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Application of Multidimensional Statistical Analysis Technology for Grouping Regions by the Investment Attractiveness Level

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Abstract: The paper is devoted to studying multidimensional statistical analysis tools for grouping regions by the level of their investment attractiveness and identifying changes in the structure of regions in the context of the continued destructive impact of the COVID-19 pandemic. An analysis of approaches to assessing investment attractiveness identified their strengths. Insufficient attention to the application of methods of multidimensional statistical analysis to a grouping of regions is stated. The authors consider the clustering of regions of Ukraine in the context of their level of investment attractiveness by the method of *k*-means and identify their structure according to the level of investment attractiveness in 2019 and 2020 in the context of the COVID-19 pandemic. To verify the correctness of the conclusions, the method of principal components with the rotation of the space of the selected factors by the quartimax technique. Further grouping of regions in the space of selected principal components showed results identical to the application of the cluster analysis method. Potential investors can use the research results to determine priority areas of investment. Also, the results are useful for local self-government bodies, as they provide information on the relative level of investment attractiveness of a specific region compared to other territorial units and also allow identifying weak points in specific areas of activity.

1 INTRODUCTION

Sustainable socio-economic development of territories is associated with the need to intensify investment activities. It is primarily aimed at forming the financial basis for improving the efficiency and effectiveness of enterprises, creating new jobs, and achieving high social standards of living. Achieving this goal requires using analytical tools as part of appropriate mechanisms for managing regional development. An essential component of such tools is economical and mathematical modeling. Using relevant data and fitting models provides quantitative and qualitative assessments of the state and socio-economic development trajectories. One of the ways to create an analytical basis for determining the strategy of regional policy in the context of financial support for socio-economic development is to assess the investment attractiveness of regions.

Significant structural and technological economic changes caused by globalization, increasing competition in foreign and domestic markets, and the consequences of the COVID-19 pandemic require increased investment, which is limited financial resources and a critical task. Therefore, ensuring the region's investment attractiveness is a strategic task for developing business structures, which will help attract investment, primarily from foreign investors.

Therefore, in the current conditions of production and economic activities, issues related to assessing the investment attractiveness of regions and their grouping to determine areas for intensification of investment processes, search and use of reserves to improve the efficiency of regional investment are of priority importance.

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2 LITERATURE REVIEW

ssessing the region's investment attractiveness is essential in developing a strategy for innovation at regional and national levels. Note that the investment volume isn't always directly determined by the high level of investment attractiveness. This is due to many other factors that determine investor decision-making. In particular, such factors are various indices and ratings regularly published by international institutions and characterize the business environment, business conditions, actual investment activities, and the attractiveness of countries for investment. In particular, it can be used such evaluations like the World Bank Ranking "Doing Business" (World Bank, 2021); Index of Economic Freedom, provided by the Heritage Foundation (Heritage Foundation, 2020); Corruption Perceptions Index (CPI), compiled by the international anti-corruption organization "Transparency International" (Transparency International, 2020); Foreign Direct Investment Confidence Index (Kearney, 2020); Global Innovation Index (WIPO, 2020); European Business Association Investment Attractiveness Index (EBA, 2020); Credit rating developed by Moody's Investors Service (Moody's, 2020); World Countries' Ranking on the Global Competitiveness Index, provided by the World Economic Forum (WEF, 2020); World Competitiveness Ranking, provided by the International Institute for Management Development (IMDWCC, 2020); The KOF Globalization Index, published by the KOF Swiss Economic Institute, reflects the scale of the country's integration into the world (KOF, 2020) and many others.

These ratings provide the necessary information for potential investors on the characteristics of the country's business environment and possible investment risks. Naturally, countries with high ratings are more attractive regarding return on investment. On the other hand, countries with low ratings may also be attractive to investors, particularly for short-term investments, resulting from competition for coverage of developing countries.

These ratings should be noted that characterize the country's business environment. At the same time, investors are usually interested in specific areas, territorial units, markets, sectors of the economy, and business entities. Such assessments of the investment attractiveness of certain regions of Ukraine are provided by the State Statistics Service of Ukraine (SSCU, 2003) and the Ministry of Development of Communities and Territories of Ukraine (MCTDU, 2021).

The issue of investment attractiveness is also the focus of research. The formation of the theoretical basis for the study of the category of investment attractiveness in the context of its relationship with the investment climate, and investment risks, taking into account current trends in economic development, is reflected in the works (Kaminskyi et al., 2019; Stadnyk et al., 2020; Korenyuk and Kopil, 2018; Kyshakevych et al., 2020; Godlewska-Majkowska, 2018; Jac and Vondrackova, 2018). Researchers presented a modern understanding of the category of investment attractiveness, its content and essential characteristics, and the impact on the socio-economic development of individual regions and the country as a whole.

An important issue in modeling investment attractiveness is forming an information base for calculating various estimates of the studied characteristics. The solution to such problems is considered in (Kyshakevych et al., 2020; Jac and Vondrackova, 2018; Bushynskyi, 2020; Leshchuk, 2020; Lagler, 2020; Swidynska and De Jesus, 2020). It should be noted that the results of scholars' investigations in this field are differed both in the number of indicators and their focus in the context of reflecting certain aspects of investment activities. At the same time, the authors' positions coincide with the views that the indicators should reflect the economic, financial, and social aspects of regional development.

Modeling the investment attractiveness of regions is mainly based on statistical methods. Their application is based on quantitatively measurable indicators that reflect social, economic, environmental, and investment development components. This approach uses regression models, that presented in papers (Windhyastiti et al., 2020; Blahun et al., 2017; Vartsaba and Leshuk, 2017; Kikkas and Krasnozhenova, 2018); correlation analysis techniques (Blaschke, 2022; Dorozynski and Kuna-Marszałek, 2016); models based on neural networks (Bruneckiene et al., 2019). At the same time, the issue of identifying the level of investment attractiveness and comparing regions on this indicator is out of the attention of researchers. The approach based on comprehensive index assessment technology is quite common. It is successfully used in solving the problems of ranking regions by socio-economic development (Hryhoruk et al., 2019b,a; Mazziotta and Pareto, 2014; Meyer et al., 2016). The application of this approach to assessing investment attractiveness is reflected in studies (Swidynska and De Jesus, 2020; Kyshakevcyh and Nakhaeva, 2021; Yelnikova, 2020; Sizova et al., 2017).

