000	56.79	12.5	2085	56.6	3.3	113
2009	17.068	0.095	3.923	1,533,000,000	58.37	12.3	860	57.2	2.9	113
2010	18.372	0.490	4.568	-4,342,000,000	56.46	12.3	736	57.2	2.6	113
2011	20.444	0.113	4.256	-1,569,000,000	55.73	10.4	657	55.5	4.1	117
2012	19.615	0.537	4.477	-4,689,000,000	57.14	12.2	657	57.1	3.9	117
2013	16.426	0.226	2.367	-8,787,000,000	59.13	11.6	488	55.4	3.7	69
2014	13.396	0.410	0.634	2,700,000,000	57.88	11.3	386	54.4	2.4	45
2015	15.933	0.042	-0.218	-367,000,000	59.12	9.5	346	52.7	2	27
2016	21.724	0.185	4.422	-293,000,000	57.62	9	346	52.2	2	16
2017	19.965	0.209	3.283	-1,800,000,000	58.71	8.7	355.5	52.3	1.9	16
2018	18.588	0.089	3.801	-2,080,000,000	57.03	11.9	327.5	37.8	1.8	16
2019	14.890	0.404	3.766	-5,134,000,000	56.99	11	327.5	41.7	1.8	15
2020	8.932	0.231	0.194	829,000,000	**56.936**	10.2	327.5	45.2	1.7	15

Source: Own elaboration.

To implement the second stage, formula (1) is used for the indicators Inst2, Inst3, E1, and E3; formula (2) is applied for the indicators Inst3 and Invest5; and formula (3) is utilized for the indicators E2, E3, and Invest5. The results of the imputed missing values are shown in Table 1.

4. Results

In accordance with the third stage of the scientific and methodical approach, the input data are normalized. Formula (4) is applied to normalize the indicators Inst1, Inst2, Inst3, Inst4, Inst5, Inst6, E1, E2, E3, Invest1, Invest3, and Invest4, as these indicators are stimulators. An increase in these indicators leads to an increase in the effectiveness of the anti-money laundering channels. Formula (5) is used to normalize the Invest2, T1, T2, T3, T4, and T5 indicators, as these indicators are destimulators. In the next step, the priority advantages of the indicators are determined via the principal component method in the STATISTICA program. For the institutional channel, a satisfactory percentage of explained variance (>75%) corresponds to three factors (Table 2).

Table 2. Eigenvalues and percentage of variance explained by the principal component method for the institutional channel

Value number	Eigenvalue	% Total variance	Cumulative Eigenvalue	Cumulative %
1	2.468	41.134	2.468	41.134
2	1.590	26.508	4.059	67.642
3	0.919	15.322	4.978	82.963
4	0.468	7.805	5.446	90.769
5	0.297	4.948	5.743	95.717
6	0.257	4.283	6.000	100.000

Source: Compiled by the authors.

The scree plot (Figure 1) confirms the necessity of distinguishing three factors since the angle of the line noticeably changes after the third factor.

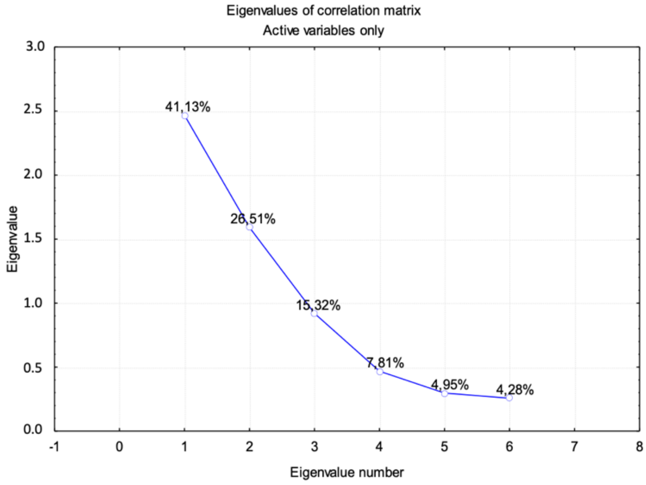

Figure 1. Scree plot of the institutional channel
Source: Compiled by the authors.

