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THE APPLICATION OF MACHINE LEARNING METHODS IN DETERMINING ATTRACTIVE DEVELOPMENT DIRECTIONS FOR TOURISM BUSINESSES

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Abstract. *This paper proposes a methodical approach to the selection of attractive development directions for tourism businesses. The approach is based on the following machine learning methods: "center of gravity" method; taxonomic indicator of the level of development; hierarchical agglomerative and iterative methods of cluster analysis; methods for analyzing panel data; and Kohonen neural networks. The developed approach includes the following core blocks: classification of countries (regional market segments) according to the level of socio-economic development and safety; formation of a diagnostic indicator system of countries' touristic attractiveness; assessment of the development dynamics of the market geographical segments (countries); classification of countries according to the level of tourist attractiveness; and selection of development directions for*

the tourism industry. The proposed approach is implemented on the data of 35 countries, including the EU countries and the countries of the post-Soviet space. The results show that the most attractive geographic market segments for tourism business development are such countries as Italy, Spain, Croatia, Greece, Portugal, and Poland. These countries are characterized by a high level of security, average cost and barriers to entry into the tourism market, a steady pace of development of the tourism industry, a favorable business environment, attractive natural resources, and developed infrastructure. Comparison of the dynamics of tourist flows with the obtained distribution of countries by the level of tourist attractiveness made it possible to single out Portugal separately, which is characterized by a high level of tourist attractiveness, but insufficient actual intensity of tourist flow. Implementation of the proposed approach in the business processes of travel companies make it possible to improve the quality of management decisions regarding the choice of tourism business development directions.

Keywords: *tourism business, development, tourism product, attractiveness assessment, machine learning*

JEL Codes: *C23, C45, C53, L83*

1. Introduction

In recent years, the tourism business has played a significant role in the global economy. Its share of global GDP demonstrated stable growth from 2010, accounted for 10.4% in 2019, and dropped dramatically to the level of only 5.5% in 2020 due to the COVID-19 pandemic. The highest growth rates of the tourism industry are observed for the developing countries cluster, and for Ukraine in particular (World Travel & Tourism Council, 2021; Statista, 2022).

According to the World Travel & Tourism Council (2021), the total contribution of travel and tourism to global GDP was 6.3% in 2019 (3.4% in 2020). The total contribution of the sector to global employment was 6.9% in 2019 (6.3% in 2020). As for Ukraine, according to forecasts (Shelemeteva, 2019), the share of tourism in Ukraine's GDP will increase to 1.7%; the number of people employed in the tourism industry will be 5.7% by 2027.

Despite the high attractiveness of this sector of the economy, its potential is not fully implemented. Despite the positive dynamics of tourist flow in 2015–2019 and the number of foreign tourists having increased by more than four times, foreign tourists' share in total flow is only 1%. The prevailing share remains outbound tourism, which accounts for 82% of the volume of tourist flow (State Statistics Service of Ukraine, 2019). Such trends in the industry make it necessary for tourism companies to pay more attention on the development of external areas.

It should be noted that the leading positions in the Ukrainian market are occupied by several large national and foreign operators (Piligrim, n.d.), such as Join UP! (27% of the market), ANEX Tour (16% of the market), Accord Tour (8% of the market), TEZ Tour (9% of the market), and Coral Travel (7% of the market). The high level of competition in traditional areas forces newly created or "second cluster" companies, which are close in terms of performance to leading companies, to look for new attractive directions for the development of their tourism businesses and to search for potentially attractive countries for tourists.