Among the shortcomings of the comprehensive index assessment technology application presented in these investigations, it should be noted that they use a fairly large set of initial indicators. This makes it difficult to identify the significance of their impact on the final result and eliminates the differentiating ability of the designed composite index. These shortcomings negatively affect the ability to group the set of studied objects due to the high density of values on the composite index scale. Also out of consideration is the definition of the level of investment attractiveness of regions, which complicates the assessment of differences between regions on the calculated index.

The problems of rating regions can also be solved with the application of multidimensional statistical analysis technology, that described, in particular, in papers (Tenreiro Machado and Mata, 2015a,b; Meyer and De Jongh, 2018; De Jongh and Meyer, 2019; Walesiak, 2017; Gorbatiuk et al., 2019; Hryhoruk et al., 2020b,a; Andrusiak et al., 2022). Adaptation of multidimensional analysis methods to assess investment attractiveness is considered in studies (Cheba, 2017; Danylchuk et al., 2019; Shinkarenko et al., 2019; Musolino and Volget, 2020; Roszko-Wójtowicz and Grzelak, 2021).

At the same time, applying these methods is focused mainly on solving the problem of grouping regions in terms of investment attractiveness. The analysis of structural shifts within the constructed homogeneous groups remains out of the attention of scientists, as well as the comparison of grouping results obtained by different techniques.

According to the results of the analysis of publications, it can be concluded that there is significant diversity in approaches to assessing the investment attractiveness of regions. Among the disadvantages, we can note that the calculations are carried out without considering the dynamic and qualitative changes in the environment.

Also, the use of a large number of baseline partial indicators, to some extent, blurs the study's results and gives only a general description of the socio-economic condition of the region and the characteristics of investment activities.

The significant variety of calculated estimates and the lack of clear conclusions and recommendations for their practical application necessitates the further study of the problem of assessing the investment attractiveness of regions in the context of their grouping by using different techniques to solve this problem with the further comparison of grouping results and structural changes within groups.

The solution to these problems has led to the direction of research in this study.

3 PROBLEM DESCRIPTION AND METHODOLOGY

A large number of different indicators characterize modern investment processes. This multidimensionality of the description makes it difficult to solve problems of assessing the various characteristics of these processes, particularly the grouping of regions by the level of investment attractiveness. As noted earlier, one way to solve classification problems is using cluster analysis techniques. Unlike combinational grouping, this approach allows you to create groups of similar objects of observation, considering all the features at once. The degree of similarity, in this case, is usually the Euclidean distance between objects in the multidimensional space of primary indicators. One of the cluster analysis methods is the k-means method, which belongs to the group of iterative clustering ones.

Consider a brief description of the mathematical model of the k-means method (Hryhoruk et al., 2021). Suppose there are m observations, each characterized by n indicators $X_1, X_2, \ldots, X_n$.

We need to divide these observations into k clusters that do not intersect. At the initial stage, we choose k points-objects that will act as centers of clusters. Denote them by $C_1^{(0)}, C_2^{(0)}, \ldots, C_k{}^{(0)}$. The weight of each cluster will initially be equal to one: $w_1^{(0)} = 1, w_2^{(0)} = 1, \ldots, w_k{}^{(0)} = 1$. The index of the corresponding center will be considered the index of the corresponding cluster. Although the selected centers may move to other clusters during the subsequent iterative procedure, the indexing of the clusters will not change.

In the first step, each of the $(n-k)$ objects that are not the clusters' centers is included in one of the formed clusters. The criterion for such movement is the minimum distance to the cluster's center. The center of the cluster and its weight are recalculated. For example, for a point M_{k+1} with coordinates ($X_{k+1,1}$; $X_{k+1,2}$;...; $X_{k+1,n}$) the recalculation is performed according to the formulas:

$$C_j^{(0)} = \frac{w_j^{(0)} c_j^{(0)} + M_{k+1}}{w_j^{(0)} + 1}, \tag{1}$$

$$w_j^{(0)} = w_j^{(0)} + 1. \tag{2}$$

In the case of equality of two or more distances to the centers of clusters, the point-object joins the cluster with a smaller sequence number. Note that in practice, such a situation is unlikely.

The resulting centers and corresponding cluster weights are taken as the initial values of the related characteristics for the next iteration.

All stages of the further iterative process use formulas (1) and (2) and the whole set of initial data $M_1, M_2, ..., M_m$. At the same time, the weight of clusters continues to increase.

The objects can also be grouped by expanding them in some new space of latent scales, which reflect the generalizing characteristics. In particular, the principal components method can be constructed in such a space.

In matrix form, the model of the method is described by the formula:

$$Z^T = W \cdot F^T, \tag{3}$$

where Z is an initial standardized indicators matrix;

W – factor loadings matrix; it reflects relations between initial indicators and principal components;

F – principal components matrix.

Factor loadings matrix is calculated using eigenvalues and appropriate eigenvectors of R – initial indicators correlation matrix:

$$W = V \cdot \Lambda^{(-1)}, \tag{4}$$

where W – factor loadings matrix;

V – normalized eigenvectors matrix;

Λ – eigenvalues matrix.

The rule obtains the initial indicators correlation matrix:

$$R = \frac{Z^T \cdot Z}{m-1}, \tag{5}$$

where R – correlation matrix;

Z – initial standardized indicators matrix.

The standardization procedure for initial indicators uses a formula:

$$Z_{ij} = \frac{X_{ij} - \bar{X}_j}{s_j}, \tag{6}$$

where Z_{ij} – initial standardized indicators values;

X_{ij} – initial indicators values;

$\bar{X}_j$ – average sample value of the indicator X_j;

s_j – sample standard deviation of the indicator X_j;

$i = 1..m; j = 1..n.$

The formula obtains the principal components matrix:

$$F = Z \cdot W \cdot \Lambda^{-1}. \tag{7}$$

This matrix contains the coordinates of objects under study in a principal components space.

