University competitiveness in the knowledge economy: a Kohonen map approach*

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Abstract

In the post-industrial knowledge economy, universities play a key role in the generation and dissemination of innovations. They are also becoming the drivers of digital transformation in science, business, countries, and society as a whole. This paper studies the factors of university competitiveness in the knowledge economy. A clustering approach is used to group countries based on their university competitiveness. The level of significance of normalized parameters is also assessed. The results of the study are used to propose an organizational design for a competitive model of the university. The key factors of the university's success in the system of open science, education, and innovation are also discussed. The findings of this study contribute to the understanding of the factors that drive university competitiveness in the knowledge economy. The proposed organizational design and key factors of success can be used by universities to improve their competitiveness and become drivers of innovation and transformation.

Keywords

university, competitiveness, knowledge economy, Kohonen map, clustering, open science

1. Introduction

Universities are essential institutions for generating and disseminating innovations in the knowledge economy. However, they face increasing competition and challenges in the global market of educational services, especially in the era of digital transformation [2]. Therefore, it is important to assess and enhance the competitiveness of universities using reliable and objective methods [3].

Many existing methods for measuring university competitiveness are based on expert opinions, subjective criteria, or simple statistical techniques. These methods often produce inconsistent, biased, or incomplete results. Moreover, they do not capture the complex and dynamic nature of university performance and its relation to various factors.

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Avralev and Efimova [4] have conducted a survey of students over the years, which showed that place in the university rankings is an increasingly important criterion for students when choosing a university. At the same time, most researchers criticize the widely used rating systems. Thus, Sayed [5] demonstrates that according to some of the world's leading ranking systems, a university may be at the top of the ranking, while in others it may not be ranked at all. Many researchers note [6, 7] that most of the global university rankings focus primarily on research, while at the same time not paying enough attention to the quality of teaching, student competences and learning outcomes, social responsibility, etc.

At the same time, most scientists agree that the main criteria that determine the competitiveness of universities are research and teaching [8, 5, 9, 10]. In addition, some authors emphasize the importance of other criteria, such as international cooperation with university research networks, involving foreign teachers and students, increasing international citation [11, 12, 13], quality of pedagogical staff [12, 14], social and environmental responsibility [15], digitization of all university functioning processes [16, 17, 18], expenditure on higher education per student [19], employability of graduates [20, 21]. The importance of cooperation with business to improve the competencies and employability of students and, as a result, the competitiveness of the university, is emphasized in the papers [20, 17, 22, 23].

As can be seen from the above review, all these works are aimed either at the analysis and criticism of known rating systems, or at the study of factors that affect the competitiveness of universities, or, at most, at the creation of own methods for calculating university ratings, which are based on the simplest statistical methods.

There are works in which advanced artificial intelligence technologies are used to analyze and rank universities according to certain areas of activity. For example, in [16] developed a fuzzy logic model for assessment and ranking of universities' websites by criterion of usability.

However, the analysis of developments in this direction did not allow to identify studies on the modeling of university competitiveness based on cutting-edge artificial intelligence technologies, moreover, which would not be based in the rating on the expertly set weights of the evaluation criteria.

2. Modeling method

Solving the task of evaluating the international competitiveness of universities is associated with a number of specific problems, because competitiveness does not have generally accepted evaluation indicator, units or measurement scales. This is a subjective category that depends on many factors affecting it. Moreover, the set of these factors and the degree of influence of each of them are also not determined by any objective circumstances and can be chosen by analysts and researchers depending on their own understanding of the essence of the category "competitiveness of universities", the development of the educational process, their own priorities, etc. All this imposes a significant imprint of subjectivism on the formation of methods of their evaluation.

It is possible to reduce the dependence on the subjective opinions of individual experts with the use of special modeling methods capable of revealing regularities in the structure of an array of heterogeneous data, when there are no predetermined values of the resulting indicator, such as for the international competitiveness of universities.

Under such conditions, the clustering approach is the most appropriate means of searching for hidden regularities in sets of explanatory variables. The main feature of this approach is that with its application, objects that belong to one cluster are more similar to each other than to objects that are included in other clusters. As a result, it becomes possible to form fairly homogeneous groups of researched objects that are characterized by similar properties.

There is a wide range of cluster analysis methods: K-means [25], K-medoids [26], Principal Component Analysis [27], Spectral Clustering [28], Dendrogram Method [29], Dendrite Method [30], Self-Organizing Maps – SOM [31, 32], Density-Based Spatial Clustering of Applications with Noise – DBSCAN [33], Hierarchical DBSCAN – HDBSCAN [34], Ordering Points to Identify the Clustering Structure – OPTICS [35], Uniform Manifold Approximation and Projection – UMAP [36], Balanced Iterative Reducing and Clustering Using Hierarchies – BIRCH [37], etc.

Each of these methods has its advantages and areas of application and tasks, where it reveals itself in the best way. Experimental studies on comparative analysis of the effectiveness of various clustering methods are described, in particular, in scientific works [38, 39, 40, 41].

Taking into account the capabilities of each of the mentioned methods and the specifics of this study, the Kohonen self-organizing maps toolkit was used to cluster countries by the level of competitiveness of universities, which, in addition to forming homogeneous groups of researched objects, provide a convenient tool for visual analysis of clustering results. In particular, in contrast to other clustering methods, the location of an object on the Kohonen map immediately indicates to the analyst how developed the investigated property is compared to others, because the best and worst objects according to the analyzed indicator are located in opposite corners of the self-organizing map.