2. Literature Review

It must be said that various aspects of the strategic management of the development of tourism companies and the tourism industry, along with problems of the assessment of the tourist attractiveness level of regions, are widely researched in the scientific literature. Thus, the works of Romanova (2004), Kuleshova and Polyakova (2015), Kun et al. (2019), and Assaf and Tsionas (2019) deal with the analysis of factors that have the greatest impact on the development dynamics of the tourism market, assessing the potential of regions for tourism business development and forming a profile of tourism service consumers to increase market share and implement a successful targeted advertising strategy. Studies by Nedelea and Aziri (2013) are devoted to the analysis of the typology of the development strategies of travel companies. Agafonova and Agafonova's monograph (2002) researches the institutional aspects of creating a business environment conducive to the development of travel companies and tourism businesses. In Beydik (2001) and Wenqi et al. (2019), the assessment of regional aspects of the development of tourism businesses and the environmental safety of tourism are researched. The Patsyuk (2007) study addresses the development of tourism businesses in the context of diversifying the activities of old industrial regions and ensuring their sustainable socio-economic development.

A review of the literature allows us to say that despite the undoubted effectiveness of the approaches proposed earlier, the issues of applying machine learning methods to solve the problem of choosing attractive directions for the development of tourism businesses are poorly studied. The implementation of machine learning methods allows us to consider the level of tourist attractiveness of countries as a multidimensional object, which is influenced by a large number of multidirectional, dynamically changing factors, which can be measured in the hundreds. These methods make it possible to compress the information space of initial indicators, conduct analysis in conditions of incomplete, missing data, investigate latent factors of tourism product demand growth, and on this basis increase the speed of preventive response and the quality of strategic management decisions in tourism businesses.

3. Methodology

This paper proposes a methodical approach to the selection of attractive development directions of tourism businesses based on the application of machine learning methods. The approach consists of four core modules, which are presented in Figure 1. The description of each module is given below.

The first module deals with the classification of countries according to the level of socio-economic development and macro regions' safety. The model allows a comparable research database to be formed. The need to build such a classification is associated with the peculiarities of organizing a tourism business and is closely linked with indicators of the socio-economic development of macro-regions. Thus, the share of tourism businesses in GDP varies from 13.2% and 14.6% in developed countries such as Italy and Portugal, to 67.1% in an island state such as the Seychelles (Knoema, n.d.).

To assess the level of socio-economic development and safety, a system of indicators was formed on the basis of a literary source review. The resulting system includes both quantitative and qualitative indicators. Quantitative indicators are GDP, unemployment, consumption, and

inflation. The group of qualitative indicators includes the Global Competitiveness Index (GCI), Global Innovation Index (GII), Human Development Index (HDI), ICT Development Index (ICTDI), and the Index of Economic Freedom (IoEF) (Fabus et al., 2019).

Classification involves dividing the initial set of macro-regions into a relatively small number of classes so that objects belonging to the same class (group) are at relatively small distances from each other. The similarity or difference between countries (classified objects) is measured with Euclidean distance and weighted Euclidean distance.

To build the grouping, hierarchical agglomerative methods were used, which give only a conditionally optimal solution in a subset of local partitions (clusters). However, the advantage of these methods is the simplicity of results interpretation.

The essence of hierarchical agglomerative methods is that in the first step each object is considered as a separate cluster. The process of cluster joining takes place sequentially: based on the distance matrix or similarity matrix, the closest objects are combined. The results of clustering, presented as a dendrogram, allow one to choose the number of clusters at which the total intergroup dispersion will take the maximum value. This number of clusters is used to select the initial conditions of the iterative algorithm of the k-means method (Guryanova et al., 2018).

The second module is aimed at forming the diagnostic space of indicators that assess the level of tourist attractiveness of geographical market segments (countries). To build the model, such methods of reducing the dimension of indicators' space as the "level of development" method and the "center of gravity" method are used.

The multi-vector nature of changes in the initial indicators complicates their analysis and requires their presentation in the form of an integral indicator. This indicator is the result of a convolution of indicators that describe the development of individual subsystems, and is based on the "level of development" method. A detailed description of the "level of development" method is given in Fabus et al. (2019). The construction of an integral indicator includes the following steps: data standardization; determination of the reference point coordinates; calculation of the Euclidean distance between objects and the reference point; and assessment of the integral indicator values. The advantages of the method include the following: it allows one to work with data of any dimension and any nature; the system of indicators can include both stimulating indicators (having a positive impact on the level of the country's tourism attractiveness) and destimulating indicators (having a negative impact); the method contains a built-in procedure for generating a reference point; and the method allows one to obtain a complex normalized estimate, which varies in the range from 0 to 1, and therefore is easily scaled and interpreted.