Accordingly, the necessary variable contributions for calculating priorities are shown in Table 3 and correspond to columns Factor 1, Factor 2 and Factor 3.

Table 3. Variable contributions to each factor for the institutional channel

Variale	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Inst1	0.080	0.341	0.001	0.512	0.053	0.013
Inst2	0.072	0.271	0.319	0.047	0.000	0.291
Inst3	0.062	0.187	0.466	0.221	0.010	0.053
Inst4	0.268	0.098	0.000	0.069	0.101	0.463
Inst5	0.255	0.065	0.097	0.079	0.327	0.178
Inst6	0.262	0.037	0.118	0.073	0.509	0.001

Source: Compiled by the authors.

The priority estimates calculated according to formula 6 are shown in Table 4, Column 1.

Table 4. Priority estimates, pairwise comparison matrix, and weighting factors for the institutional channel

Priority	Indicator	Inst1	Inst2	Inst3	Inst4	Inst5	Inst6	w
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0.149	Inst1	1.000	0.140	0.170	0.200	0.250	0.330	0.031
0.182	Inst2	7.000	1.000	3.000	4.000	5.000	6.000	0.424
0.177	Inst3	6.000	0.330	1.000	3.000	4.000	5.000	0.255
0.165	Inst4	5.000	0.250	0.330	1.000	3.000	4.000	0.150
0.165	Inst5	4.000	0.200	0.250	0.330	1.000	3.000	0.088
0.164	Inst6	3.000	0.170	0.200	0.250	0.330	1.000	0.052

Source: Compiled by the authors.

Using formulas 7 and 8, a Satti pairwise comparison matrix is built (columns 2–8 of Table 4). To calculate the weighting coefficients of the integral indicator of the anti-money laundering institutional channel effectiveness, formula (9) is employed. The results of the calculations are presented in column 9 of Table 4.

The calculations for the educational, tax, and investment channels of anti-money laundering are displayed in Tables 5–7.

Table 5. Eigenvalues and percentages of variance explained by the principal component method for the tax, investment, and educational channels

Value number	**Eigenvalue**	**% Total variance**	**Cumulative Eigenvalue**	**Cumulative %**
The tax channel				
1	3.491	69.813	3.391	69.813
2	0.764	15.283	4.255	85.096
3	0.382	7.646	4.637	92.742
4	0.290	5.794	4.927	98.536
5	0.073	1.464	5.000	100.000
The investment channel				
1	2.268	45.362	2.268	45.362
2	1.088	21.764	3.356	67.126
3	0.977	19.549	4.334	86.675
4	0.584	11.675	4.918	98.351
5	0.082	1.649	5.000	100.000
The educational channel				
1	2.435	81.163	2.435	81.163
2	0.412	13.723	2.847	94.886
3	0.153	5.114	3.000	100.000

Source: Compiled by the authors.

Table 6 presents the weighting coefficients calculated for the integral indicators of the anti-money laundering channels, demonstrating the relative importance of each channel in the overall effectiveness assessment.

Table 6. Variable contribution to each factor for the tax, investment and educational channels

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
The tax channel					
T1	0.155	0.493	0.175	0.010	0.166
T2	0.198	0.041	0.634	0.125	0.002
T3	0.168	0.442	0.044	0.156	0.191
T4	0.220	0.021	0.025	0.704	0.029
T5	0.259	0.002	0.122	0.005	0.611
The investment channel					
Invest1	0.297	0.022	0.234	0.073	0.373
Invest2	0.119	0.027	0.517	0.335	0.002
Invest3	0.397	0.000	0.054	0.000	0.548
Invest4	0.094	0.392	0.185	0.305	0.025
Invest5	0.092	0.559	0.010	0.286	0.052
The educational channel					
E1	0.315	0.491	0.193		
E2	0.371	0.000	0.629		
E3	0.314	0.508	0.178		

Source: Compiled by the authors.

Table 7 displays a comprehensive summary of the calculation results for the educational, tax, and investment channels of anti-money laundering, illustrating the findings and comparisons among the different channels.