The result of constructing the Kohonen map is a visual representation of a two-dimensional lattice of neurons that reflect the organizational structure of the countries of the world, forming clusters in which countries are similar to each other according to the group of indicators of evaluating the competitiveness of universities (figure 1).

The Kohonen self-organizing algorithm is a clustering method that reduces the dimension of multidimensional data vectors. It can be used to visualize clusters and to detect nonlinear patterns in input data structures. The main feature of such neural networks is unsupervised learning, when information about the desired network response is not needed to correctly set the parameters. In this study, self-organizing maps are used to summarize a complex set of data and clustering of countries by indicators that have the greatest impact on the international competitiveness of universities.

Thus, each neuron of the Kohonen layer receives information about the research object in the form of a vector $\mathbf{x}$, which consists of n explanatory variables (in our case, these are the characteristics that determine the competitiveness of universities). When a new data vector arrives at the input layer of the network, all neurons of the self-organization map participate in the competition to be the winner. As a result of such a competition, the winner is the neuron

$$o = \operatorname{argmin}\left\{\left\|\mathbf{x} - \mathbf{w}^j\right\|\right\} \quad (1)$$

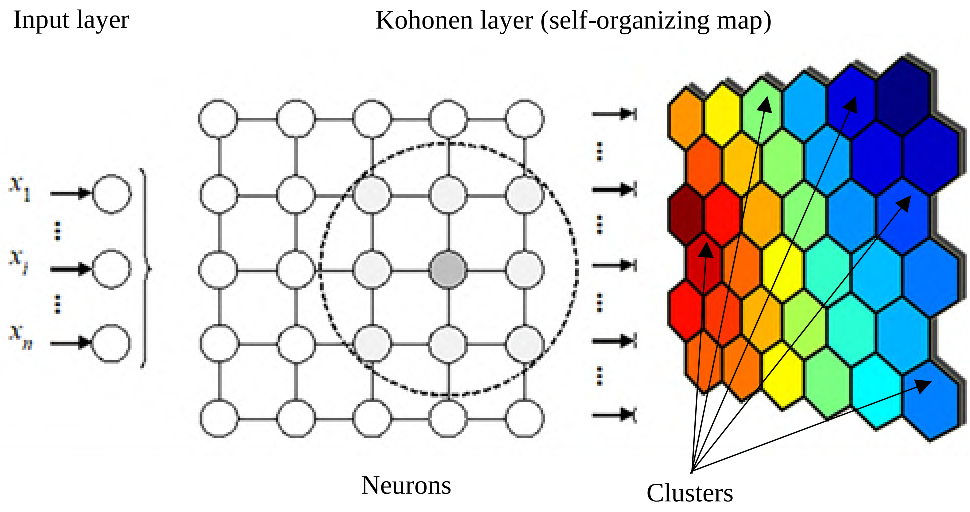

Figure 1: Visual representation of clusters on the self-organizing map [42].

that is more similar to the input data vector than others, usually by Euclidean distance:

$$\|\mathbf{x} - \mathbf{w}^j\| = \sqrt{\sum_{i=1}^{n} \left(x_i - w_i^j\right)^2}, j = \overline{1, K} \tag{2}$$

where $\mathbf{x}$ is a vector of input data consisting of indicators $\{x_1, \dots, x_i, \dots, x_n\}$ that describe the objects under study; $\mathbf{x}^j$ is the vector of parameters of j^{th} neuron of the Kohonen map, which consists of elements $\{w_1^j, \dots, w_i^j, \dots, w_n^j\}$; K is the number of neurons of the Kohonen map.

After determining the neuron-winner, we adjust the vector of its parameters and its neighbors according to the input vector:

$$\mathbf{w}^j(t+1) = \mathbf{w}^j(t) + \alpha(t) \cdot h_{oj}(t) \cdot \left[\mathbf{x}(t) - \mathbf{w}^j(t)\right], j = \overline{1, K} \tag{3}$$

where $\alpha(t)$ is the rate of learning ($0 < \alpha(t) \leq 1$), which decreases with each learning epoch t; $h_{oj}(t)$ is the strength of mutual influence for any pair of neurons o and j, determined as a function (usually Gaussian) of the distance between them on the map topology:

$$h_{oj}(t) = \exp\left[-\frac{\|\mathbf{r}_o - \mathbf{r}_j\|^2}{2 \cdot \sigma^2(t)}\right] \tag{4}$$

where $\mathbf{r}_o$, $\mathbf{r}_j$ are the two-dimensional vectors of coordinates of geometric location of the neuron-winner o and the j^{th} neuron on the map; $\sigma(t)$ is the effective width of the topological neighborhood (a specially chosen function of time that monotonically decreases in the learning process).

In the process of self-organization of the Kohonen map, the topological neighborhood narrows. This is caused by a gradual decrease in the width of the function $\sigma(t)$. The neuron-winner is located in the center of the topological neighborhood. It affects neighboring neurons, but this effect decreases with increasing distance to them according to (4). As a result, closely located map nodes acquire similar characteristics.

The result of the learning process will be the tuning of parameters of the Kohonen layer neurons, which will correspond to different examples from the training set. Thus, the self-organization of the structure of the Kohonen map is carried out, which acquires the ability to combine multidimensional data vectors in a cluster by identifying similar statistical characteristics in them. As a result, the initial high-dimensional space is projected onto a two-dimensional map. Since self-organization maps are characterized by the generalization property, they can recognize input examples on which they have not previously been tuned – the new input data vector corresponds to the map element to which it is mapped.

