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CORRUPTION RISKS IN THE CONTEXT OF REGIONAL FINANCIAL SECURITY: ANALYSIS BASED ON KOHONEN NEURAL NETWORKS

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ABSTRACT

During the war, threats to national security related to illegal financial transactions with the aggressor country, circumvention of sanctions, fraud in the distribution of investment and humanitarian aid, earmarked funds for the reconstruction of destroyed infrastructure, and new schemes for legalizing dirty money are becoming more acute. Therefore, the study of the risks of illegal financial transactions at the regional level in Ukraine is a primary step towards understanding the specifics of corruption, identifying the main factors that shape them, and developing targeted measures to overcome them. To analyze corruption risks in the regions of Ukraine and the city of Kyiv, this article uses a base of 10 indicators covering key aspects of financial support, economic activity, public opinion, trust in government, and digital transformation to provide a holistic picture of regional security and development. Clustering by the level of corruption risk, which was implemented using Kohonen's self-organizing maps, allowed to identify 4 groups of Ukrainian regions with similar characteristics: Cluster 1 (Vinnytsia, Lviv and Ternopil regions) – regions with a high level of development and medium corruption risks; Cluster 2 (Volyn, Dnipropetrovs'k, Donetsk, Zhytomyr, Ivano-Frankivsk, Kharkiv, Khmelnytskyi and Chernihiv regions) – regions with an average level of development and moderate corruption risks; Cluster 3 (Zakarpattia, Kirovohrad, and Rivne regions) - regions with an average level of development and problems in governance; Cluster 4 (Zaporizhzhia, Kyiv, Luhansk, Mykolaiv, Odesa, Poltava, Sumy, Kherson, Cherkasy, Chernivtsi regions and the city of Kyiv) – regions with high corruption risks. The implemented clustering facilitates the development of individualized and targeted anti-corruption strategies for each group of regions. The results of the study allow us to focus anti-corruption efforts on the most problematic areas and develop targeted programs to effectively reduce corruption risks.

Keywords: corruption risks, regional financial security, self-organizing Kohonen maps, risk analysis, financial control, public administration, anti-corruption measures

JEL Classification: C45, H83, R58, G32

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INTRODUCTION

Corruption is one of the biggest problems of modern society, which negatively affects all aspects of public life. Corruption is associated with such phenomena as money laundering, terrorist financing, and other forms of financial crimes that pose a threat to the security of the state. It undermines public trust in government institutions, weakens the rule of law, and creates unfavourable conditions for economic development. Corruption can lead to the misallocation of resources, which in turn reduces the effectiveness of public administration, increases social inequality and hinders innovative development.

The urgency of the problem is exacerbated by the need to develop effective strategies to identify and reduce corruption risks at the local level. Effective strategies should be based on a comprehensive analysis of corruption threats specific to each region and be aimed at increasing transparency, accountability and efficiency of financial resource management. Implementation of such strategies includes not only improving the system of control and monitoring of financial flows but also the active participation of the public in the processes of governance and oversight. This allows for the creation of an adaptive system capable of responding quickly to changes in the corruption situation and adjusting policies based on new data. Research on corruption risks is also important for developing evidence-based recommendations for improving anti-corruption mechanisms. Regular and systematic monitoring allows to identify corruption schemes that may be invisible in a superficial analysis. In addition, the analysis of corruption risks contributes to the formation of indicators reflecting specific aspects of corruption activities and the development of targeted measures aimed at improving the effectiveness of the fight against corruption.

All this makes the anti-corruption fight an extremely urgent task for Ukraine, which is on its way to stabilizing the economic situation under martial law and integrating with the European Union. Researching the level of corruption risks in Ukraine's regions is a priority, as the regional level of government is key to ensuring the effective implementation of public policy. Since Ukraine's regions have different levels of socio-economic development and unique challenges, studying corruption risks at the regional level will allow us to take into account these specific conditions and develop more targeted and effective anti-corruption strategies.

LITERATURE REVIEW

The theoretical framework for understanding corruption risks is well documented in the works of Rose-Ackerman (1975). Scholar highlights the economic and institutional factors that determine corrupt behaviour, emphasizing the role of incentives and deterrence. Kaufmann et al. (2009) developed the World Governance Indicators (WGI), which provide a comprehensive framework for assessing governance and corruption at different levels, including the regional level.

Kaya (2023). conducted research in the direction of finding the main variables related to corruption in public institutions, and finding the relationships between possible changes. Flatters, et al., (1995) examined in more detail such type of corruption collusion as administrative corruption, in which taxpayers and collectors collude, this problem is the cause of tax evasion in developing countries. Bijańska et al., (2018) proposed a mechanism to combat fiscal corruption by providing incentives and concluded that corruption at the highest levels should be curbed.

Statistical methods are crucial for quantifying corruption risks. Djouadi et al. (2024). used cross-country regressions to identify the determinants of corruption, such as economic development and political history. Based on this, Kovbasyuk et al. (2024) used econometric methods to investigate the relationship between decentralization and corruption, finding that fiscal decentralization can either mitigate or exacerbate corruption depending on the institutional context.