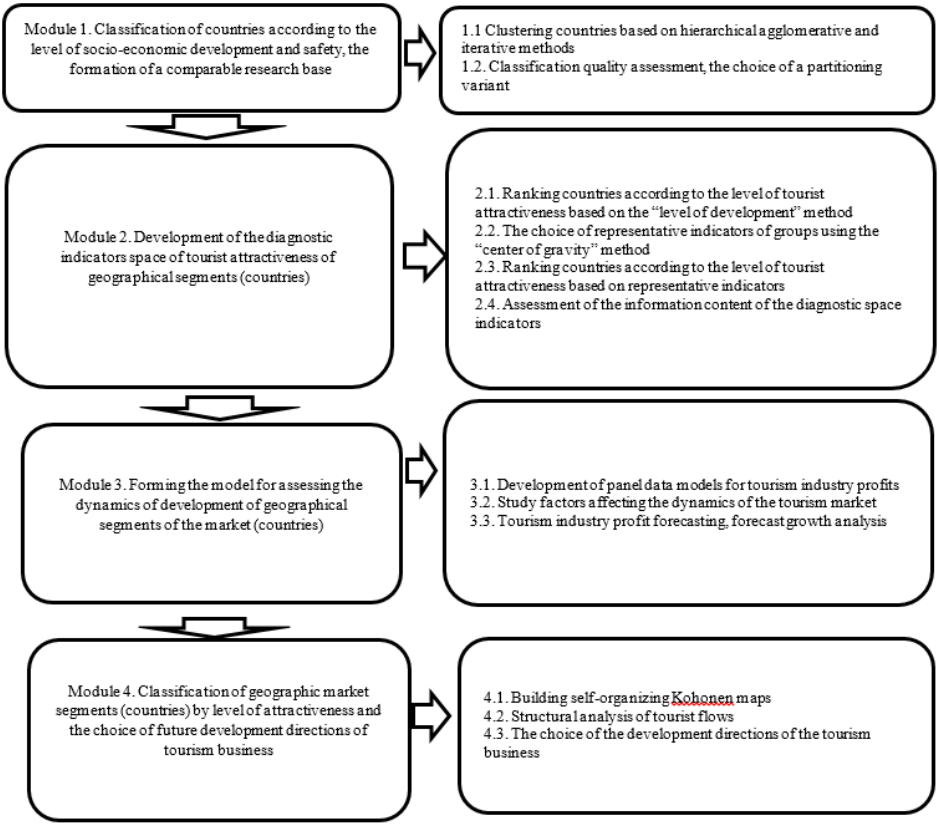


Figure 1. *Module interconnection scheme*
Source: *made by authors*

The "center of gravity" method makes it possible to obtain a system of diagnostic indicators with the following properties: final indicators are closely correlated with the indicators of the group and carry the information loading inherent to the group of indicators; and final indicators do not correlate with each other, so duplication of information is excluded. The formation of the diagnostic indicators system includes data standardization; distance matrix calculation; and representative indicator selection. A more detailed description of the method is given in Guryanova (2013).

The aim of the third module is to assess the dynamics of the development of geographical segments of the market (countries). To build the model, a panel data technique is used. The following panel data models were considered: a conventional panel data model; a fixed effect model; and a model with a random effect with and without lag variables. To evaluate the parameters of the models, the intra-group transformation and the two-step FGLS procedure were used. A more

detailed description of the algorithm for constructing and choosing a model specification is given in Guryanova (2013).