3. Collection of data for modeling

In order to correctly identify regularities in the development of the scientific and educational sphere, it is necessary to select the key properties that characterize the processes under study, taking into account the task. That is, it is necessary not only to choose the maximum possible set of characteristics of the objects of study, but to form a set of those features that describe the most significant aspects of activity in the context of the analysis. In this case, the selected features will make it possible to group the studied objects or processes according to their similarity. That is, if the task of analyzing the competitiveness of universities is being solved, then it is necessary to determine a set of characteristics of countries that will influence this indicator. And as a result of clustering the countries of the world according to these characteristics, we will get a number of clusters, each of which will group countries with a similar level of international competitiveness of universities (since they will have fairly close values of the characteristics that determine this competitiveness).

Therefore, we will conduct an analysis of publicly available databases that contain information on indicators that can influence the level of competitiveness of universities.

Thus, the World Bank's "World Development Indicators" database contains the ranking of the world's countries by the level of "Government expenditure on education, total (% of GDP)" indicator [43]. The indicator is calculated annually (for 266 countries) based on data from national statistics and international organizations, including data from the UN. Information on individual countries has been available in this database since 1970, in the last decade the data is presented quite fully, but only until 2018 (later data by countries is much less). Other indicators presented in this database are much poorer and less related to higher education.

In the Human Development Reports of UNDP [44] there are data for 195 countries for 2021 according to the indicators: "Human Development Index (HDI)" (both in general and by male and female sexes, in addition, by this indicator also shows the dynamics and increases in dynamics since 1990), "Government expenditure on education, % of GDP", "High-skill to low-skill ratio", "Research and development expenditure, % of GDP" (during 2014-2018), "Ratio of education and health expenditure to military expenditure" (during 2010-2017), "Foreign direct investment, net inflows, % of GDP", "International student mobility, % of total tertiary enrollment", indicators of employment and unemployment both in general and among young people, migrants, population by age group, etc.

The Global Competitiveness Index from the World Economic Forum for 2019 [45] can also be informative in assessing the international competitiveness of the country's universities. On this resource, this index is given for 141 countries. Later, in 2020, the Global Competitiveness Index has been paused.

Another resource with information on competitiveness is the annual reports of the European Commission [46], in particular in the areas of: "Competitiveness & Innovation", which contains separate reports and the following sections: "Global Innovation Index", "Global Attractiveness Index", "Global Talent Competitiveness Index", "Elcano Global Presence Index", "Innovation Output Indicator"; "Learning & Research", which presents reports: "European Skills Index", "European Lifelong Learning Indicators (ELLI-Index)", "Higher Education Rankings", "Composite Learning Index".

The work "Global Talent Competitiveness Index: 2019" [47] contains integrated assessments and ranking places of countries for a number of top-level indices, as well as for basic indicators.

To assess the competitiveness of world universities, the resource [48] can be useful, which provides fairly detailed country-level aggregated information on the research and educational activities of universities in 50 countries for 2020. Here are the indicators grouped into four generalized categories – "Resources", "Environment", "Connectivity", "Output". Each of these categories consists of a set of basic indices, all of which are listed in the header of the table 1.

In addition, we add to the database the overall competitiveness score and rank number in the general list (these indicators will not be taken into account when clustering countries, but will serve as a reference when analyzing clusters).

To carry out clustering based on Kohonen maps, it is necessary to avoid gaps in the data. Since there are only 50 countries in this database, moreover, the scores for each individual indicator for different countries are quite close to each other, so we will not divide countries into groups and replace the blanks with the corresponding average values for all countries. This will not lead to distortions of the clustering results, since the percentage of gaps in this database is very small.

4. Modeling the university competitiveness

The construction of Kohonen self-organizing maps in our study was carried out using the analytical platform Deductor Studio Academic. In the process of constructing a map, the task of finding its optimal dimension (number of neurons) arises, which is implemented experimentally on the basis of statistical data. The dimension of the self-organizing map was chosen from various options according to the mean weighted quantization error criterion, which reflects the average distance between the data vector given to the map inputs and neurons' parameters.

A hexagonal lattice of neurons with dimensions of 8 by 8 was determined as the most adequate structure of a self-organizing map for this task according to a given set of indicators (table 1). Self-organization occurs over 1500 learning epochs.The map parameters are initialized with small random variables. Gaussian (4) was chosen as a function of the neighborhood of neurons. Since all indicators for assessing the competitiveness of universities are already presented on an identical scale from 0 to 100, none of them will have a decisive influence on the clustering process.

Table 1

Indicators of evaluation of international competitiveness of countries' universities.