Not all the principal components are selected for practical application, but only the most essential part in explaining the variance of the initial indicators (information contained in the initial indicators). Given that the eigenvalues of the correlation matrix are considered to be ordered in descending their values in the calculation procedure, the weight of each subsequent principal component is reduced. Usually, the first two principal components are sufficient to achieve an "acceptable" level of explanation of the information contained in the set of initial indicators, at least 70 %.

Meaningful interpretation of the selected principal components (search for names for them) is carried out by considering the absolute values of the respective factor loads. The initial indicators that will be used to interpret the appropriate principal component include those for which the factor loadings absolute value between them and the corresponding principal component is not less than 0.75. The factor load reflects the correlation between the principal component and the related indicator. To improve the procedure of interpretation of the principal components by the problem's content, the constructed factor space is rotated with a corresponding change in both factor loadings and values of the principal components. The result is a "simple structure" space where the principal components are closely related to some initial indicators and weak to others.

4 RESULTS AND DISCUSSIONS

Consider the application of cluster analysis of the grouping of Ukraine's regions by indicators that reflect their investment attractiveness. The choice of the initial indicators set will be made based on the following considerations:

- indicators should reflect both the characteristics of investment activities of the region's business entities and the socio-economic development of the region;
- indicators should be comparable by the values for different regions;
- the indicators must be standardized, i.e., have a sample mean equal to zero and a sample standard deviation equal to one. This procedure is needed because clustering is based on a matrix of differences between the studied points-regions in the multidimensional space of the initial indicators, which is essentially a matrix of Euclidean distances between them. Therefore, for the objectivity of the calculations, it is necessary to remove the measurement units' influence on estimates of distances between objects.

Based on the recommendations of scholars presented in studies (Korenyuk and Kopil, 2018; Kyshakevych et al., 2020; Godlewska-Majkowska, 2018; Jac and Vondrackova, 2018; Bushynskyi, 2020; Leshchuk, 2020; Lagler, 2020; Vartsaba and Leshuk, 2017; Dorozynski and Kuna-Marszałek, 2016) and taking into account the above considerations, we have formed the following set of initial indicators for calculations:

X_1 – Volume of capital investments per capita, UAH;

X_2 – Volume of foreign direct investment per capita, USD;

X_3 – Gross regional product (at actual prices) per capita, UAH;

X_4 – Disposable income per capita, UAH;

X_5 – Volume of exports of goods per capita, USD;

X_6 – Volume of sold industrial products per capita, UAH;

X_7 – Total of construction work per capita, UAH;

X_8 – Employment rate of the population aged 15-70, in percent;

X_9 – Unemployment rate of the population aged 15-70 years (according to the methodology of the ILO), in percent.

We use data for 2019 and 2020 from the materials of the State Statistics Service of Ukraine (SSSU, 2022) and the Ministry of Development of Communities and Territories of Ukraine (MCTDU, 2021) for calculations. Obtained results will also be compared to assess changes in regions' position in the groups in which the regions are located. To present the region's names conveniently and briefly, we point out the correspondence between each region's name and the appropriate code (table 1). Initial data for calculations are written in table 2 and table 3.

Table 1: The relationships between the quantitative values of the desirability scale and qualitative development levels of group.

Code	Region	Code	Region
C_1	Vinnytsia	C_13	Mykolaiv
C_2	Volyn	C_14	Odesa
C_3	Dnipro	C_15	Poltava
C_4	Donetsk	C_16	Rivne
C_5	Zhytomyr	C_17	Sumy
C_6	Zakarpattia	C_18	Ternopil
C_7	Zaporizhzhia	C_19	Kharkiv
C_8	Ivano-Frankivsk	C_20	Kherson
C_9	Kyiv	C_21	Khmelnytskyi
C_10	Kyrovohrad	C_22	Cherkasy
C_11	Luhansk	C_23	Chernivtsi
C_12	Lviv	C_24	Chernihiv

Let us cluster Ukraine's regions according to the selected set of indicators using the *k*-means method. Define the number of clusters for grouping regions as equal to three: a cluster of regions with a high level of investment attractiveness, a cluster of regions with a medium level of investment attractiveness, and a cluster of regions with a low level of investment attractiveness. We make calculations using "Statistica" software. The results of clustering are shown in figure 1 and figure 2. The numbering of clusters, in this case, is determined by the used software arbitrarily. Let us provide a meaningful description of each cluster according to 2019 data.

Cluster number 1 contains 6 regions: Volyn, Donetsk, Zakarpattia, Kyrovohrad, Luhansk and Ternopil. In our opinion, this cluster can be called a group of regions with a low level of investment attractiveness. Note that the regions of this cluster are not industrially developed, which negatively affects their attractiveness for investment. In addition, the effects of the COVID-19 pandemic have had a significant negative impact on the development of these regions. Cluster number 2 contains regions with an average level of investment attractiveness. It is the most complete and consists of 14 points, which is quite natural in compliance with the essence of the division of the typical characteristics. The cluster with a high level of investment attractiveness includes cluster number 3, which includes Dnipro, Kyiv, Zaporizhzhia, and Poltava regions. For these regions, there are high values of the indicators presented in table 2, particularly the volume of foreign direct investment and relatively high employment rate, which allowed to give the cluster just such an interpretation. In addition, these regions have developed industries, which is also reflected in the indicator's values.

Comparing the cluster's structure obtained from 2020 data (figure 2), we can conclude that the fullness of clusters has not changed compared to the previous year. This indicates that there have been no significant changes in the investment attractiveness of Ukraine's regions in 2020. Although several normative acts have been adopted at the legislative level to facilitate attracting investments into Ukraine's economy, their positive impact has not yet manifested itself. On the other hand, it is possible to state a certain stabilization of indicators of socio-economic development of Ukraine's regions during the COVID-19 pandemic.

Let us consider the data of application of the principal components method for grouping Ukraine's regions by the level of investment attractiveness. We create the two-dimensional space of latent indicators obtained by applying this method and project points-regions on this space. To construct latent indicators, we use the quartimax method for rotations of factor space, which will contribute to an adequate representation of points in the new space and the identification of meaningful interpretation of new axes.