Composite indicators, which combine several variables into a single index, are important to capture the multifaceted nature of corruption. Tiutiunyk et al. (2022) provide a detailed guide to composite indicator construction, discussing normalization methods that ensure comparability across regions. They advocate the use of z-scores and minimal normalization to standardize the data, which is crucial for the subsequent application of clustering methods.

Cluster analysis groups regions with similar characteristics, which facilitates the development of targeted anti-corruption strategies. Mazurenko et al. (2023) used cluster analysis to categorize countries by corruption and institutional quality, demonstrating the usefulness of this method in policymaking. In a regional context, Hrytsenko et al. (2023) emphasized the importance of spatial econometrics and cluster analysis in understanding regional differences in corruption.

The clustering algorithm is widely used to divide data into homogeneous groups. Ivashchenko et al. (2010) reviewed various clustering methods, noting that K-means is particularly effective for large datasets and produces clear and interpretable results. Its application in regional corruption studies allows for the identification of clusters of regions with similar corruption risk profiles, as demonstrated by Vasylieva and Kasyanenko (2013) in their analysis of corruption in Chinese provinces.

Regional Analysis of Corruption in Ukraine Ukraine is a unique case study for regional corruption due to its diverse economic and political landscape. Mentel et al. (2018) examined the regional dimensions of corruption in Ukraine, emphasizing the role of political connections and economic disparities. His findings emphasize the need for region-specific anti-corruption measures that can be effectively designed using the methodologies discussed.

Despite the large number of studies on corruption in different countries, there is a noticeable gap in the scientific discourse, in particular, the lack of a comprehensive analysis that would outline a regional analysis of corruption risks and their clustering, which would allow identifying the most vulnerable regions and developing strategic programs to increase transparency and accountability at the local level. This gap is especially important given the key role of corruption in the country's financial security, as a comprehensive regional analysis allows to identify specific factors and conditions that contribute to the emergence of corruption risks in different regions "on the ground" and to develop targeted strategies to reduce them.

AIMS AND OBJECTIVES

The purpose of the article is to analyze corruption risks in the regions of Ukraine in the context of ensuring regional financial security using Kohonen neural networks. The study is aimed at identifying regional differences in the levels of corruption threats and developing targeted recommendations to reduce corruption and improve governance.

To achieve this goal, the following objectives were set:

- to assess the level of corruption risks in the regions of Ukraine using self-organized Kohonen maps;
- to develop differentiated recommendations for each cluster of regions aimed at reducing corruption risks, increasing transparency of governance and improving financial control at the regional level;
- to provide a summarizing conclusion on the possibility and effectiveness of using Kohonen neural networks for analyzing corruption risks.

METHODS

To analyze the level of corruption risk in the regions of Ukraine and the city of Kyiv, 10 indicators were identified that cover key aspects of financial support, economic activity, public opinion, trust in government, and digital transformation, which allows us to get a holistic picture of regional security and development. The selected indicators are presented in Table 1.

This selection of indicators was based on the theory of the economics of crime developed by Becker (1968) and the theory of corruption control studied by Klitgaard (1988). These studies provide an expanded view of important indicators for analyzing domestic corruption. In addition, the study of Shah (2006) was used, in which the researcher considers indicators that include the possibility of the existence of a vertically cohesive network of corrupt officials.

Table 1. Input indicators.

Indicator	Description	Characteristics
K1 (Prokhorov et al., 2020)	State support for utilities, 2019, UAH billion	Reflects the amount of financial support to municipal enterprises from the state in 2019, which is an indicator of state intervention and regulation in the economic development of enterprises.
K2 (Ukrstat, 2023a)	Number of utility companies by region, 2018	Characterizes the structure of local government and the level of decentralization of economic activity.
K3 (IRI, 2023a)	Approval of law enforcement agencies - police, 2021	It is an indicator of public trust in law enforcement agencies and their effectiveness.
K4 (IRI, 2023a)	Level of trust in the judiciary, 2021	It is an indicator of the legitimacy of legal institutions and the rule of law.
K5 (Ukrstat, 2023c)	Gross regional product per capita, UAH	It is a key indicator of the economic productivity and well-being of the region's population.
K6 (The Digital, 2023)	Index of digital transformation of regions, 2023	Reflects the level of implementation of information technologies in public administration and socio-economic processes.
K7(Transparentcities, 2023)	Transparency rating	It is used to assess openness, accountability and compliance with the principles of good governance.
K8 (Ukrstat, 2023e)	Gini index (coefficient of concentration of per capita equivalent total income), 2018	Measures the degree of economic inequality in income among the population, and is an important indicator of social justice and living standards.
K9 (IRI, 2023b)	Feeling safe in the city of residence	An indicator of the subjective sense of security in the place of residence, which characterizes social stability and quality of life in the region.
K10 (IRI, 2023b)	Approval of local media activities	The level of approval of the local media, which is an indicator of public confidence in the media and the level of public awareness.

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It should be noted that due to limited data, due to the martial law in Ukraine, which has been in effect since February 2022, as well as active hostilities in certain territories of Ukraine, obtaining up-to-date regional data has become much more difficult. This is the main reason why data from previous years is used to analyze regional corruption risks.