	OVERALL RANKING				RESOURCES 2020 SCORES					ENVIRONMENT 2020 SCORES					CONNECTIVITY 2020 SCORES					OUTPUT 2020 SCORES								
Country	Rank 2020	Rank 2019	Score 2020	Score 2019	Government expenditure on tertiary education as a percentage of GDP	Total expenditure on tertiary education as a percentage of GDP	Total expenditure per student USD PPP	Expenditure in tertiary institutions for R&D as a percent of GDP	Expenditure in tertiary institutions for R&D per head of population	Proportion of female students	Proportion of female academic staff	Data quality	Qualitative index of environment	WEF Survey	Proportion of international students	Proportion of articles with international collaborators	Webometrics VISIBILITY index divided by population	Rating of knowledge transfer between university and companies	Percentage of university research publications co-authored with industry	Total number of documents produced by higher education institutions	Total documents produced per head of population	Average impact of articles	Weighted Shanghai ranking scores for universities per head of population	Shanghai scores for best three universities	Tertiary enrollment rates	Percentage of population aged 24-64 with a tertiary qualification	Number of researchers in the nation per head of population	Unemployment rate of the tertiary educated compared with school leavers
Argentina	40	38	46	45,1	56,7	48,4	13,8	13,4	4,7	100	97,1	100	67,8	51,3	9,1	52,4	7	54,1	19,5	2,1	6,2	45,9	2,6	13,1	90	61,6	14,9	30,9
Australia	9	8	82,2	80,9	37,7	70,6	42,9	64	51,2	100	91,3	100	98,1	81,9	78,9	72,8	56	68,1	41,4	15,9	85,3	84,3	76,8	39,3	100	79	55	32,6
Austria	12	12	79,3	77,2	81,9	64,8	48,7	68,6	63,7	100	84,7	100	72	68,3	63,1	86,9	54	84,8	100	3,3	49,4	86	57	22	85,1	56,5	62,5	31,3
Belgium	13	13	75,6	73,6	63,8	55,4	48,3	53	45	100	97,1	100	75,8	82,2	31,8	89,3	28,4	82,5	78,8	4,8	56,6	94,2	51,4	31,4	79,7	70,2	59,9	39,1
Brazil	41	40	45,6	44,1	49,9	66,5	37,9	n.a.	n.a.	100	91,4	88,6	63,8	41,8	0,9	43,8	6,9	40,3	26,2	11,6	7,5	45,3	3,8	21,2	51,3	31,8	10,7	39,7
Bulgaria	45	44	42,7	41,8	32,3	40,3	17,8	4,3	1,6	100	97,9	93,2	53,1	54,7	16,8	57,5	10,9	46	44,3	0,8	14,6	55,2	3,3	2,7	71,2	38,1	25,8	45,2
Canada	7	6	83,2	81,9	62,5	86,8	62,9	63,6	53	100	88,6	90,9	73,3	87,1	47,4	68,8	69,2	86,3	59	17,2	62,6	82	44	42,9	88,2	100	51,8	33,7
Chile	31	32	54,3	51,3	48,4	100	22,3	14,8	6	100	85,1	100	81,4	54,8	1,4	81,6	14,3	62,3	28,3	2,2	16,1	63,4	8,2	11,8	88,5	43,5	6,1	30,2
China	26	27	56,8	54,7	42,5	50,7	20	15	4,4	100	n.a.	88,6	76,6	73	1,3	34,1	8,4	65,9	32	70,7	6,8	59,3	7,5	39,6	49,1	16,7	15	n.a.
Croatia	43	43	43,6	42,1	49,9	36,8	18	24,9	11,2	100	97,8	93,2	47,3	47	1,6	58,3	11	35,5	50,8	0,9	30,4	52,9	17,2	8	66,5	39,2	22,6	31,2
Czech Rep.	29	26	54,8	55,2	36,3	35,1	26,6	34,4	22,2	100	76,9	100	69,3	61,1	46,1	62	29,3	53,6	55,7	2,9	37	62,8	22	14,7	64,1	41,9	44,7	40,4
Denmark	3	5	85,7	82,5	80,4	62,7	44,9	100	91,4	100	88,6	95,5	67,4	80,6	39,5	85,3	47,5	89,2	85,2	4,3	100	97,1	83,3	38,8	80,6	65,7	95,7	21
Finland	8	9	82,8	80,4	80,8	61,9	46,6	68,5	54,6	100	100	100	81,6	93,8	30	82,3	64,7	90	77	2,9	70,8	86	72,2	23,9	88,2	78,1	81,3	41,3
France	17	17	68,6	67,6	57	53,6	43	44,3	35	100	87,9	100	73,1	69,6	37,4	77,7	23,8	70,3	68,8	13,5	28,2	75,6	28,9	40,6	65,6	63,7	53,8	39,8
Germany	16	16	70,5	69,6	51,3	44,9	46,3	51,2	46	97	78,6	100	61,6	86,8	30,8	67,8	38,6	87,9	76	21	34,2	79,1	32,9	39,7	70,2	50,2	61	37
Greece	37	37	47,4	47	35,1	26	10,9	31,8	15,5	97,1	68,6	93,2	26,9	49,2	12,5	68,7	35,2	43,7	61,5	2,5	31,2	73,3	21	14,1	100	54,8	38,2	36
Hong Kong	14	15	72,7	70,2	50,1	55,6	64,7	39,8	43,3	100	n.a.	90,9	97,2	76,7	42	54,3	48,2	82,5	35,8	3,5	63,7	95,9	54,9	26,3	74,3	50,9	41,4	41,4
Hungary	33	35	51,3	48,5	34,7	39,7	30	17,6	8,8	100	80,5	100	51,6	47	36,6	70,9	22,1	58,6	82,8	1,6	22,3	69,2	14,4	10,7	48,5	43,4	35,4	54,6
India	49	49	39,6	38,8	54,8	59,1	13	2,4	0,3	96,2	81,2	90,9	58,1	74,6	0,5	27,2	0,9	57,8	19	14,9	1,5	47,1	0,6	12,5	27,4	18,3	2,6	12,6
Indonesia	50	50	35	33,5	25,7	25	7,9	4,6	1	100	86,2	100	64,7	71,6	0,3	23,6	4,4	72,5	31,4	3,1	1,6	45,3	0	0	36,4	20,5	2,6	26,4