Calculations also are performed using Statistica software. The calculations' results of factor loadings are presented in table 4, and the values of points-

Table 2: Initial data for calculation for 2019 (MCTDU, 2021; SSSU, 2022).

Code	Values								
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
C_1	9196.8	153.2	71104	64729	937.3	52478.4	6650.5	58.0	9.4
C_2	11800.5	297.5	58297	52879	671.6	30585.3	2259.4	50.9	10.6
C_3	19841.6	1191.1	114784	87130	2477.8	142289.0	6291.1	59.5	7.7
C_4	6789.2	338.4	45959	39141	1116.8	68439.6	1691.2	50.9	13.6
C_5	6095.3	202.7	62911	61961	592.3	37457.1	2227.8	58.5	9.6
C_6	7010.9	288.1	41706	47495	1186.9	19086.0	1770.8	55.4	9.1
C_7	8246.3	538.3	85784	75407	1815.8	114981.1	2270.5	58.1	9.5
C_8	5969.9	529.3	57033	55537	665.1	48750.1	2701.6	56.6	7.2
C_9	27299.0	930.2	112521	75146	1098.1	68058.8	5833.2	59.3	5.9
C_10	7536.1	80.0	67763	58290	752.7	34338.9	2194.2	55.6	11.0
C_11	1303.0	209.0	16301	24477	71.3	10219.1	310.2	58.8	13.7
C_12	10137.4	446.8	70173	65691	874.9	41829.4	4391.2	57.8	6.5
C_13	10394.4	271.6	70336	63685	1912.6	55148.1	3864.1	59.1	9.3
C_14	8372.1	540.3	72738	72805	581.9	25815.1	7557.4	58.3	5.9
C_15	15316.4	841.3	123763	71627	1508.9	120922.5	5472.7	56.6	10.6
C_16	5225.1	116.7	49044	54183	381.1	37058.2	2872.8	58.4	8.3
C_17	6399.4	184.6	62955	65310	821.9	44941.0	1448.5	59.8	7.7
C_18	8016.4	47.7	46833	49843	416.7	19914.5	2325.0	53.8	10.0
C_19	7953.8	287.6	86904	65534	530.6	69605.2	5603.2	62.1	5.0
C_20	11420.8	237.9	52922	57110	259.6	29604.1	1777.3	58.9	9.6
C_21	6812.2	161.6	59583	58008	509.9	34392.0	3061.2	57.0	8.0
C_22	8143.2	298.7	76904	58808	720.1	61514.6	1732.7	59.3	8.3
C_23	3716.9	58.9	37441	48255	236.8	15093.2	2347.4	59.0	6.9
C_24	7965.9	447.4	69725	58904	808.6	34334.3	1907.2	58.9	10.2

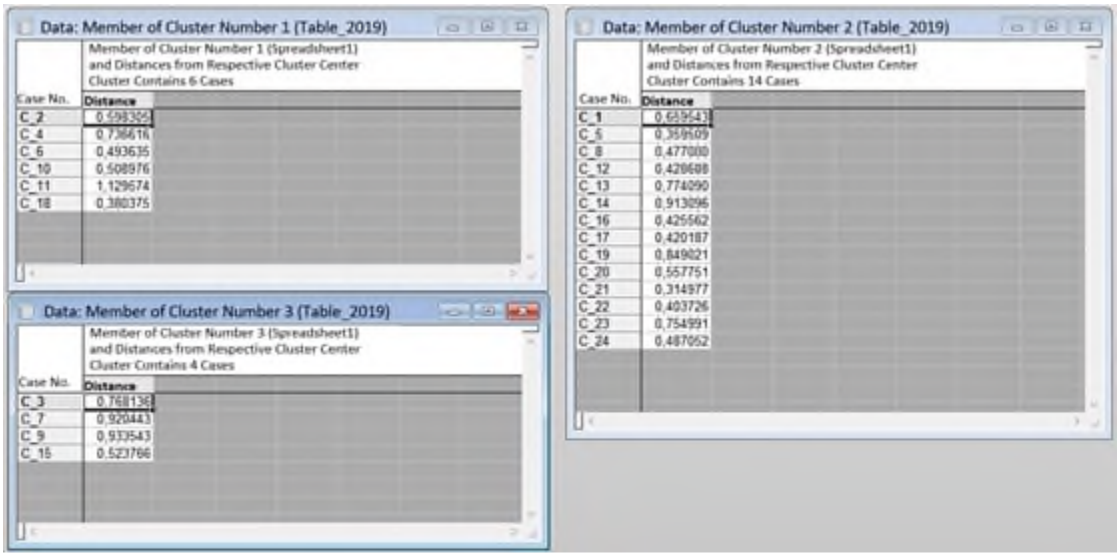

Figure 1: Clustering results of Ukraine‘s regions for data 2019.

objects in the new space – are in table 5. Note that in this case, the degree of explanation of the variance of the initial indicators by selected factors (degree of latent indicators informativeness) is 77 % for 2019 and 79 % for 2020 data. These indicators indicate the sufficiency of allocating exactly two principal components as latent indicators for further analysis.

Table 4 analysis allows us to provide such an interpretation of the selected principal components. Component F_1 has high factor loadings values for the initial indicators $X_1 - X_6$, and low for X_8 and X_9. Therefore, we can conclude that F_1 is an economic compo-

Table 3: Initial data for calculation for 2020 (MCTDU, 2021; SSSU, 2022).