Despite the limited data, its use is not a problem for the analysis. Retrospective data allows modelling and forecasting of corruption risks based on previous trends that may be relevant in times of war. This approach helps to create a reasonable picture of the risks, even if current data is partially unavailable or unreliable. The initial data are shown in Table 2.

Table 2. Input data.

Region	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10
Vinnytsia region	0,5	328	1,5	0,8	88380	0,796	78,9	0,229	2,1	2
Volyn region	0,1	181	1,5	1	75193	0,72	62,4	0,218	2,1	1,8
Dnipropetrovsk region	5,2	415	1,4	0,8	126209	0,916	84,2	0,214	1,5	1,4
Donetsk region	3,9	252	1,6	1,1	50124	0,469	91	0,243	1,7	1,6
Zhytomyr region	0,7	277	1,3	1	76017	0,692	64,7	0,23	1,6	1,7
Transcarpathian region	0	178	1,5	0,9	49538	0,756	53,5	0,258	2	1,7
Zaporizhzhia region	4,1	315	1,4	0,8	99738	0,37	53,8	0,207	1,4	1,4
Ivano-Frankivsk region	0,9	230	1,6	1	66245	0,683	63,5	0,171	2,1	2
Kyiv region	0,4	453	1,4	0,7	135817	0,588	59,1	0,238	1,6	1,5
Kirovohrad region	0	212	1,7	1	81166	0,431	62,5	0,218	1,6	1,9
Luhansk region	0	119	1,5	1,1	20297	0,404	38,3	0,232	1,7	1,4
Lviv region	1	483	1,5	0,8	94317	0,799	85,5	0,207	1,8	1,7
Mykolaiv region	0,2	226	1,4	1	86750	0,431	71,4	0,221	1,6	1,6
Odesa region	0,8	421	1,2	0,7	92823	0,836	57,6	0,224	1,5	1,4
Poltava region	0,7	329	1,4	0,7	136608	0,814	37,9	0,232	1,6	1,5
Rivne region	0,2	204	1,6	1	62485	0,794	48,5	0,201	1,7	1,8
Sumy region	0,3	186	1,5	0,8	75815	0,534	62	0,213	1,8	1,7
Ternopil region	0	226	1,7	1,1	60565	0,91	79,6	0,182	2	1,9
Kharkiv region	8,5	457	1,5	1,1	97428	0,571	52,7	0,217	1,9	1,6
Kherson region	0,1	337	1,5	1,1	66973	0,5	49,7	0,221	1,4	1,7
Khmelnytskyi region	0	301	1,6	1,1	77153	0,61	76,2	0,19	2,1	1,9
Cherkasy region	0	234	1,4	0,8	91817	0,761	54,2	0,213	1,7	1,7
Chernivtsi region	0,2	157	1,5	1,1	50110	0,54	56	0,183	1,7	1,6
Chernihiv region	0,3	214	1,5	1	85435	0,522	54	0,251	1,8	1,7
Kyiv city	111,91	211	1,4	0,7	342247	0,588	59,1	0,266	1,6	1,5

Also, it is important to note that the regions of Ukraine, in particular, Donetsk and Luhansk, are taken into account in the calculation of corruption risks due to the increased corruption threats in the areas of military operations or occupation, where state control is weakened and vulnerability to illegal activities is increased. In times of war, these regions are hotbeds of increased corruption risks due to disruption of the normal functioning of institutions, abuse of power and illegal activities, which require special attention to risk assessment and management.

The analysis of corruption risks in this study was conducted in three stages:

Stage 1 – data normalization: In order to allow further analysis, the data had to be normalized, as each of the selected indicators has different dimensions and values. For this purpose, we chose the nonlinear normalization method, as it allows us to obtain more efficient estimates than linear normalization within the range [0, 1]. This procedure was carried out according to formula (1):

$$X_{ij} = \left(1 + e^{\frac{\bar{k}_j + k_{ij}}{\partial(k)}}\right)^{-1} \quad (1)$$

where X_{ij} is the normalized value of the j-th indicator in the context of the i-th region; $\bar{k}_j$ – is the average value of the j-th indicator within the studied list of Ukrainian regions; k_{ij} – is the actual value of the j-th indicator in the context of the i-th region of Ukraine; $\partial(k)$ – is the standard deviation of the j-th indicator within the studied list of Ukrainian regions.

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Stage 2 – using Kohonen's self-organized maps: after preparing the data, the level of corruption risks of Ukrainian regions was analyzed using Kohonen's self-organized maps (SOM) with the help of Viscovery SOMine software. The choice of Viscovery SOMine software was based on its ability to efficiently process large amounts of data and visualize multidimensional structures in a clear two-dimensional space. Viscovery SOMine provides a high level of flexibility in setting model parameters, which allows it to be adapted to the specifics of regional data and has built-in tools for data preprocessing, analysis, and clustering, which significantly increases the accuracy and visibility of the results. Thanks to its interactivity, ability to identify hidden patterns and integration of results in various formats, Discovery SOMine is the best choice for researching corruption risks, ensuring high efficiency and scientific validity of the analysis.