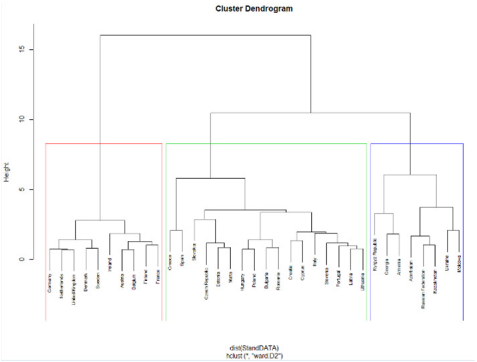
The aim of the fourth module is to classify geographical segments of the market (countries) according to the level of attractiveness and choose the development direction of the tourism business. The classification uses both actual and predicted data series of the dynamics of the development of the tourism market, obtained on the basis of panel data models. To construct the classification, Kohonen self-organizing maps are used – the appropriate algorithm is given in more detail in Kononova (2012).

The implementation of the proposed methodological approach was carried out on the data of 35 macro-regions according to indicators of socio-economic development, tourist attractiveness, and the dynamics of the tourism industry. The information base of the research was generated from the following sources: World Bank (http://data.worldbank.org), World Economic Forum (http://reports.weforum.org/), Global Innovation Index (https://www.globalinnovationindex.org/), United Nations Development Program (http://hdr.undp.org/en/content/human-development-index-hdi), ICT Development Index (https://www.itu.int/net4/ITU-D/idi/), Index of Economic Freedom (https://www.heritage.org/index/explore?view=by-region-country-year), and World Travel & Tourism Council (https://www.wttc.org/).

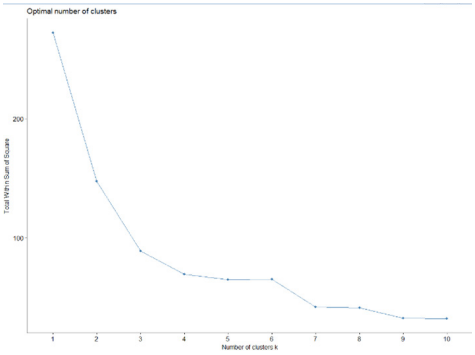
Data processing was carried out using Statistica, R, Deductor Studio, and EViews.

4. Results and discussion

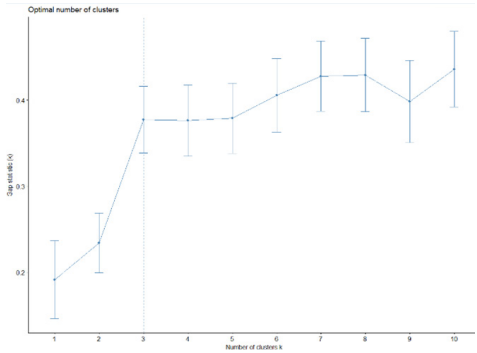
In the first module of the study (see Figure 1), countries were grouped according to the level of socio-economic development and safety. The information base for building a grouping, as mentioned earlier, consists of such indicators of socio-economic development and safety as GDP, consumption, unemployment, inflation, global competitiveness index, etc. The data set describes 35 countries, including EU countries and post-Soviet countries. The results of clustering based on the hierarchical agglomerative Ward method are shown in Figure 2a. The dendrogram indicates that the initial set should be divided into three clusters. To justify the number of clusters into which it is necessary to divide the initial population, the "scree" method, the GAP method, and the method based on the NbClust function (Figures 2b–d) were also used.



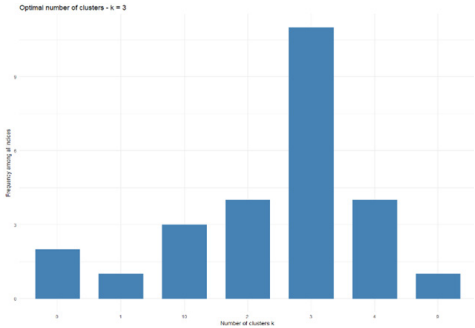
a) Classification dendrogram (Ward method)



b) Schedule of "scree"