Code	Values								
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
C_1	6226.8	249.9	83175	70691	896.3	50771.9	7042.7	56.2	10.7
C_2	9319.5	240.8	73215	56603	624.7	31231.1	2465.0	48.9	12.5
C_3	15208.9	1426.0	122379	92083	2403.0	135366.4	5723.9	58.0	8.6
C_4	5355.9	424.0	49422	41662	956.0	62158.9	2470.6	49.2	14.9
C_5	5615.5	266.6	70247	67187	567.0	39163.6	1783.2	55.3	10.9
C_6	3192.3	193.3	48861	51073	1078.1	19249.3	1546.7	53.7	10.6
C_7	5864.6	851.4	91498	81949	1743.8	111716.8	1871.0	56.0	10.7
C_8	3630.9	402.0	63254	60276	555.3	45016.0	2822.3	54.1	8.4
C_9	12929.1	735.8	123267	79263	1102.6	70505.2	7089.9	57.8	6.9
C_10	5562.3	188.4	77816	63472	985.0	37684.9	1486.2	53.1	12.7
C_11	1086.3	74.4	18798	26714	60.9	8904.5	339.1	56.4	15.4
C_12	5880.9	639.3	85198	71150	927.4	44425.4	5709.3	56.0	7.6
C_13	5422.3	318.8	82149	68289	2018.3	55878.6	3017.5	57.3	10.7
C_14	6757.9	470.7	82903	80164	573.4	29687.1	12078.5	56.8	7.1
C_15	11829.0	1411.6	134449	77547	1680.3	115483.4	5940.1	54.8	12.0
C_16	3165.9	229.4	58332	58814	408.0	38908.7	2862.1	56.1	9.3
C_17	4763.8	321.9	70576	71117	918.7	43165.9	1612.1	56.8	9.4
C_18	5510.9	47.5	54833	55570	433.2	20508.6	2511.5	51.6	11.5
C_19	6178.4	344.0	92864	73218	556.1	66393.8	5509.5	59.9	6.2
C_20	3536.8	155.6	59987	63073	275.3	32008.3	1279.4	56.8	11.3
C_21	5784.0	94.8	65916	64824	531.1	37850.9	5301.7	54.8	9.9
C_22	4627.2	176.7	86319	64254	684.1	64414.0	2171.5	57.0	9.5
C_23	2533.5	61.8	46136	53875	187.5	15525.8	2428.7	56.5	8.9
C_24	5599.5	455.0	78118	64933	905.4	35004.1	2501.6	56.4	11.9

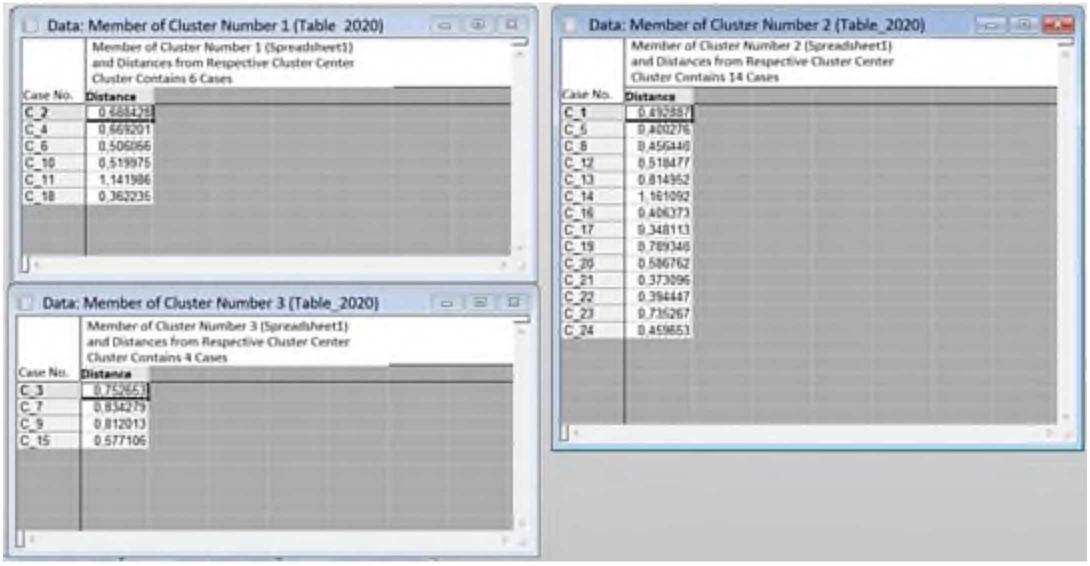

Figure 2: Clustering results of Ukraine‘s regions for data 2020.

nent of investment attractiveness, as the corresponding indicators $X_1 - X_6$ are characteristics of economic activity. For indicators X_8 and X_9 there are high values of factor loadings for component F_2 and low for F_1. Based on the essence of indicators X_8 and X_9, we can conclude that F_2 can be interpreted as a social component of investment attractiveness. For indicator X_7, the value of factor loadings for the principal component F_1 in 2019 exceeds the corresponding value for component F_2, although this excess is insignificant. In 2020, the situation was reversed. Based on the essence of indicator X_7, we can conclude that it can characterize both the economic and social components of regional development; that is, the interpretation of the results is not essentially affected by this indicator.

Table 4: Principal components' factor loadings values for data 2019 and 2020.

Indicators	Principal components			
	2019		2020	
	F_1	F_2	F_1	F_2
X_1	0.82	0.08	0.89	0.07
X_2	0.89	0.01	0.93	0.01
X_3	0.93	0.22	0.90	0.31
X_4	0.83	0.44	0.77	0.53
X_5	0.84	-0.25	0.87	-0.15
X_6	0.89	-0.13	0.93	-0.02
X_7	0.65	0.49	0.41	0.64
X_8	0.14	0.78	0.16	0.75
X_9	-0.25	-0.88	-0.21	-0.90

Table 5: Principal components' values for data 2019 and 2020.

Code	2019		2020	
	F_1	F_2	F_1	F_2
C_1	-0.55	0.49	0.04	0.53
C_2	1.31	-1.74	-0.02	-1.46
C_3	-6.03	-1.21	2.75	0.02
C_4	1.94	-3.29	-0.03	-2.32
C_5	0.90	0.38	-0.32	-0.11
C_6	1.59	-0.61	-0.70	-0.56
C_7	-1.98	-1.24	1.23	-0.58
C_8	0.42	0.29	-0.46	0.20
C_9	-4.30	0.56	1.13	1.24
C_10	1.25	-0.69	-0.10	-0.94
C_11	4.42	-0.63	-1.68	-1.16
C_12	-0.75	0.91	0.14	0.87
C_13	-0.92	-0.33	0.42	-0.16
C_14	-1.30	1.93	-0.08	2.09
C_15	-3.60	-1.78	2.25	-0.85
C_16	1.44	0.93	-0.75	0.42
C_17	0.47	0.92	-0.22	0.31
C_18	2.19	-0.49	-0.73	-0.67
C_19	-1.36	2.47	-0.07	1.84
C_20	1.14	0.51	-0.79	0.11
C_21	0.96	0.65	-0.47	0.42
C_22	0.09	0.40	-0.20	0.35
C_23	2.22	1.68	-1.28	0.65
C_24	0.44	-0.10	-0.07	-0.23

Graphic representations of the regions in the space of the identified principal components according to the data of 2019 and 2020 are respectively presented in figures 3 and 4.