Stage 3 – drawing conclusions based on the clustering, providing recommendations, which involves analyzing the results of clustering the regions of Ukraine using self-organized Kohonen maps.

RESULTS

Kohonen maps are a type of unsupervised learning neural network that projects data from a multidimensional space into a two-dimensional one. This tool was developed by Finnish scientist Teuvo Kohonen in 1982 [11].

In general, there are different approaches to organizing data in a multidimensional space, but the SOM method has many advantages in data visualization, identifying hidden characteristics of objects that are not described by the values of input indicators. The method allows you to process arrays with missing values. It also allows you to analyze object trajectories. SOM is a clustering method based on artificial neural networks. It was first applied by Kohonen in various fields in the 80s.

As noted earlier, the first stage of analysis is the normalization of indicators. The normalized data are shown in Table 3.

Table 3: Normalized values.

Region	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10
Vinnytsia region	0,0045	0,5742	0,6000	0,2500	0,2115	0,7802	0,7721	0,6105	1,0000	1,0000
Volyn region	0,0009	0,1703	0,6000	0,7500	0,1705	0,6410	0,4614	0,4947	1,0000	0,6667
Dnipropetrovsk region	0,0465	0,8132	0,4000	0,2500	0,3290	1,0000	0,8719	0,4526	0,1429	0,0000
Donetsk region	0,0348	0,3654	0,8000	1,0000	0,0926	0,1813	1,0000	0,7579	0,4286	0,3333
Zhytomyr region	0,0063	0,4341	0,2000	0,7500	0,1731	0,5897	0,5047	0,6211	0,2857	0,5000
Transcarpathian region	0,0000	0,1621	0,6000	0,5000	0,0908	0,7070	0,2938	0,9158	0,8571	0,5000
Zaporizhzhia region	0,0366	0,5385	0,4000	0,2500	0,2467	0,0000	0,2994	0,3789	0,0000	0,0000
Ivano-Frankivsk region	0,0080	0,3049	0,8000	0,7500	0,1427	0,5733	0,4821	0,0000	1,0000	1,0000
Kyiv region	0,0036	0,9176	0,4000	0,0000	0,3588	0,3993	0,3992	0,7053	0,2857	0,1667
Kirovohrad region	0,0000	0,2555	1,0000	0,7500	0,1891	0,1117	0,4633	0,4947	0,2857	0,8333
Luhansk region	0,0000	0,0000	0,6000	1,0000	0,0000	0,0623	0,0075	0,6421	0,4286	0,0000
Lviv region	0,0089	1,0000	0,6000	0,2500	0,2299	0,7857	0,8964	0,3789	0,5714	0,5000
Mykolaiv region	0,0018	0,2940	0,4000	0,7500	0,2064	0,1117	0,6309	0,5263	0,2857	0,3333
Odesa region	0,0071	0,8297	0,0000	0,0000	0,2253	0,8535	0,3710	0,5579	0,1429	0,0000
Poltava region	0,0063	0,5769	0,4000	0,0000	0,3613	0,8132	0,0000	0,6421	0,2857	0,1667
Rivne region	0,0018	0,2335	0,8000	0,7500	0,1310	0,7766	0,1996	0,3158	0,4286	0,6667
Sumy region	0,0027	0,1841	0,6000	0,2500	0,1724	0,3004	0,4539	0,4421	0,5714	0,5000
Ternopil region	0,0000	0,2940	1,0000	1,0000	0,1251	0,9890	0,7853	0,1158	0,8571	0,8333
Kharkiv region	0,0760	0,9286	0,6000	1,0000	0,2396	0,3681	0,2787	0,4842	0,7143	0,3333
Kherson region	0,0009	0,5989	0,6000	1,0000	0,1450	0,2381	0,2222	0,5263	0,0000	0,5000
Khmelnytskyi region	0,0000	0,5000	0,8000	1,0000	0,1766	0,4396	0,7213	0,2000	1,0000	0,8333
Cherkasy region	0,0000	0,3159	0,4000	0,2500	0,2221	0,7161	0,3070	0,4421	0,4286	0,5000
Chernivtsi region	0,0018	0,1044	0,6000	1,0000	0,0926	0,3114	0,3409	0,1263	0,4286	0,3333
Chernihiv region	0,0027	0,2610	0,6000	0,7500	0,2023	0,2784	0,3032	0,8421	0,5714	0,5000
Kyiv city	1,0000	0,2527	0,4000	0,0000	1,0000	0,3993	0,3992	1,0000	0,2857	0,1667

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After performing the procedures of the Kohonen mapping algorithm, 4 clusters were obtained, and a map was constructed for each of the selected indicators. The results are presented in Figure 1.