Iran	47	48	42,2	39,2	50,2	51,9	15	n.a.	n.a.	92,1	62,2	81,8	67	52,8	1,6	33,7	5,1	52,1	10,6	7,3	12	51,7	5	15,2	69,6	36,9	8,1	n.a.
Ireland	19	19	66	64,7	28,7	29,6	35,2	25,2	33,7	100	90	100	68,6	87,6	32,6	75,1	60,1	88,2	63	2,4	64,8	80,8	47,6	18,7	77,8	81,1	49,8	36,8
Israel	18	18	67,4	67,3	39,4	52,1	29,6	50,9	34,6	100	n.a.	95,5	73,3	74,9	10,6	66,3	34,6	91,1	49,5	3,2	48,5	77,9	51,5	30,6	63,4	88	100	34,6
Italy	30	30	54,5	53,4	28,6	33	30,8	32,1	22,5	100	74,2	100	63,8	60	19,5	62,9	18	60,5	54,2	15,7	34,9	77,3	29,4	24,6	61,9	33,4	27,8	35,6
Japan	20	20	61,9	61,7	21,2	51,2	51	37,6	28,9	95,4	56,8	100	83,2	70,8	15,7	39	18,9	57	78	17,2	18,4	50,6	14,5	42,9	63,6	89,7	64,3	34,5
Korea	24	23	58	57,4	32,7	64,4	27,8	37,7	25,7	83,4	70,2	100	58	56,3	8,3	37,9	14,8	62,6	61,4	12,4	32,3	56,4	24,1	24,8	94,3	84,7	91,1	25,2
Malaysia	27	28	56,1	54,5	56,5	75,1	39,4	48	22,9	100	100	95,5	78,6	83,7	29,6	59,5	7,5	79,4	16,3	3,6	15,1	55,8	5,8	14	43,7	37,7	28,6	21,6
Mexico	48	47	41,7	41,1	47,2	50,5	19,5	12,7	4,1	100	n.a.	95,5	82,4	48,5	2,1	53	3,8	52,9	19,5	3	3,2	42,4	0,8	11,1	40,2	31,1	3	20,7
Netherlands	10	10	81,6	80,2	59,8	62,7	51,8	58,3	54,3	100	91,7	100	79,3	88	40,4	82,5	47,5	96,7	85,4	9	70,7	97,7	59,4	37,5	85	66,2	60,7	34,7
New Zealand	14	14	72,7	71,5	44,1	64,5	39,7	33,6	21,4	100	99,7	100	89,7	86,5	72	77,3	55,8	76,1	46,4	2,2	59,5	79,1	64,6	18,4	82	67,9	49,1	33,9
Norway	11	11	80,5	77,8	89,9	70,7	58,4	68,8	74,8	100	92,6	100	66,9	85,9	11,6	80,8	58,9	81	61,8	3,1	78,2	87,2	63	28,1	82	75,3	78,5	32,2
Poland	32	31	52,6	52,2	48,4	43,9	23,8	33,3	17,2	100	90	100	81,9	58,3	15,1	42,3	17,3	60,4	32,3	6,4	22,8	58,1	7,3	14,1	67,8	53,4	30,6	49,1
Portugal	25	25	57,6	56,8	39,4	42,6	29,3	55,3	31	100	88,6	100	60,9	71,7	23,5	71,9	33,9	64,5	41,5	3,6	47,2	66,9	26,7	18,7	63,9	43,1	52	33,7
Romania	44	45	43	41,7	32,9	42,8	28,9	5,2	2,4	100	100	95,5	76	45,2	17,7	36,6	10,2	54	32,1	2,3	15,9	50,6	2,7	5,9	48,2	29,6	10,8	45,8
Russia	35	35	49,1	48,5	37,3	42,5	22,5	9,8	4,6	100	100	100	70,2	60,1	15	36,2	8,4	43,9	20,1	8,8	8,3	47,7	2,9	21,7	81,9	97,9	34,6	47,7
Saudi Arabia	22	22	59,3	59,3	100	77,7	53,1	n.a.	n.a.	96,3	81,7	79,5	50,5	69,3	17,1	100	3,9	68,9	29,6	3,1	12,7	76,7	7,8	24,8	69,7	41,2	n.a.	9,4
Serbia	42	41	44,2	43,4	55,8	48,7	17,4	32,9	8,8	100	93,1	90,9	42,3	52,9	16,3	62,1	8,5	52,1	23,7	1,1	20,5	53,5	9,3	7,4	66,5	37,2	25,2	28,7
Singapore	4	7	84,5	81,3	50,1	53,7	100	63,4	100	100	74,1	95,5	82	94	100	87,7	36,7	91,7	38,6	2,8	66,5	94,8	41,4	26,5	84,8	86,5	81,6	30,6
Slovakia	38	33	47,2	49,6	35,8	37	30,3	21,2	11,9	100	91,5	100	64,2	44,8	25,3	57,7	16,8	35,6	64,4	1	24,2	63,4	4,7	2,9	46,6	42,5	33,9	46,4
Slovenia	28	29	55,4	53,6	44,5	38,3	29,9	20,3	12,6	100	85,1	100	63,7	65,3	14,3	71,1	25,1	63,1	53,6	0,7	48,8	67,4	31,4	7,4	78,6	56,1	54,2	35,9
SAR	34	34	49,7	48,7	37,4	49,9	28,9	26,2	6,1	100	n.a.	88,6	86,7	45,3	11,9	68,6	3,7	54,8	36,9	3,7	8,6	69,8	5,8	18,6	22,4	12,4	6	100
Spain	23	24	58,6	57,3	41,6	45,9	33,5	32	21,6	100	86,9	100	69,9	59,5	11,9	61,6	30,7	57	46,2	12,7	37	65,7	29,9	22	88,9	64,4	34,8	39,7
Sweden	5	4	84,3	82,9	71,2	59,7	64,6	83,2	73,7	100	89,7	100	75,2	76,9	24,8	86,8	59,6	83,1	86,2	6,3	83,5	89,5	82,5	38,8	67	74,7	92	24,4
Switzerland	2	2	90,1	88,6	64,9	51,7	75,4	88	97,6	99,4	71	100	69,5	100	65,2	91,3	79,7	100	76,9	5,8	91,7	100	100	44,2	59,6	75,6	63,7	30,4
Taiwan	21	21	60,5	60,5	33,5	51,8	32,8	29,3	26,2	100	72	93,2	86,9	72,3	16,2	45,4	44,3	80	38,3	5,1	29,1	55,2	20,3	19,7	84,5	84,5	76,1	25
Thailand	46	46	42,3	41,2	32,1	34,8	13,7	13,7	4,2	100	100	95,5	71,9	60,1	4,8	57,8	10,2	65,5	34,7	2,1	4,3	53,5	1,8	11,3	49,3	28,1	14,7	18,2
Turkey	39	42	46,3	43,3	71,1	70,5	27,9	31,5	14,8	92	88	100	44,9	51,3	5,5	30,6	7,6	57,4	16,6	7,2	11,9	44,2	4,1	11,2	94,7	35,9	16,8	23,2
Ukraine	36	38	47,8	45,1	76,4	63,9	10,8	3,2	0,5	100	n.a.	90,9	60,6	62,4	11,6	41,2	8	45,8	60,4	1,3	4,2	33,1	0	0	83,4	84,4	12	58,3
UK	6	3	83,6	84,5	28,2	64,7	63,1	38,8	29,7	100	89,5	100	89,5	75,5	65,8	72,1	63,7	82,1	68,9	31,1	63,1	86	58,1	73,7	60	79,1	53,1	34,4
USA	1	1	100	100	42,6	91,2	80,1	35,7	37,7	100	98,2	100	100	90,8	19	45	100	92,3	58,4	100	41,2	78,5	43,4	100	88,2	81,9	51,6	48,7