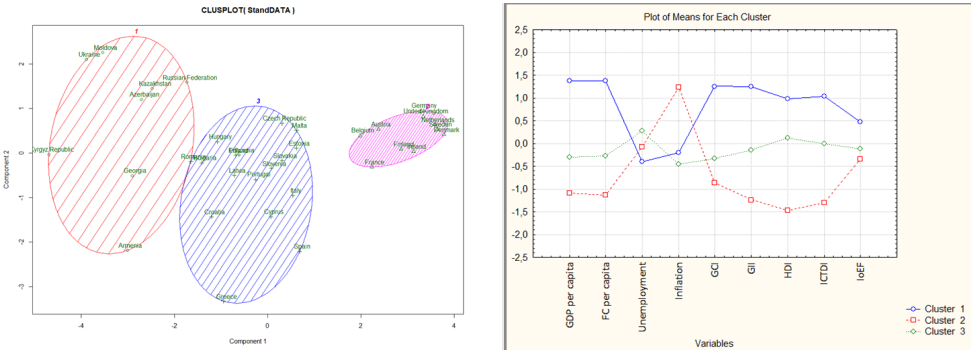
c) GAP method results



d) NbClust function results

Figure 2. *The rationale for the number of clusters*
Source: *made by authors*

The obtained optimal number of clusters was used for clustering countries using the "*k*-means" method (the results are presented in Figure 3).



a) Cluster composition *b) Plot of means for each cluster*

Figure 3. *Classification results based on the k-means method*

Source: *made by authors*

As can be seen from Figure 3, the first cluster was formed by countries with a high level of socio-economic development. They are characterized by high values of per capita GDP, consumption, global competitiveness index, global innovation index, and human development index. Moreover, the inflation level and unemployment level are the lowest here. This group of countries includes Austria, Belgium, Finland, France, Germany, Ireland, the Netherlands, Sweden, and the United Kingdom. This group is characterized by a developed infrastructure, a high level of safety, and political stability. At the same time, this cluster demonstrates the highest levels of competition and has barriers to entry into the market. The second group includes countries with low levels of socio-economic development. This group includes Russia, Moldova, Kyrgyzstan, Kazakhstan, Georgia, Azerbaijan and Armenia. Ukraine belongs to this cluster, too. Low living standards, low infrastructure development, and an unstable political situation are all factors which negatively affect the development of the tourism industry. In particular, the negative influence of the political factor can be easily seen in Ukraine in 2015, when the flow of tourists decreased by 17% due to political events in 2014 (State Statistics Service of Ukraine, 2019). The third cluster includes countries with medium levels of socio-economic development and competitiveness. These countries are characterized by medium per capita income, medium consumption, and low inflation. This cluster is the most attractive for travel companies in terms of the formation of new tourism products. The latter is explained by the fact that the favorable state of the business environment in these countries is combined with acceptable entry barriers. This group includes Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Greece, Hungary, Italy, Latvia, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain.

The second module of the study (see Figure 1) was aimed at ranking the countries of the third cluster and Ukraine by the level of attractiveness of the tourism industry.

The World Travel & Tourism Council data were considered as initial data. The study included such groups of factors as: natural and cultural; political and institutional; socio-demographic; material and technical; and financial and economic. Since the indicators are multidirectional and difficult to interpret, the integral indicator of tourism attractiveness was calculated according to

the "level of development" method. The results are shown in Table 1.

As can be seen from the Table 1, such countries as Spain, Portugal, Greece, Estonia and the Czech Republic have the highest levels of tourism industry competitiveness according to all selected criteria (natural and cultural; political-institutional; socio-demographic; logistical; and financial and economic factors). At the same time, a low level of attractiveness is typical for Ukraine and Romania.

To select factors that have a dominant influence on the development of different groups of factors – such as natural and cultural, political and institutional, socio-demographic, material and technical, and financial and economic – the "center of gravity" method was used. The results of this analysis are provided in Table 2.