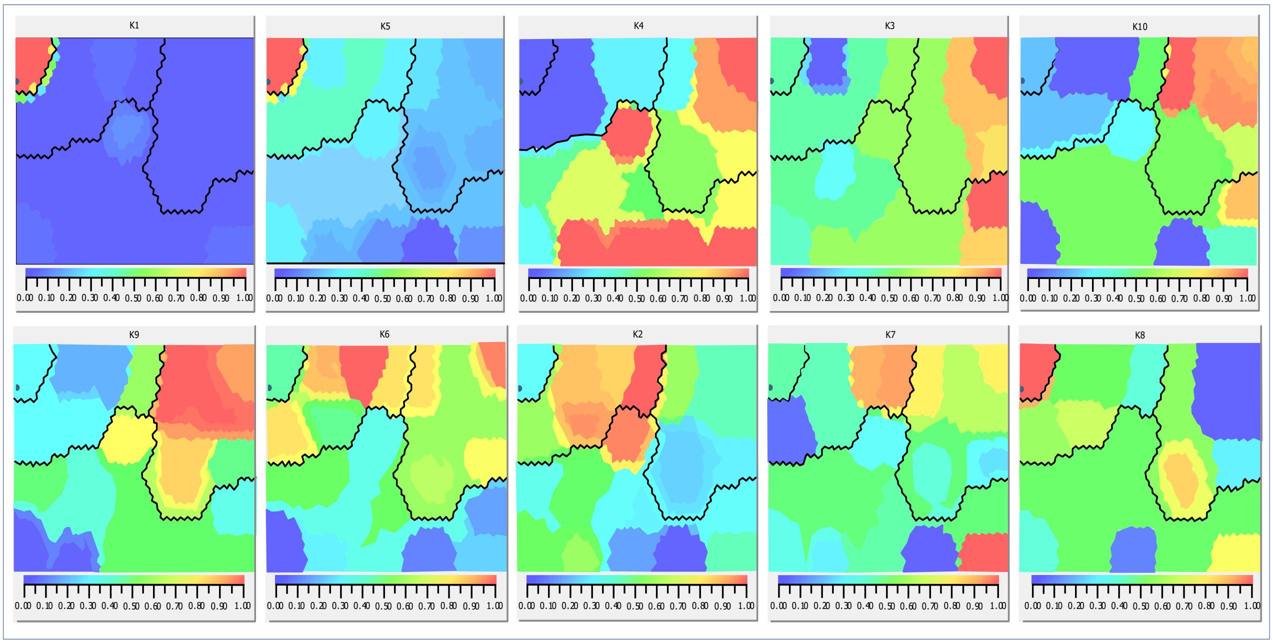

Figure 1. Kohonen maps of corruption risk indicators.

The map analysis revealed 3 regions with quantization errors exceeding 10%, which is about 10% of the total number of countries. It can be assumed that this is an acceptable level of deviation for clustering models.

As a result of the analysis of corruption risks using self-organized Kohonen maps, 4 clusters of Ukrainian regions were identified that differ in terms of development and corruption threats (Figure 2).

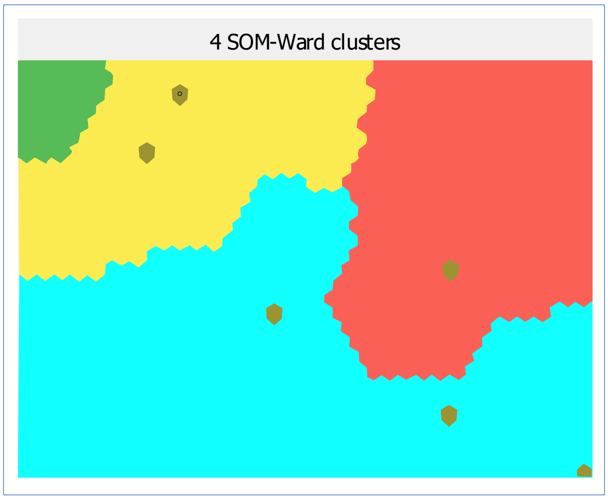

Figure 2. Kohonen's clustering map.

Table 4 shows the results of clustering the regions of Ukraine by the level of corruption risks, including a description of each cluster and recommendations for fighting corruption in each of them.

Table 4. Cluster distribution.

Cluster number	Areas	Level of corruption risk	Description.	Recommendations.
1st cluster (blue)	Vinnytsia region, Lviv region, Ternopil region	Low level	The regions of this cluster demonstrate a high level of development with medium corruption risks. These regions have well-developed economic and social infrastructure, as well as effective state institutions.	Maintain and develop successful governance and transparency practices; use positive experience to improve other regions; continue investing in infrastructure and social programs to maintain positive development dynamics.
2nd cluster (red)	Volyn, Dnipropetrovska region, Zhytomyrska region, Ivano-Frankivska region, Kharkivska region, Khmelnytska region, Chernihivska region	Moderate level of corruption risk (above average)	The regions of this cluster have a medium level of development with moderate corruption risks. Although these regions show a stable level of development, there are certain problems in governance and transparency.	Develop specialized programs to improve transparency and accountability in the public sector; regularly evaluate the effectiveness of anti-corruption measures and adjust strategies based on new challenges and results.
3rd cluster (yellow)	Transcarpathian region, Kirovograd region, Rivne region	Medium level of risk	These regions have an average level of development but with some problems in governance and transparency. Risks of corruption may be associated with insufficient efficiency of management processes.	Implement measures to increase the effectiveness of local authorities and control the implementation of government programs; regularly review and adjust anti-corruption strategies based on new data and analysis.
4th cluster (green)	Zaporizhzhia region, Kyiv region, Luhansk region, Mykolaiv region, Odesa region, Donetsk region, Poltava region, Sumy region, Kherson region, Cherkasy region, Chernivtsi region, Kyiv city	High level of risk	The regions in this cluster have high corruption risks. There is a significant problem with managerial efficiency and transparency.	Develop and implement effective strategies to combat high corruption risks; strengthen control over public spending and local government activities; implement reforms to improve management processes, increase the efficiency of public services, and ensure stricter control over the implementation of budget programs.