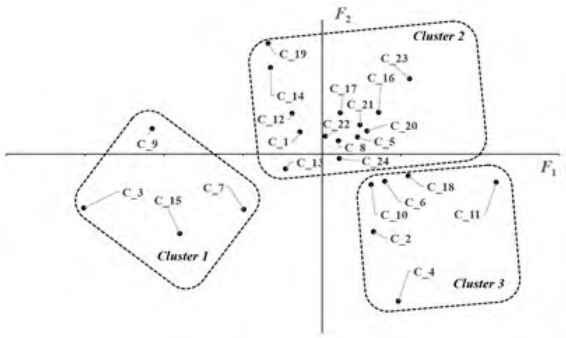

Figure 3: Grouping results of Ukraine's regions in the latent scale space for data 2019.

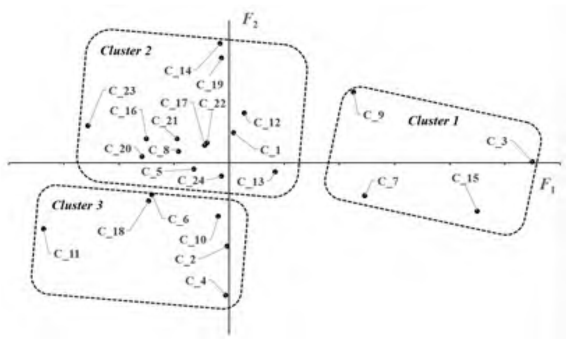

Figure 4: Grouping results of Ukraine's regions in the latent scale space for data 2020.

Figure 3 analysis allows us to conclude that we can also identify three clusters of regions. The resulting clusters in terms of content correspond to the formed clusters obtained by the k-means method. A similar situation occurs in figure 4. The results of a grouping of regions obtained using the principal components method are identical to those obtained from the clustering method.

However, it is worth noting. Figure 3 shows that cluster number 1 can be divided into at least two smaller clusters, including points C_7 (Zaporizhzhia region) and C_15 (Poltava region) to one of them and points C_3 (Dnipro region) and C_9 (Kyiv region) to the other. Similarly, points C_7 and C_15 can be allocated from cluster number 2 to a separate cluster. In the third cluster, we can distinguish points C_4 (Donetsk region) and C_11 (Luhansk region), which form two different clusters. So, the cluster structure may be more complex and require a more complex interpretation of the results. A similar situation occurs in figure 4.

However, according to the task, our study proceeded from a predetermined number of clusters. And the methods used in the study gave identical results.

5 CONCLUSIONS

Investment activity is always associated with a specific risk. Decision-making by potential investors requires a comprehensive study of the object of investment, mainly through the various assessments of the investment climate, business environment, and business conditions provided by multiple institutions. However, such estimates characterize the business environment of countries as a whole, while investors are usually interested in the separate territories and business units that are located there. Therefore, it is necessary to conduct a comprehensive analysis of the investment object to reduce the potential risks when investing. One of the approaches is to assess its investment attractiveness. For individual territorial entities, which are regions, it is advisable to determine the quantitative measures of the level of investment attractiveness and group them according to this indicator. This will identify regions with roughly the same investment climate. Given the significant multidimensionality of the description of the studied phenomenon, the solution of the grouping problem can be solved by applying the methods of multidimensional statistical analysis. In our study, we used the *k*-means method of clustering, which allowed us to divide the regions of Ukraine into relatively homogeneous groups according to the level of investment attractiveness.

Data for 2019 and 2020 were chosen for the study. These periods are characterized by the fact that at this time, the economy of Ukraine, like most other countries, came under the destructive influence of the COVID-19 pandemic. We limited ourselves to the selection of three clusters, which were given a meaningful interpretation: the first one is a cluster with regions that have a high level of investment attractiveness, the second cluster contains regions with a medium level of investment attractiveness, and the third cluster includes regions with a low level of investment attractiveness. Comparing clustering results for selected periods showed that the cluster structure of Ukrainian regions has not changed. To verify the correctness of the obtained grouping of regions, the regions of Ukraine were deployed in the space of latent indicators, which were calculated on the same data set by the method of principal components. A meaningful analysis of factor loads showed that one latent axis of the new space characterizes the economic component of investment attractiveness, and the other - is the social component. The results of grouping Ukraine's regions turned out to be identical to those obtained by the *k*-means method. It was also concluded that it would be more appropriate to allocate more clusters, which would provide a more accurate picture of the grouping of regions by the level of investment attractiveness. Such an assessment can be helpful for local governments, as they provide information on the relative level of investment attractiveness of a particular region compared to other territorial units and identify weaknesses in the areas of activity on which the assessment was based. Such results can be used to create and adjust regional socio-economic development programs, particularly in terms of planning to attract investment into the region's economy.

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REFERENCES

Andrusiak, N. O., Andrusiak, V. M., and Danylchuk, H. B. (2022). Assessment of ecological and economic competitiveness of regions using factor analysis. 1049(1):012084. https://doi.org/10.1088/1755-1315/1049/1/012084.

Blahun, I., L., D., and H., L. (2017). Simulative model for evaluation of investment processes in the regions of Ukraine. *Investment Management and Financial Innovations*, 14(3):322–329. https://cutt.ly/UVTu9zE.

Blaschke, P. (2022). Investment incentives in the environment of the Czech Republic. *E+M Economics and Management*, 25(1):4–23. https://doi.org/10.15240/tul/001/2022-1-001.

Bruneckiene, J., Jucevicius, R., Zykiene, I., Rapsikevicius, J., and Lukauskas, M. (2019). Assessment of investment attractiveness in european countries by artificial neural networks: What competences are needed to make a decision on collective well-being. *Sustainability*, 11:6892. https://www.mdpi.com/2071-1050/11/24/6892/htm.