Table 1. *Distances to the reference point and the integral indicator of tourism attractiveness*

Country	Euclidean distance (C_{i0})	Integral indicator of tourism attractiveness (d_i^*)	Country	Euclidean distance (C_{i0})	Integral indicator of tourism attractiveness (d_i^*)
Ukraine	12.09	0.12	Malta	6.68	0.38
Bulgaria	7.64	0.29	Poland	8.08	0.25
Croatia	7.86	0.27	Portugal	4.92	0.55
Cyprus	8.10	0.25	Romania	9.64	0.11
Czech	6.47	0.40	Slovakia	7.89	0.27
Estonia	5.89	0.46	Slovenia	7.68	0.29
Greece	6.53	0.40	Spain	4.18	0.61
Hungary	7.85	0.27	Italy	7.22	0.33
Latvia	7.15	0.34			

Source: *made by authors*

The selected representative indicators were used to build a complex assessment of the level of attractiveness of the tourism industry. The value of the correlation coefficient between integral indicators found on the basis of a complete and truncated system of indicators is 0.85, which indicates the presence of a strong connection. This allowed us to conclude that the formed system of diagnostic indicators is rather informative and can be used for further analysis. The above approach makes it possible to reduce the dimension of the information space of indicators and conduct a comprehensive analysis of the level of attractiveness of the tourism industry in conditions of low information availability of indicators without losing information significant for decision-making, since the values of integral indicators on both the original and reduced systems give identical ranking results.

Table 2. *List of representative indicators found on the basis of the "center of gravity" method*

Group	Representative indicator	Symbol
Natural and cultural	Natural resources	**X1**
Political and institutional	Prioritization of the tourism industry	**X4**
Socio-demographic	Human resources and employment	**X8**
Material and technical	Marine and land infrastructure	**X9**
Financial and economic	Business environment level of development	**X15**

Source: *made by authors*

In the third module (see Figure 1), a model is built that allows the dependence between tourism industry profits (Y) and exogenous factors (X1, X4, X8, X9, and X15) to be studied. The following options for the panel data model were considered: the regular model; the fixed model; and the random effect model with and without lag variables. Among all possible specifications of the model according to the quality criteria, the model with a fixed effect was selected, taking into account lag variables:

$$Y_{i,t} = c_i + 18590.2 + 830.7 \cdot X1_{i,t-1} - 1406.3 \cdot X9_{i,t-1} - 1333.5 \cdot X15_{i,t-1} + \varepsilon_{it}, \quad (1)$$

c_i – i-th country fixed effect.

The values of the Student's criterion (t_{a0}=16.31; t_{a1}=4.91; t_{a2}=-7.04; t_{a2}=-26.31) allow us to conclude that the model parameters are statistically significant with a 99% confidence level. The values of the coefficient of determination, Fisher's criterion, and Durbin-Watson statistics (R^2=0.99; F=5231.08; DW=1,78) indicate the statistical significance and adequacy of the model as a whole.

It should be noted that the panel data model was developed with and without lag effects. The values of the Student's criterion showed the presence of a lag in the influence of such factors as natural resources, the level of development of the business environment, etc., on the profit dynamics of the tourism industry. The version of the model without taking into account lag involves the development of local forecasts of the factor variables X1, X9, and X15 for 17 countries of the 3rd cluster, i.e., the development of the 51 local forecasts to find the predicted value of tourism industry profit (Y). Accounting for lag variables allows us to reduce the dimension of the forecasting problem. Model (1) was characterized by a higher approximation accuracy (m.a.p.e. = 6.19%) compared to the model without lag variables (m.a.p.e. = 6.87%). The predicted profit values found on the basis of the model (1) are given in Table 3.