The analysis of the clustering of Ukrainian regions by the level of corruption risks presented in Table 4 demonstrates a clear differentiation of territories based on their impact on financial security. The use of Kohonen's neural networks for clustering allowed us to identify specific patterns in the distribution of corruption risks among regions, which allows us to develop targeted recommendations to improve the effectiveness of the fight against corruption. The results of the clustering show that regions with high levels of corruption risks require a comprehensive approach to reforming the governance system and strengthening control over financial flows. For such regions, it is recommended to introduce more detailed monitoring and transparency mechanisms, improve the skills of personnel involved in the management of financial resources, and use technology to automate control processes.

In general, in the context of this study, special attention should be paid to the regions of the 4th cluster, where the vast majority of regions are currently in the zone of active military operations or in high-risk areas, which significantly complicates their socio-economic situation and management processes.

In general, the results of clustering emphasize the need for a differentiated approach to fighting corruption depending on the specifics of corruption risks in each region. The use of Kohonen's neural networks allows to create a flexible and adaptive system of corruption risk management, which contributes to the improvement of regional financial security and sustainable development of territories.

DISCUSSION

The analysis of corruption risks at the regional level in Ukraine using the methods of statistical processing of integral indicators and cluster analysis allows for a deeper understanding of the multifaceted nature of corruption and its implications for governance and development.

The study is based on the theoretical framework laid out by Rose-Ackerman (1975), with a focus on the economic and institutional determinants of corruption. This study employs statistical methods (in particular, data normalization), which is consistent with previous studies by Djouadi et al. (2024) and Kovbasyuk et al. (2024), who used econometric methods to analyze the determinants of corruption and their impact on governance structures.

The use of cluster analysis facilitates the segmentation of regions based on their corruption risk profiles. This methodology is consistent with previous studies by Yarovenko (2020) and Vasylieva and Kasyanenko (2013), who used cluster analysis

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to categorize countries or regions by corruption. Identifying clusters of regions with similar corruption characteristics allows policymakers to prioritize anti-corruption measures and allocate resources efficiently.

The results of the study have a significant impact on anti-corruption policy in Ukraine. By identifying regions with high corruption risks and grouping them according to similar characteristics, policymakers can tailor measures aimed at addressing specific corruption drivers in each cluster. This approach is in line with the recommendations of Mentel et al. (2018), who emphasized the importance of region-specific anti-corruption measures. In addition, assessing the effectiveness of interventions through pre- and post-analysis of corruption levels provides valuable information on the impact of anti-corruption initiatives, as advocated by Ivashchenko et al. (2010) and others.

While the study offers valuable insights, it is not without limitations. Relying on quantitative data may leave out qualitative aspects of corruption, such as social norms and cultural factors that may influence the dynamics of corruption in regions. Future research could integrate qualitative methods such as interviews and case studies to provide a more holistic understanding of corruption risks.

In summary, the analysis of corruption risks at the regional level in Ukraine provides valuable insights into the complex nature of corruption and its implications for governance and development. Through the use of advanced statistical techniques and cluster analysis, the study provides a basis for evidence-based anti-corruption policy, emphasizing the importance of regional responses designed to address the unique challenges faced by each region.

CONCLUSIONS

The article provides a comprehensive analysis of corruption risks at the level of Ukrainian regions using statistical data processing (data normalization) and cluster analysis The use of self-organized Kohonen maps to analyze regional corruption risks has shown effectiveness in identifying hidden patterns and structuring regions by the level of corruption threats and management features. The first cluster (Vinnytsia, Lviv, and Ternopil regions) demonstrates a relatively high level of economic development and functioning of state institutions, accompanied by medium corruption risks. It is recommended to support effective management practices and invest in infrastructure modernization to maintain positive dynamics. The second cluster (Volyn, Dnipro, Donetsk, and other regions) is characterized by stability but has problems with transparency and management processes. Implementation of targeted anti-corruption initiatives and regular monitoring of the effectiveness of measures are recommended. The third cluster (Zakarpattia, Kirovohrad, Rivne) requires strengthening of governance institutions and continuous evaluation of anti-corruption strategies.

The fourth cluster (Zaporizhzhia, Kyiv, Odesa, and other regions) has the most critical corruption risks that require intensive reforms and strengthened control over public spending. A differentiated approach to each cluster allows for the development of effective strategies aimed at reducing corruption risks and strengthening regional financial security, which is key to ensuring sustainable development and improving the efficiency of public administration in Ukraine.

The identified groups of regions require further research for a more detailed study of corruption. Each group has its own advantages and disadvantages that affect the overall level of corruption and require the development of specific anti-corruption strategies adapted to their unique conditions.