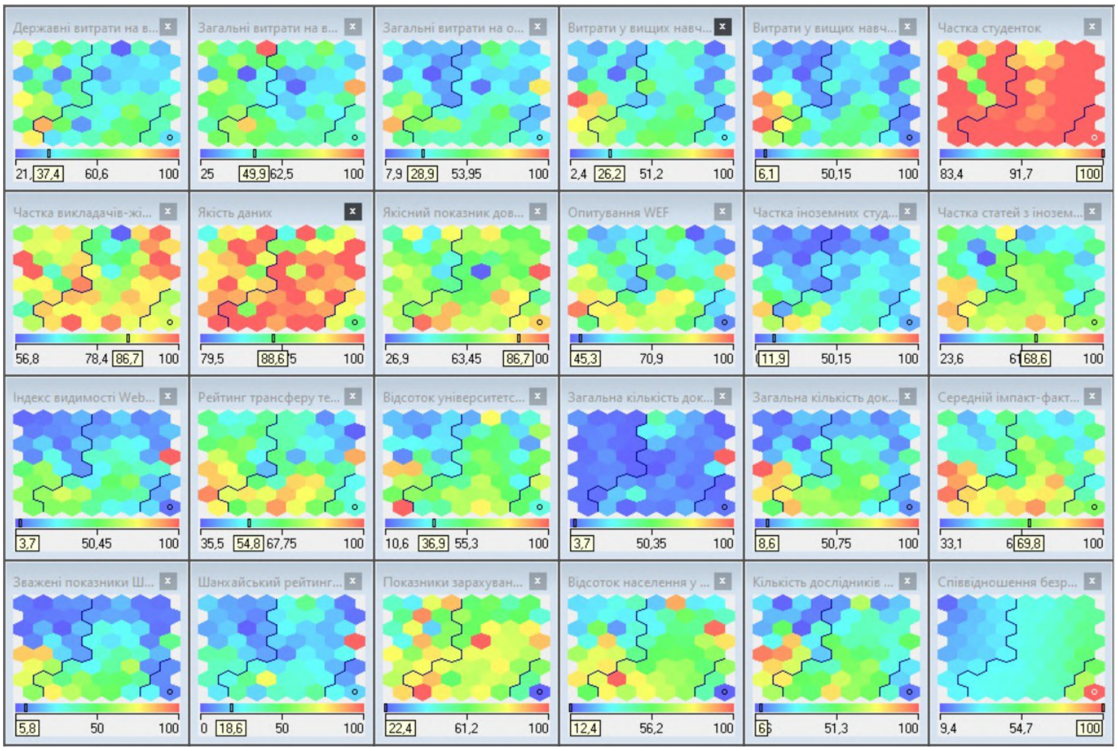

Figure 2: Kohonen topological maps for all indicators of university competitiveness assessment.

Therefore, it was decided to build Kohonen maps on the original data without processing them. As a result of the process of self-organization, the countries from the table 1 were distributed among three clusters, which can be seen in figure 2.

As can be seen from the topological maps for all indicators in figure 2, for the vast majority of them there is no clear demarcation of their levels between clusters. That is, their low, medium and high values are evenly distributed throughout the map, which, together with the low levels of significance of many indicators (figure 3), does not contribute to the quality of the countries segmentation process.

Given the low significance of a large number of indicators selected for the study, a series of experiments was conducted on the construction of Kohonen maps on different sets of input variables, when various combinations of the least influential factors were alternately removed. However, each time the same low quality of the distribution of countries by the levels of university competitiveness evaluation indicators remained. For example, for all clustering options, Bulgaria, South Africa, Poland, the Russian Federation, Romania, Slovakia, Hungary, and Croatia were located next to Ukraine on Kohonen map, but the United States was also a neighbor in this cluster. Of course, such segmentation of countries cannot be considered acceptable.