Bushynskyi, Y. (2020). Kontsept faktoriv, shcho vyznachaiut investytsiinu pryvablyvist rehionu [The concept of factors determining the investment attractiveness of the region]. *Herald of Khmelnytskyi National University Economic sciences*, 2(6):185–190. http://journals.khnu.km.ua/vestnik/wp-content/uploads/2021/03/38.pdf.

Cheba, K. (2017). Multidimensional analysis of investments attractiveness of selected european countries from japanese investors' perspective. In *Proceedings of Carpathian Logistics Congress - CLC 2017*, pages 204–209, Ostrava Slovakia. TANGER Ltd. https://cutt.ly/mU2xq8p.

Danylchuk, H., Chebanova, N., Reznik, N., and Vitkovskyi, Y. (2019). Modeling of investment attractiveness of countries using entropy analysis of regional stock markets. *Global J. Environ. Sci. Manage*, 5:227–235.

De Jongh, J. J. and Meyer, D. F. (2019). The multidimensional regional economic development index (MREDI) applied in the north-west province: A rural regional application. *Administratio Publica*, 27(3):162–185. https://cutt.ly/EVTaGVA.

Dorozynski, T. and Kuna-Marszałek, A. (2016). Investment attractiveness. The case of the Visegrad Group countries. *Comparative Economic Research. Central and Eastern Europe*, 19(1):117–138. https://doi.org/10.1515/cer-2016-0007.

EBA (2020). Indeks investytsiinoi pryvablyvosti Ukrainy 2020 [Investment attractiveness index of Ukraine 2020]. https://cutt.ly/MU2j5w5.

Godlewska-Majkowska, H. (2018). Investment attractiveness of polish municipalities in relation to local entrepreneurship. *Olsztyn Economic Journal*, 13(2):103–122. https://doi.org/10.31648/oej.2764.

Gorbatiuk, K., Mantalyuk, O., Proskurovych, O., and Valkov, O. (2019). Analysis of regional development disparities in ukraine using fuzzy clustering. In Kiv, A., Semerikov, S., Soloviev, V. N., Kibalnyk, L., Danylchuk, H., and Matviychuk, A., editors, *Proceedings of the Selected Papers of the 8th International Conference on Monitoring, Modeling & Management of Emergent Economy, M3E2-EEMLPEED 2019, Odessa, Ukraine, May 22-24, 2019*, volume 2422 of *CEUR Workshop Proceedings*, pages 194–210. CEUR-WS.org. http://ceur-ws.org/Vol-2422/paper16.pdf.

Heritage Foundation (2020). Index of Economic Freedom 2020. https://www.heritage.org/index/ranking.

Hryhoruk, P., Grygoruk, S., Khrushch, N., and Hovorushchenko, T. (2020a). Using non-metric multidimensional scaling for assessment of regions' economy in the context of their sustainable development. In Kiv, A., editor, *Proceedings of the Selected Papers of the Special Edition of International Conference on Monitoring, Modeling & Management of Emergent Economy (M3E2-MLPEED 2020), Odessa, Ukraine, July 13-18, 2020*, volume 2713 of *CEUR Workshop Proceedings*, pages 315–333. CEUR-WS.org. http://ceur-ws.org/Vol-2713/paper35.pdf.

Hryhoruk, P., Khrushch, N., and Grygoruk, S. (2019a). An approach to design a composite index of economic development and identifying the bounds of its levels. In *Proceedings of the 2019 9th International Conference on Advanced computer information technologies ASIT'2019*, pages 48–51, Ceske Budejovice Czech Republic.

Hryhoruk, P., Khrushch, N., and Grygoruk, S. (2019b). The rating model of Ukraine's regions according to the level of economic development. *Periodicals of Engineering and Natural Sciences*, 7(2):712–722. https://cutt.ly/BjAgnAL.

Hryhoruk, P., Khrushch, N., and Grygoruk, S. (2020b). Using multidimensional scaling for assessment economic development of regions. *Journal of Industrial Engineering & Production Research*, 31(4):597–607. https://cutt.ly/hVTsxRJ.

Hryhoruk, P., Khrushch, N., and Grygoruk, S. (2021). Environmental safety assessment: a regional dimension. *IOP Conference Series: Earth and Environmental Science*, 628:012026. https://doi.org/10.1088/1755-1315/628/1/012026.

IMDWCC (2020). IMD World Competitiveness Center. World Competitiveness Ranking. https://cutt.ly/RU2kryT.

Jac, I. and Vondrackova, M. (2018). The perception of selected aspects of investment attractiveness by businesses making investments in the Czech Republic. *E+M Ekonomie a Management*, 20(3):103–122. https://dspace.tul.cz/bitstream/handle/15240/20918/EM_3_2017_08.pdf.

Kaminskyi, A., Miroshnychenko, I., and Pysanets, K. (2019). Risk and return for cryptocurrencies as alternative investment: Kohonen maps clustering. *Neiro-Nechitki Tekhnolohii Modelyuvannya v Ekonomitsi*, 2019(8):175–193.

Kearney (2020). Kearney Foreign Direct Investment (FDI) Confidence Index. https://www.kearney.com/foreign-direct-investment-confidence-index.

Kikkas, X. N. and Krasnozhenova, E. (2018). Modeling investment attractiveness of Germany. In *Proceedings of the 5th International Multidisciplinary Scientific Conference on Social Sciences and Arts SGEM 2018*, pages 515–522, Sofia Bulgaria.

KOF (2020). KOF Globalization Index. https://cutt.ly/DU2kuCW.

Korenyuk, P. and Kopil, E. (2018). Conceptual approaches and methods for determining the investment attractiveness of the national economy. *Economic Journal of Lesya Ukrainka Eastern European National University*, 2(14):56–62. https://doi.org/10.29038/2411-4014-2018-02-56-62.

Kyshakevcyh, B. and Nakhaeva, M. (2021). Intehralna otsinka investytsiinoi pryvablyvosti rehioniv Ukrainy [Integrated assessment of investment attractiveness of regions in Ukraine]. *Herald of Khmelnytskyi National University Economic sciences*, (4):51–58. https://cutt.ly/MVTpdJ3.