Table 7. Priority estimates, pairwise comparison matrix and weighting factors for the tax, investment, and educational channels

Priority	The tax channel	T1	T2	T3	T4	T5	w
0.216	T1	1.000	7.000	0.500	5.000	3.000	0.299
0.169	T2	0.140	1.000	0.170	0.200	0.140	0.046
0.217	T3	2.000	6.000	1.000	7.000	2.000	0.363
0.184	T4	0.200	5.000	0.140	1.000	0.200	0.085
0.213	T5	0.330	7.000	0.500	5.000	1.000	0.207
The investment channel		**Invest1**	**Invest2**	**Invest3**	**Invest4**	**Invest5**	**w**
0.214	Invest1	1.000	5.000	0.200	7.000	4.000	0.302
0.186	Invest2	0.200	1.000	0.170	0.330	0.250	0.065
0.220	Invest3	5.000	6.000	1.000	0.250	5.000	0.317
0.189	Invest4	0.140	3.000	4.000	1.000	0.250	0.150
0.191	Invest5	0.250	4.000	0.200	4.000	1.000	0.167
The educational channel		**E1**	**E2**	**E3**			**w**
0.315	E1	1.000	0.170	3.000			0.271
0.371	E2	6.000	1.000	5.000			0.536
0.314	E3	0.330	0.200	1.000			0.194

Source: Compiled by the authors.

To calculate the integral indicators for evaluating the effectiveness of anti-money laundering channels, formula (10) is utilized. The results of these calculations are presented in Table 8 and illustrated in Figure 2.

Table 8. Integral indicators

Year	Institutional channel (IC)	Educational channel (EC)	Investment channel (INV)	Tax channel (TC)
2006	0.499	0.401	0.374	0.498
2007	0.480	0.402	0.405	0.468
2008	0.441	0.409	0.388	0.466
2009	0.406	0.385	0.378	0.423
2010	0.449	0.406	0.439	0.413
2011	0.449	0.427	0.409	0.421
2012	0.417	0.416	0.434	0.429
2013	0.379	0.418	0.408	0.405
2014	0.400	0.435	0.404	0.376
2015	0.443	0.434	0.378	0.353
2016	0.420	0.454	0.392	0.345
2017	0.415	0.489	0.391	0.342
2018	0.418	0.455	0.404	0.345
2019	0.401	0.453	0.440	0.347
2020	0.461	0.456	0.419	0.345

Source: Compiled by the authors.

According to the data in Figure 2, the dynamics of changes in the effectiveness of the anti-money laundering channels from 2006–2020 can be observed. From 2009–2014, the effectiveness of the channels fluctuated at a consistent level, and after 2014, a dispersion in the effectiveness of the anti-money laundering channels became apparent. The differences in the channels' effectiveness are attributed to the active implementation of reforms in Ukraine following 2013–2014. As part of the institutional channel, the investigative bodies' system's modernization is reflected in the growth spurt of this channel's efficiency after 2019.