Table 3. *Forecasts of tourism industry profits based on panel data model*

Country	Tourism industry profits forecast, millions of UAH	Growth rate	Country	Tourism industry profits forecast, millions of UAH	Growth rate
Ukraine	2532.86	0.63	Latvia	1377.24	1.07
Bulgaria	3594.30	0.94	Malta	2389.69	1.07
Croatia	9849.24	1.01	Poland	10191.34	0.93
Cyprus	4386.43	0.99	Portugal	17820.13	1.03
Czech	6789.13	0.94	Romania	1829.60	0.97
Estonia	1707.29	0.96	Slovakia	2453.76	1.01
Greece	17640.09	1.00	Slovenia	3105.97	0.99
Hungary	7421.21	1.05	Spain	58954.62	0.98

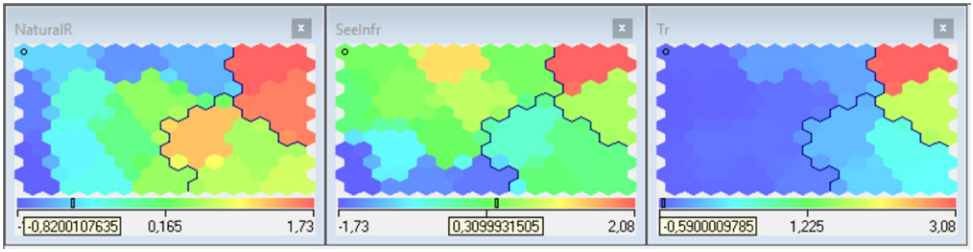
Source: *made by authors*

The chain rate of profit growth, found on the basis of a comparison of forecast data (Table 3) and actual data, made it possible to identify geographical segments with increasing demand (where growth rate exceeds 5%) and stable demand. According to the forecast, the positive dynamics of the development of the tourism industry are typical for Latvia, Malta and Hungary. Sustainable development is observed in Croatia, Greece, Portugal and Slovakia. The rest of the countries are characterized by damping dynamics.

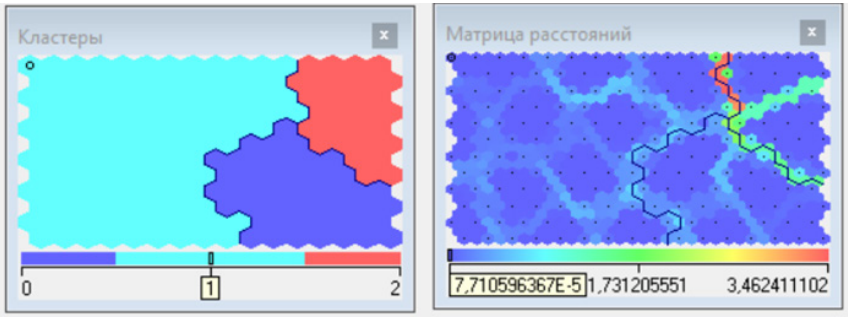
In the fourth module (see Figure 1), a classification of geographical segments of the market (countries) by level of attractiveness was implemented. As model input, we used the predicted profit values (Table 3) and the values of representative indicators X1, X4, X8, X9, and X15 (Table 2), reflecting the influence of natural-cultural, political-institutional, socio-demographic, material-technical, financial, and economic factors. The model allows one to choose the direction of the development of the tourism business. Self-organizing Kohonen maps were used as mathematical research tools; the classification results are shown in Figure 4.

According to the clustering results (see Figure 4), the cluster with code "2" (red color on Figure 4b) was formed by such countries as Italy and Spain. They are characterized by high values of the "Natural Resources" and "Level of Infrastructure Development" factors (Figure 4a). This cluster is attractive enough for investment, as for the countries there are fairly stable trends in the development of the tourism business.

The cluster with code "0" (blue color on Figure 4b) includes Croatia, Greece, Portugal, and Poland. These countries have a fairly developed infrastructure and a favorable business environment for the development of the tourism sector. In addition, the "Natural Resources" factor also shows significant potential and opportunities for further development (Figure 4a).