Kyshakevych, B., Nahayeva, M., and Kryński, A. (2020). The economic essence of the investment attractiveness of the regions. *Scientific Journal of Polonia University*, 37(6):46–53. https://doi.org/10.23856/3704.

Lagler, K. (2020). Use of world experience in increasing investment attractiveness of Ukraine regions. *Economics, Finance And Management Review*, 2:63–70.

Leshchuk, H. (2020). Systematyzatsiia pidkhodiv do otsiniuvannia investytsiinoi pryvablyvosti rehionu [Systematization of the approaches to estimating the investment attractiveness of a region]. *Uzhorod National University Herald. International Economic Relations and World Economy*, (29):93–98. https://doi.org/10.32782/2413-9971/2020-29-18.

Mazziotta, M. and Pareto, A. A. (2014). Composite index for measuring Italian regions' development over time.

Rivista Italiana di Economia Demografia e Statistica, LXVIII(3/4):127–134. https://cutt.ly/UVTo3op.

MCTDU (2021). Reitynhova otsinka rehioniv [Rating assessment of regions]. https://cutt.ly/olpWxkF.

Meyer, D. F. and De Jongh, J. (2018). An alternative multi-dimensional regional economic development index: a provincial application in South Africa. *International Journal of eBusiness and eGovernment Studies*, 10(1):97–113. https://cutt.ly/VVTaO7l.

Meyer, D. F., De Jongh, J., and Meyer, N. (2016). The formulation of a composite regional development index. *International Journal of Business and Management Studies*, 8(1):100–116. https://cutt.ly/cf5q8J2.

Moody's (2020). Credit rating. https://www.moodys.com/.

Musolino, D. and Volget, S. (2020). Towards a multidimensional approach to the study of territorial attractiveness. https://hal.archives-ouvertes.fr/hal-02501582.

Roszko-Wójtowicz, E. and Grzelak, M. M. (2021). Multidimensional analysis of regional investment attractiveness in Poland. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 16(1):103–138. https://cutt.ly/yVTdK70.

Shinkarenko, V., Matskul, M., and Linok, D. (2019). Investment attractiveness modeling using multidimensional statistical analysis methods. *SHS Web of Conferences*, 65:04007. https://doi.org/10.1051/shsconf/20196504007.

Sizova, N. D., Petrova, O. O., Solodovnik, G. V., and Perun, M. U. (2017). Otsinka investytsiinoi pryvablyvosti z vykorystanniam informatsiinoi systemy [Evaluation of investment attractiveness using information system]. *Young Scientist*, 4.4(44.4):90–93. http://molodyvcheny.in.ua/files/journal/2017/4.4/21.pdf.

SSCU (2003). Pro zatverdzhennia Metodyky rozrakhunku intehralnykh rehionalnykh indeksiv ekonomichnoho rozvytku. Nakaz Derzhavnoho komitetu statystyky Ukrainy № 114 vid 15.04.2003 r. [On approval of the Methodology for calculating integrated regional indices of economic development. Order of the State Statistics Committee of Ukraine № 114 of April 15, 2003]. https://zakon.rada.gov.ua/rada/show/v0114202-03#Text.

SSSU (2022). Derzhavna sluzhba statystyky Ukrainy [State Statistics Service of Ukraine]. http://www.ukrstat.gv.ua.

Stadnyk, V., Izhevskiy, P., Khrushch, N., Lysenko, S., Sokoliuk, G., and Tomalja, T. (2020). Strategic priorities of innovation and investment development of the ukraine's economy industrial sector. In Kiv, A., editor, *Proceedings of the Selected Papers of the Special Edition of International Conference on Monitoring, Modeling & Management of Emergent Economy (M3E2-MLPEED 2020), Odessa, Ukraine, July 13-18, 2020*, volume 2713 of *CEUR Workshop Proceedings*, pages 145–166. CEUR-WS.org. http://ceur-ws.org/Vol-2713/paper12.pdf.

Swidynska, N. and De Jesus, I. (2020). Determinants of potential investment attractiveness of a commune. *Olsztyn Economic Journal*, 15(2):129–140. https://czasopisma.uwm.edu.pl/index.php/oej/article/view/5836/4421.

Tenreiro Machado, J. A. and Mata, M. E. (2015a). Analysis of world economic variables using multidimensional scaling. *PLoS ONE*, 10(3):e0121277. https://cutt.ly/nH4a5HP.

Tenreiro Machado, J. A. and Mata, M. E. (2015b). Multidimensional scaling analysis of the world economy during the period 1972-2012. *Acta Polytechnica Hungarica*, 12(1):67–82. https://cutt.ly/4VTsSjT.

Transparency International (2020). Corruption Perceptions Index 2020. https://www.transparency.org/en/cpi/2020.

Vartsaba, V. and Leshuk, H. (2017). Evaluation of investment attractiveness indicators of regions in Ukraine. *Baltic Journal of Economic Studies*, 3(5):38–44. https://doi.org/10.30525/2256-0742/2017-3-5-38-44.

Walesiak, M. (2017). The application of multidimensional scaling to measure and assess changes in the level of social cohesion of the Lower Silesia region in the period 2005-2015. *Econometrics*, 3(57):9–25. https://cutt.ly/OVTaMeB.

WEF (2020). World Countries' Ranking on the Global Competitiveness Index. https://cutt.ly/rVR9tLo.

Windhyastiti, I., Hidayatullah, S., and Khouroh, U. (2020). Investment attractiveness rating and factors affecting. *Accounting*, pages 161–166. http://www.growingscience.com/ac/Vol7/ac_2020_143.pdf.

WIPO (2020). Global Innovation Index. https://cutt.ly/dU2kqQw.

World Bank (2021). The World Bank. Doing business 2020. https://cutt.ly/qU2j9bN.

Yelnikova, Y. (2020). Reitynhuvannia rehioniv Ukrainy za rivnem pryvablyvosti dlia vidpovidalnykh investytsii [Ranking of the Ukraine regions by the level of responsible investments attractiveness]. *Investytsiyi: praktyka ta dosvid*, (17-18):63–68. http://www.investplan.com.ua/?n=17-18&y=2020.

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