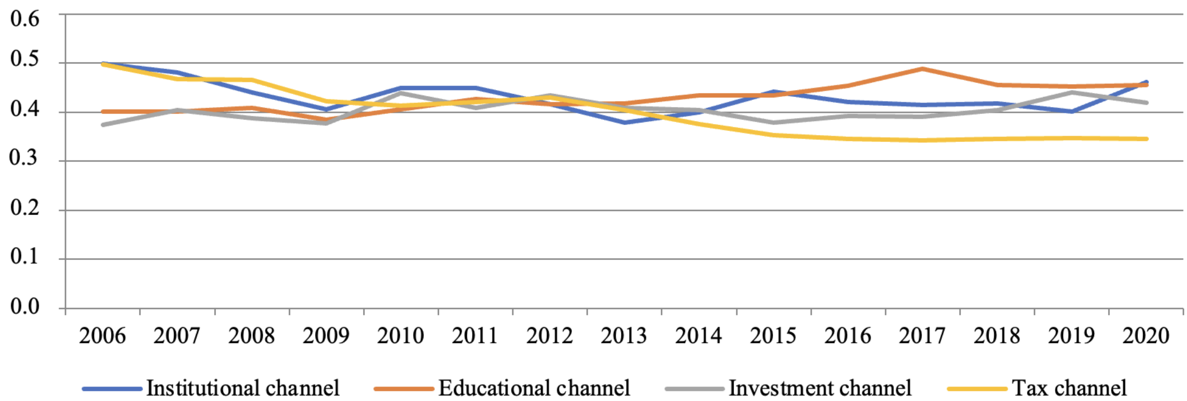

Figure 2. Integral indicators of the anti-money laundering channels
Source: Compiled by the authors.

Notably, the increasing effectiveness of the educational channel of anti-money laundering, along with the rise in financial literacy and the share of highly qualified workers with higher education, has a positive effect on combating money laundering.

The fixed nonlinear regression module of the STATISTICA program is implemented for the fourth stage of the scientific-methodical approach to forecast the effectiveness of anti-money laundering channels. The results of the nonlinear regression for the institutional channel are presented in Table 9.

Table 9. Regression Summary for Dependent Variable: IC

R = 0.709, R^2 = 0.502, Adjusted R^2 = 0.464 F(1,13) = 13.124 p < 0.003, Std. Error of estimate: 0.024						
	Beta	**Std. Err. of Beta**	**B**	**Std. Err. of B**	**t(13)**	**p-level**
Intercept			0.411	0.008	48.929	0.000
1/IC	0.709	0.196	0.094	0.026	3.623	0.003

Source: Compiled by the authors.

According to Table 10, formula 11 takes the form:

$$\widehat{IC} = 0.411 + \frac{0.094}{t} \tag{14}$$

The adequacy of the calculated model is confirmed: the standard error is small and equal to 0.024, the F test value (13.124) indicates the significance of the model, and a p-level < 0.05 indicates a statistically significant result at the 95% confidence level.
For the investment channel, Formula (11) takes the form:

$$\widehat{INV} = 0.412 - \frac{0.036}{t} \tag{15}$$

The standard error of the model is 0.020, but the p-level = 0.124, and the value of the F test (2.705) does not support the statistical significance of the result at the 95% confidence level. This model is adequate at the 85% confidence level: F85 (2.34) < F (2.705). Therefore, it is accepted with an 85% confidence level.

For the educational channel, Formula (12) takes the form:

$$\widehat{EC} = 0.403 + 0.00032 \times t^2 \tag{16}$$

The standard error for the constructed model is equal to 0.015, and the p-level is < 0.05, indicating the statistical significance of the obtained result. The value of the F test (33.018) with p<0.05 indicates the adequacy of the model.

For the educational channel, formula (13) takes the form:

$$\widehat{TC} = 0.554 - 0.057 \times \sqrt{t} \tag{17}$$

On the basis of the standard error value of 0.014, the F test, and Student's t statistic, with a p value of less than 0.05, the constructed model is adequate at the 95% confidence level and can be applied in forecasting.

The forecasted values of the model are given in Table 10.

Table 10. Forecast values of integral indicators of the effectiveness of anti-money laundering channels

Year	Institutional channel (IC)	Educational channel (EC)	Investment channel (INV)	Tax channel (TC)
2021	0.417	0.485	0.410	0.324
2022	0.417	0.496	0.410	0.316
2023	0.416	0.507	0.410	0.307
2024	0.416	0.519	0.410	0.303
2025	0.416	0.531	0.410	0.296

Source: Compiled by the authors.

For a visual representation of the obtained results, a plot of the forecast integral indicators of the anti-money laundering channels' effectiveness is constructed (Figure 3).

On the basis of the obtained forecast values (Table 11, Figure 3), it can be concluded that the effectiveness of the institutional and investment anti-money laundering channels will remain nearly constant until 2025.

Table 11. Priority ratings, pairwise comparison matrix and weighting coefficients for the institutional channel

Priority	Indicator	Institutional channel	Educational channel	Investment channel	Tax channel	w
1	Institutional channel	1.000	4.000	3.000	2.000	0.393
4	Educational channel	0.250	1.000	0.500	0.330	0.136
3	Investment channel	0.330	2.000	1.000	0.500	0.193
2	Tax channel	0.500	3.000	2.000	1.000	0.278

Source: Compiled by the authors.