a) Initial data maps



b) Distance matrix and clusters

Country	NaturalR	SeeInfr	Tr	Номер ячейки	Расстояние до центра ячейки	Номер кластера	Расстояние до центра кластера
Україна	-1,4	-1,73	-0,6	160	5,381711443084 62E-13	1	0,521943873238003
Болгарія	0,44	-1,59	-0,45	182	1,960915702771 81E-14	1	0,497461197332355
Кіпр	-0,65	-0,79	-0,53	97	1,568463525945 85E-13	1	0,187752417929493
Чехія	-1,15	1,32	-0,27	9	1,065111534946 45E-13	1	0,483555750501468
Естонія	-0,82	0,31	-0,59	34	5,443641054740 22E-12	1	0,171767678976043
Угорщина	-0,99	0,31	-0,24	6	1,332162298759 34E-13	1	0,320144195246759
Латвія	-1,26	0,03	-0,63	0	1,640771301835 28E-11	1	0,273938780551148
Мальта	-0,43	0,43	-0,61	68	9,110498082826 43E-12	1	0,180191759507812
Румунія	-0,54	-1,46	-0,57	179	2,698646573782 22E-13	1	0,362912589121659

c) Composition of clusters (fragment

Figure 4. *Kohonen network classification results*
Source: *made by authors*

The classification results were compared with the rating of the top 10 countries (UN World Tourism Organization, https://www.unwto.org/) in terms of the number of foreign tourists (Table 4).

As can be seen from Table 4, countries from the 1st and 2nd clusters (the highest level of tourism business attractiveness) are situated within the mentioned rating (they account for more than 90% of the flow of foreign tourists). The exception is Portugal, which is situated in the cluster with a high level of attractiveness, but is not present in the rating. This allows us to make a conclusion about the priority and prospects of this segment for the development of the tourism services market.

Table 4. *Rating of the top 10 European countries by the number of foreign tourists*

Country	The number of foreign tourists, million people	Share of tourists,%	Cluster according to the level of tourist attractiveness
France	82,570	20.38%	not included in the sample
Spain	73,315	18.09%	Cluster with code "2" (Figure 4b) – very high attractiveness level
Italy	52,372	12.92%	Cluster with code "2" (Figure 4b) – very high attractiveness level
Great Britain	35,814	8.84%	not included in the sample
Germany	35,555	8.77%	not included in the sample
Austria	28,121	6.94%	not included in the sample
Greece	24,799	6.12%	Cluster with code "0" (Figure 4b) – high attractiveness level
Poland	17,471	4.31%	Cluster with code "0" (Figure 4b) – high attractiveness level
Croatia	13,809	3.41%	Cluster with code "0" (Figure 4b) – high attractiveness level
Denmark	13,333	3.29%	not included in the sample

Source: *made by authors*

5. Conclusions

Thus, the studies conducted in this work allow us to draw the following conclusions.

A methodical approach to the selection of attractive development directions of tourism businesses based on the application of machine learning methods has been developed. This approach is based on: the methods of cluster analysis; reduction of the indicator space dimension methods; the panel data technique; and Kohonen neural network models (Figure 1). The approach allows one to improve the quality of management decisions regarding the choice of investment direction when creating a new product and developing a tourism business.

The results obtained during the practical implementation of the methodological approach are listed below. A classification of countries according to the level of socio-economic development and safety has been developed (Figures 2–3); a diagnostic indicator space for the touristic attractiveness of geographical segments (countries) has been formed (Tables 1–2); a model for assessing the dynamics of development of geographical segments of the market (countries) has been developed (Table 3); and models for classifying geographical segments of the market (countries) according to the level of attractiveness (Figure 4) have been developed.

The results showed that the most attractive geographical segments of the market for the development of tourism businesses are such countries as Italy, Spain, Croatia, Greece, Portugal, and Poland. These countries have high levels of safety, medium costs, low market entry barriers (Figure 3), steady growth rates of the tourism industry (Table 3), favorable business environments, attractive natural resources, and developed infrastructure (Figure 4).

It should also be noted that a comparison of the dynamics of tourist flows with the obtained distribution of countries according to tourist attractiveness (Table 4) allows us to distinguish such a geographical segment of the market as Portugal, which is characterized by a high level of tourist attractiveness, but low actual intensity of tourist flow.

The application of the obtained results in travel agencies' activities will improve the quality of management decisions regarding the choice of development directions of tourism businesses.

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