Further research could be aimed at developing and implementing regional anti-corruption programs focused on the specific corruption risks of each cluster; analyzing the factors that influence differences in the level of corruption risks between different clusters; studying the effectiveness of existing anti-corruption measures in different regions in order to adapt and improve them; studying socio-economic, political and cultural factors that contribute to corruption at the regional level.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

REFERENCES

1. Becker, G. (1968). Crime and punishment: An economic approach. *Journal of Political Economy, 76*(2), 169-217. https://www.nber.org/system/files/chapters/c3625/c3625.pdf
2. Klitgaard, R. E. (1988). Controlling corruption. University of California Press. https://www.perlego.com/book/552047/controlling-corruption-pdf
3. Shah, A. (2006). Corruption and decentralized public governance (Policy Research Working Paper No. 3824). The World Bank. https://openknowledge.worldbank.org/bitstreams/dd83ffb5-d1d8-52fc-a17c-d99c335d175a/download
4. Harrington, E. C. (1965). The desirability function. *Industrial Quality Control, 21*, 494-498.
5. BRDO. (2021). Regional doing business - 2020. https://brdo.com.ua/wp-content/uploads/2021/02/Regional-Doing-Business-2020.pdf
6. Prokhorov, B., & Lonevskyi, O. (2020). 141 mlrd z byudzhetu: chomu AMKU turbue finansuvannya komunal'nykh pidpryyemstv? Center for Economic Strategy. https://ces.org.ua/financing-of-utilities/
7. Ukrstat. (2023a). Kil'kist' komunal'nykh pidpryyemstv za oblastyamy, 2018. https://ukrstat.gov.ua/operativ/operativ2013/fin/kp_ed/kp_ed_u/kp_ed_u_2019.htm
8. IRI (2023a). Seventh all-Ukrainian municipal survey. https://iri.org.ua/sites/default/files/surveys/IRI%20Survey%202021.pdf
9. Ukrstat. (2023b). Dokhody naselennya po rehionakh Ukrayiny. https://www.ukrstat.gov.ua/operativ/operativ2022/gdn/dvn/dn_reg2021.xlsx
10. Ministerstvo finansiv Ukrayiny. (2023). Byudzhet Ukrayiny. https://mof.gov.ua/storage/files/2_Budget_of_Ukraine_2020_(for_website).pdf
11. Ukrstat. (2023c). Valovyy rehional'nyy produkt. https://www.ukrstat.gov.ua/operativ/operativ2021/vvp/kvartal_new/vrp/VRP_%20reg_04_20_II_ue.xls
12. Ukrstat. (2023d). Kil'kist' administratyvno-terytorial'nykh odynyts' za rehionamy Ukrayiny. https://www.ukrstat.gov.ua/operativ/operativ2016/ds/ator/ator2016_u.htm
13. Ministry of Digital Transformation of Ukraine. (2023). Indeks tsyfrovoyi transformatsiyi rehioniv Ukrayiny. https://oda.zht.gov.ua/wp-content/uploads/2023/04/Indeks_tsyfrovoyi_transformatsiyi_regioniv_Ukrayiny.pdf
14. Ukrstat. (2023e). Indeks Dzhyni po oblastyam Ukrayiny. https://ukrstat.gov.ua/operativ/menu/menu_u/tda.htm
15. IRI (2023b). Rating of Ukrainian cities. https://iri.org.ua/sites/default/files/surveys/Rating%20of%20Ukrainian%20cities%202021.pdf
16. Rose-Ackerman, S. (1975). The economics of corruption. *Journal of Public Economics, 4*, 187-203. https://gpde.direito.ufmg.br/wp-content/uploads/2019/08/rose-ackerman1975-1.pdf
17. Flatters, F., & Macleod, W. B. (1995). Administrative corruption and taxation. *International Tax and Public Finance, 2*, 397-417. https://www.academia.edu/20587334
18. Kaya, H.D. (2023). The global crisis, government contracts, licensing and corruption. *SocioEconomic Challenges, 7*(4), 1-7. https://doi.org/10.61093/sec.7(4).1-7.2023
19. Kovbasyuk, L., Vakulenko, Y., Ivanets, I., Bozhenko, V., & Kharchenko, D. (2024). Forecast of Corruption: From Ethical to Pragmatic Considerations. *Business Ethics and Leadership, 8*(2), 184-199. https://doi.org/10.61093/bel.8(2).184-199.2024
20. Bijańska, J., Kuzior, A., & Wodarski, K. (2018). Social Perception of Hard Coal Mining in Perspective of Region's Sustainable Development. *Management Systems in Production Engineering, 26*(3) 178-183. https://doi.org/10.1515/mspe-2018-0029
21. Djouadi, I., Zakane, A., & Abdellaoui, O. (2024). Corruption and Economic Growth Nexus: Empirical Evidence From Dynamic Threshold Panel Data. *Business Ethics and Leadership, 8*(2), 49-62. https://doi.org/10.61093/bel.8(2).49-62.2024
22. Tiutiunyk, I., Mazurenko, O., Spodin, S., Volynets, R., & Hladkovskyi, M. (2022). THE NEXUS BETWEEN INTERNATIONAL TAX COMPETITIVENESS AND THE SHADOW ECONOMY: A CROSS-COUNTRIES ANALYSIS. *Financial and Credit Activity Problems of Theory and Practice*, *1*(42), 196–205. https://doi.org/10.55643/fcaptp.1.42.2022.3703
23. Mazurenko, O., Tiutiunyk,I., Grytsyshen, D., Daňo, F., Artyukhov, A., & Rehak., R. (2023). Good governance: Role in the coherence of tax competition and shadow economy. *Problems and Perspectives in Management*, *21*(4), 757-770. https://doi.org/10.21511/ppm.21(4).2023.56
24. Hrytsenko, L., Zakharkina, L., Zakharkin, O., Novikov, V., & Hedegaard, M. (2023). The influence of information transparency on the value indicators of securities during the crisis, taking into account the time horizon of investment. *Financial and Credit Activity Problems of Theory and Practice*, *2*(49), 88–98. https://doi.org/10.55643/fcaptp.2.49.2023.4011