However, the investment channel shows positive growth dynamics, whereas the efficiency of the institutional channel is expected to gradually decrease. The effectiveness of the educational anti-money laundering channel is projected to increase from 2020--2025, whereas the effectiveness of the tax channel is anticipated to decline.

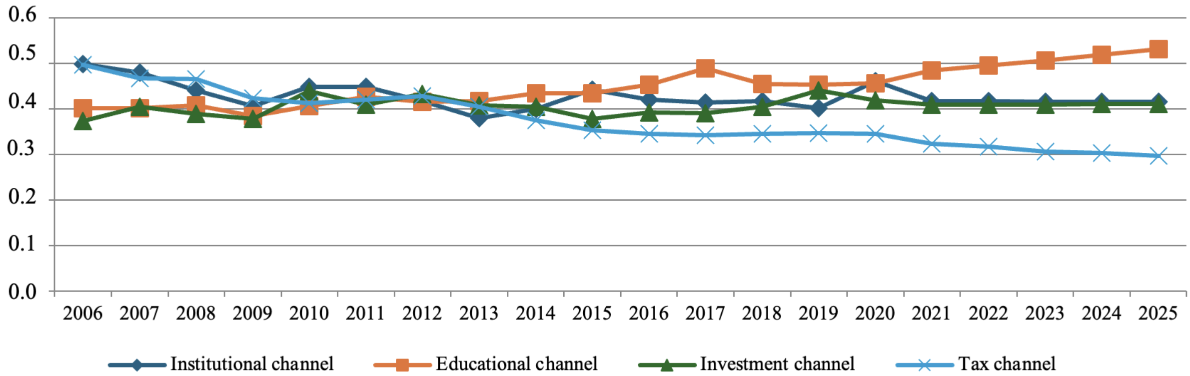

Figure 3. Forecast integral indicators of the anti-money laundering channels' effectiveness
Source: Compiled by the authors.

The results indicate that the tax anti-money laundering channel requires modernization, as its effectiveness has consistently decreased throughout the entire period under study and is expected to continue to decline in the future.

During the fifth stage of the scientific-methodical approach to forecasting the effectiveness of the anti-money laundering channels, a Saati matrix of pairwise comparisons is constructed to determine the weighting coefficients of the overall integral indicator of the anti-money laundering channels' effectiveness (formulas 9 and 10). The Saati matrix is presented in Table 11.

To calculate the weighting coefficients of the integral indicator of the anti-money laundering channels' effectiveness, formula (9) is utilized. The results of these calculations are shown in column w of Table 11. To calculate the integral indicator for evaluating the effectiveness of the anti-money laundering channels, formula (10) is utilized. The results of these calculations are presented in Figure 4.

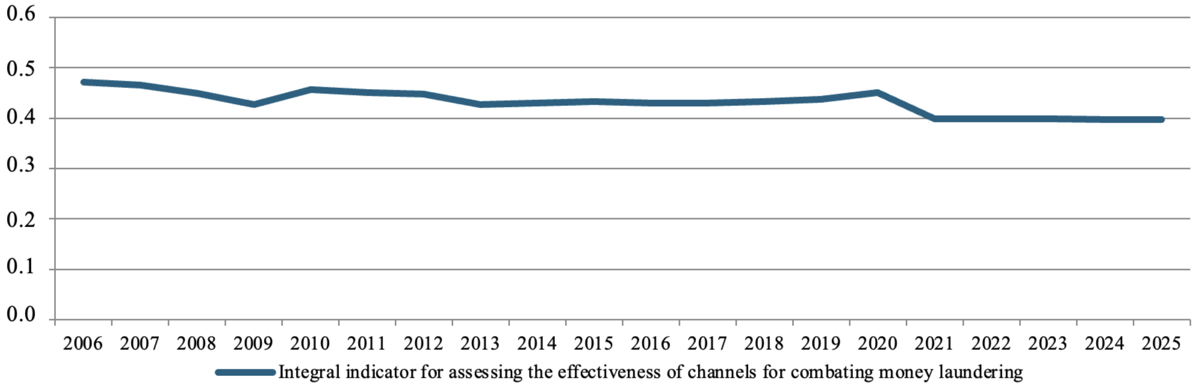

Figure 4. Integral indicator for evaluating the effectiveness of anti-money laundering channels
Source: Compiled by the authors.