Therefore, it was decided to apply z-score standardization to process the initial values of the variables. As a result of forming a map on the full set of standardized explanatory variables, 5

Indicator	Significance of the indicator			
	Cluster 1	Cluster 2	Cluster 3	In all
	29 (58,0%)	18 (36,0%)	3 (6,0%)	
Proportion of female students	48,1%	61,4%	45,0%	66,3%
Data quality	46,3%	33,6%	71,7%	64,7%
Total expenditure per student USD PPP	35,6%	14,2%	74,5%	56,8%
Total expenditure on tertiary education as a percentage of GDP	38,3%	55,9%	23,4%	47,8%
Proportion of international students	31,8%	29,6%	29,2%	25,7%
Proportion of female academic staff	22,5%	22,1%	27,6%	16,4%
Proportion of articles with international collaborators	4,1%	9,1%	12,2%	2,3%

Figure 3: Levels of significance of a number of indicators for evaluating the competitiveness of universities.

clusters were obtained (figure 4).

Figure 4 shows that the levels of indicators change when crossing from cluster to cluster, which indicates a successful delimitation of countries based on a given set of explanatory variables. Ukraine got to the upper right corner of the Kohonen map next to Argentina, Bulgaria, Poland, the Russian Federation, Serbia, Turkey, Croatia, and Chile. Somewhat lower in the same cluster

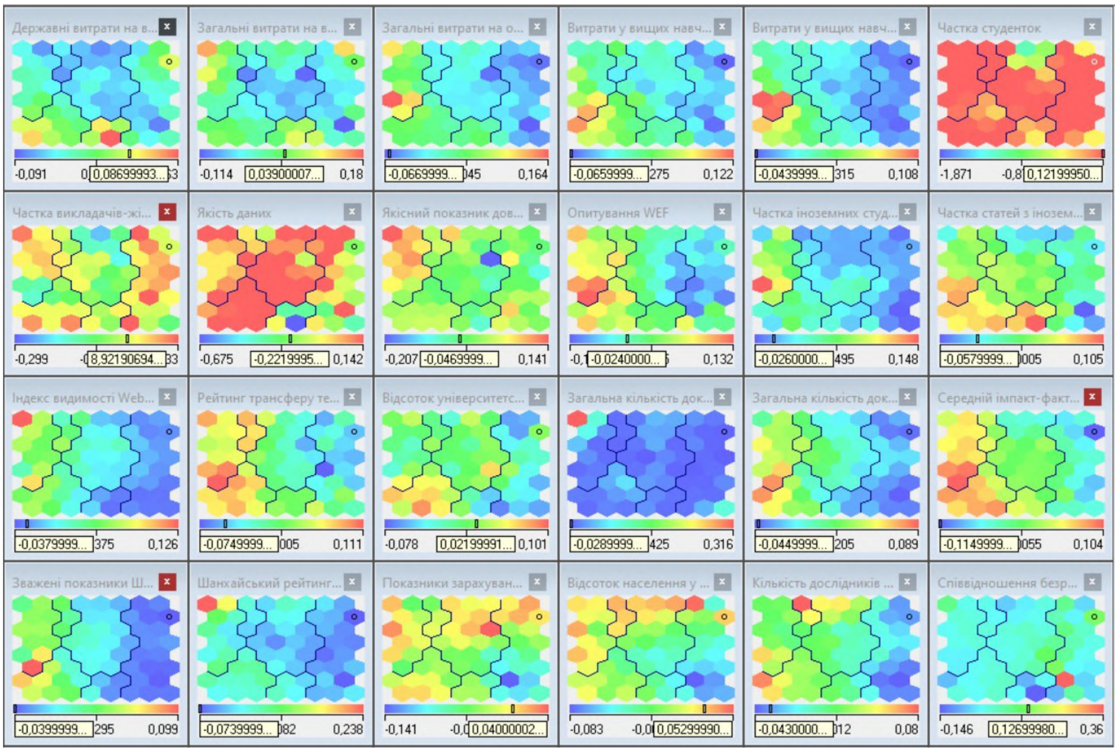

Figure 4: Kohonen topological maps according to the normalized indicators of university competitiveness assessment.

were Brazil, India, Indonesia, Iran, China, Malaysia, Mexico, South Africa, Romania, Slovakia, and Thailand.

Austria, Denmark, the Netherlands, Norway, Singapore, Finland, Switzerland, Sweden are located in the opposite corner of the map from Ukraine (bottom left). The United States and Great Britain were located in the upper left corner of the map. They are surrounded by Australia, Hong Kong, Israel, Canada, and Taiwan.

It should be noted that since, in accordance with the given task, polar objects are located on the Kohonen map in opposite corners, this self-organization of countries indicates that the competitiveness of Ukrainian universities is currently quite far from the competitiveness of universities in developed countries.

The analysis of the characteristics of the universities of the countries of the most developed cluster makes it possible to determine the priority areas of development and tasks that must be solved in order to increase the international competitiveness of Ukrainian universities.

Research and generalization of traditional, entrepreneurial, innovative and creative models of universities, their selection depending on objective endogenous and exogenous conditions and imperatives of the development of Ukrainian higher education made it possible to substantiate the most adaptive competitive model of the university, which is shown in figure 5.