DOI: 10.55643/ser.3.53.2024.567

25. Mentel, G., Vasilyeva, T., Samusevych, Y., & Pryymenko, S. (2018). Regional differentiation of electricity prices: Social-equitable approach. *International Journal of Environmental Technology and Management, 21*(5-6), 354-372. https://doi.org/10.1504/IJETM.2018.100583

26. Ivashchenko, A., Kornyliuk, A., Polishchuk,Y., Romanchenko, T., & Reshetnikova, I. (2020). Regional smart specialization in Ukraine: JRC methodology applicability. *Problems and Perspectives in Management, 18*(4), 247-263. doi:http://dx.doi.org/10.21511/ppm.18(4).2020.21

27. Vasylieva, T. A., & Kasyanenko, V. O. (2013). Integral assessment of innovation potential of Ukraine's national economy: A scientific, methodical approach and practical calculations. *Actual Problems of Economics, 144*(6), 50-59. Retrieved from https://www.scopus.com/record/display.uri?eid=2-s2.0-84923539973&origin=resultslist

28. Yarovenko, G. M. (2020). THE USE OF KOHONEN MAPS TO ANALYZE THE LEVEL OF INFORMATION SECURITY OF COUNTRIES TAKING INTO ACCOUNT THEIR DEVELOPMENT. *Economic space*, *157,* 118-124. https://doi.org/10.32782/2224-6282/157-21

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КОРУПЦІЙНІ РИЗИКИ В КОНТЕКСТІ РЕГІОНАЛЬНОЇ ФІНАНСОВОЇ БЕЗПЕКИ: АНАЛІЗ НА ОСНОВІ НЕЙРОННИХ МЕРЕЖ КОХОНЕНА

В умовах війни загострюються загрози національній безпеці, пов'язані з незаконними фінансовими операціями з країною-агресором, обходом санкцій; махінаціями при розподілі інвестиційної та гуманітарної допомоги, цільових коштів на відбудову зруйнованої інфраструктури; новими схемами легалізації «брудних» грошей. Тому дослідження ризиків незаконних фінансових операцій на регіональному рівні в Україні є першочерговим кроком до розуміння специфіки корупції, виявлення основних чинників, що її формують, та розробки цілеспрямованих заходів для її подолання. Для аналізу корупційних ризиків у регіонах України та місті Києві в цьому дослідженні використано базу з 10 індикаторів, що охоплюють ключові аспекти фінансового забезпечення, економічної активності, громадської думки, довіри до влади та цифрової трансформації для формування цілісної картини регіональної безпеки та розвитку. Кластеризація за рівнем корупційного ризику, здійснена з використанням карт самоорганізації Кохонена, дозволила виокремити 4 групи регіонів України зі схожими характеристиками: Кластер 1 (Вінницька, Львівська й Тернопільська області) – регіони з високим рівнем розвитку та середніми корупційними ризиками; Кластер 2 (Волинська, Дніпропетровська, Донецька, Житомирська, Івано-Франківська, Харківська, Хмельницька та Чернігівська області) – регіони з середнім рівнем розвитку та помірними корупційними ризиками; Кластер 3 (Закарпатська, Кіровоградська та Рівненська області) – регіони із середнім рівнем розвитку та проблемами в управлінні; Кластер 4 (Запорізька, Київська, Луганська, Миколаївська, Одеська, Полтавська, Сумська, Херсонська, Черкаська, Чернівецька області та м. Київ) – регіони з високими корупційними ризиками. Здійснена кластеризація сприяє розробці індивідуалізованих і цілеспрямованих антикорупційних стратегій для кожної групи регіонів. Результати дослідження дозволяють сконцентрувати антикорупційні зусилля на найбільш проблемних сферах та розробити цільові програми для ефективного зниження корупційних ризиків.

Ключові слова: корупційні ризики, фінансова безпека регіонів, самоорганізаційні карти Кохонена, аналіз ризиків, фінансовий контроль, державне управління, антикорупційні заходи

JEL Класифікація: C45, H83, R58, G32