According to Figure 4, a downwards trend in the effectiveness of anti-money laundering channels can be observed, with a decrease in the indicator of 0.052 points after 2021, followed by an expected annual decrease of 0.0004 units. This slight decrease suggests the stable effectiveness of the anti-money laundering channels; however, this stability is maintained by the offsetting decline in the efficiency of the tax channel due to the growth in the efficiency of the educational channel, whereas the institutional and investment channels exhibit constant efficiency.

The tax channel of anti-money laundering is characterized by a significant tax burden, which contributes to the growth of the shadow economy and stimulates the accumulation of illegal income. Additionally, the time spent paying taxes—equivalent to 41 working eight-hour days per year—could be optimized through the implementation of digital solutions and the simplification of tax payment procedures. Therefore, if anti-money laundering channels operate without interruptions, the overall effectiveness of the anti-money laundering system gradually decreases. Furthermore, the model does not account for the impact of socioeconomic disturbances arising from the COVID-19 pandemic and the full-scale invasion of Russia into Ukraine, which cannot be fully assessed.

Accordingly, to ensure the effectiveness of the anti-money laundering system, the focus should first be on the tax channel to reduce the tax burden and simplify tax administration. Thus, additional strategies can be developed to increase the efficiency of institutional and investment channels.

5. Conclusions

Four anti-money laundering channels were identified: institutional, investment, tax, and educational. The key indicators of these channels were defined, and via the Saati hierarchy analysis method, weighting coefficients were determined to assess the impact of each anti-money laundering channel. The priorities of each indicator were established via the principal component method. The forecasting models for the anti-money laundering channels were specified in different forms: a hyperbolic function for the institutional and investment channels, a parabolic function for the educational channel, and a square root function for the tax channel.

The forecasts highlighted trends in the effectiveness of the anti-money laundering channels, enabling the identification of areas that require attention to improve the anti-money laundering system. A slowly decreasing trend in the efficiency of the institutional channel was observed, declining from 0.417 units in 2021 to 0.416 units in 2025. The investment channel exhibits a weak upwards trend in efficiency, increasing from 0.410 units in 2021 to 0.411 units in 2025. In contrast, the tax channel demonstrates a rapidly decreasing efficiency trend, dropping from 0.324 units in 2021 to 0.296 units in 2025. The effectiveness of the educational channel is expected to increase in the coming years, rising from 0.485 units in 2021 to 0.531 units in 2025. However, the influence of the educational channel on the anti-money laundering system is expressed through indirect relationships.

The analysis in this paper is limited by several factors, including the availability and quality of data on anti-money laundering effectiveness, which can vary across jurisdictions and time periods. Incomplete or inconsistent data may weaken the robustness of the findings. Additionally, the forecasting models used—hyperbolic, parabolic, and square root functions—rely on assumptions that might not fully capture the complexities of anti-money laundering dynamics, potentially affecting prediction accuracy. The study also does not account for external socioeconomic disturbances, such as the COVID-19 pandemic or geopolitical events, which can significantly influence the effectiveness of anti-money laundering efforts.

Future investigations should consider expanding the analysis to include additional anti-money laundering channels and emerging technologies for a more comprehensive understanding of the system. Research will also explore long-term trends beyond 2025 and how changes in the regulatory environment may impact the effectiveness of these channels. The incorporation of external factors into the models will increase their predictive power and relevance, providing deeper insights into the challenges and opportunities within the anti-money laundering framework.

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A.Z.; supervision, A.B., A.Z.; project administration, A.Z.; funding acquisition, A.B. All authors have read and agreed to the published version of the manuscript.

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