Critically important in the proposed model is the development of strategic partnership in the triangle "science – business – education", public-private partnership and consolidated social

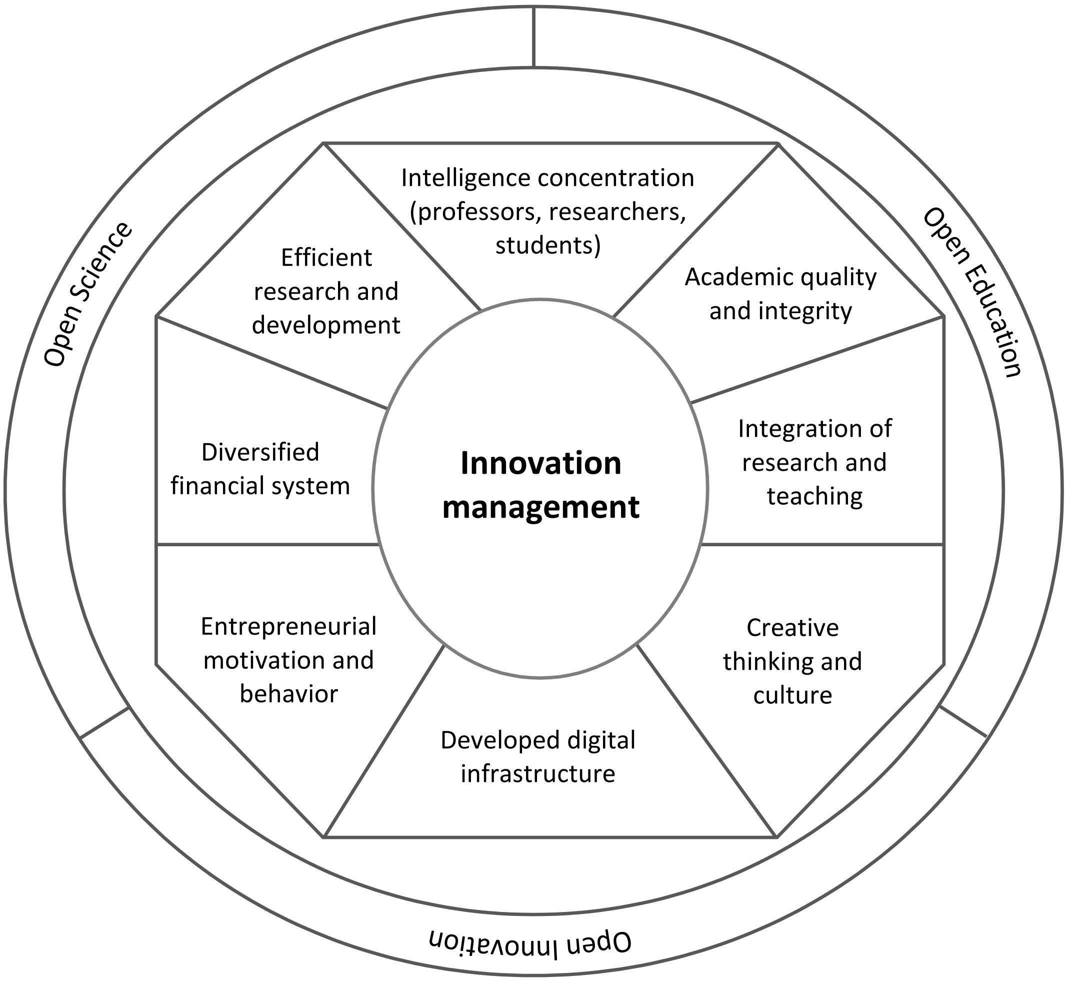

Figure 5: Competitive model of the university.

responsibility.

5. Conclusions

The evolving global landscape of university education presents fresh challenges for educational authorities and university administrations, urging them to bolster competitiveness in the international educational services market. Amidst the modern era of globalization, there arises a need to efficiently manage universities, necessitating the assessment of their international competitiveness.

In today's ever-changing world, organizations like corporations and universities must navigate political, market, and social turbulence. This calls for continuous generation of unconventional ideas, strategic concepts, and behaviors to drive innovation.

This research is driven by a mission to establish a fresh methodological approach for evaluating the often elusive indicator of university competitiveness. Given the lack of standardized evaluation indicators and measurement scales, a clustering approach was chosen to uncover hidden patterns within a set of explanatory variables.

The study involved a comprehensive exploration of existing approaches to assessing university competitiveness and identified unresolved issues in the field. Diverse clustering methods were analyzed, comparing their strengths and characteristics to identify the most fitting approach.

The innovation proposed in this paper lies in the application of artificial neural networks, particularly Kohonen maps, for modeling university competitiveness. Kohonen maps facilitate data clustering based on similarity and visual representation in a lower-dimensional space. Using these maps, we clustered countries based on parameters such as research output, teaching quality, internationalization, social responsibility, digitization, expenditure, and employability. We also employed Kohonen maps to rank the significance of these parameters for distinct country clusters.

The utilization of Kohonen self-organizing maps demonstrated its worth, not just in forming homogenous groups of research subjects, but also as a powerful tool for visually dissecting clustering outcomes. Moreover, this methodology aids in identifying lagging indicators, enabling strategic interventions to enhance the competitiveness of Ukrainian universities in the global educational services market.

This method boasts multiple advantages over existing ones. Firstly, it operates without depending on expert judgments or predefined parameter weights. Secondly, it accommodates vast and diverse datasets with differing variable types. Thirdly, it uncovers latent patterns not immediately apparent with conventional techniques. Lastly, it offers intuitive, interactive visualizations, facilitating comprehension and communication.

The culmination of this research yielded a competitive university model, unraveling the competitive strengths of universities within the most competitive cluster countries. This underscores the practical applicability and potency of the proposed approach in assessing and elevating university competitiveness in the contemporary educational landscape.

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